ESSAYS ON LIMITED ATTENTION IN INFORMATION-RICH ENVIRONMENTS

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Abstract

If information is abundant, the resource that in turn becomes scarce and in need of allocation is what information consumes – the attention of its recipients. Drawing from recent advances in behavioural decision theory, this thesis presents three essays on issues relating to limited attention in information-rich environments. In the first essay, we attempt to explain recent empirical discrepancies suggesting that despite low material costs, consumers continue to search for a very narrow number of alternatives in online contexts. We appeal to the idea of a general economy of attention and suggest that this discrepancy can be understood through the lens of a fundamental attention allocation problem. In the second essay, we build on this analysis and ask whether individuals that prioritise the expansion of alternatives in their decision making process suffer a decline in their ability to exercise deliberative judgement. We draw on the psychological literature on heuristics and biases and demonstrate that individuals attempting to 'behaviourally maximise' are more susceptible to rudimentary judgemental fallacies as compared to decision makers that directly confront their own cognitive limitations. Finally, the third essay, draws on these insights and investigates the interplay between selective attention, enduring personal dispositions and task complexity on the facility with which individuals can deploy simplifying selection policies when choosing between items within a bundle. We demonstrate that alongside the information structure characterising task environments, individuals' capacity to efficiently allocate attention has implications on their ability to simplify the problem space within contexts where multiple conflicting objectives need to be taken into account and counterbalanced.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright Statement

Dedication

To the memory of my grandfather Shri. K.C. Joshi

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1

Introduction

"The Library exists ab-aeterno."

– Jorge Luis Borges, *The Library of Babel*

1.1 Motivation

One of the driving forces of the information age was the view that more information is always better, a notion that is succinctly captured in Godfrey & Parkhill's (1979) maxim "all information in all places at all times". This rallying call has heralded the tremendous progress of our society from one where information was an imminently scarce resource to where information abundance has not only been realised but emphatically so, bordering on the precipice of epistemic ambivalence. As a stark reminder of this progress, we need only to venture as far as the Queen's college library holdings at Cambridge. In 1472, as the largest library in the world, it housed 199 books, today it holds a collection of 20,000 'early printed volumes' and performs the role of a historical archive drawing visitors that marvel at the nostalgia of a bygone era. In contrast, the latest available statistics from the last decade suggest that in the year 2013, nearly 200,000 thousand books were published in the United Kingdom alone (Flood, 2014) – some quick arithmetic will tell us that this equates to roughly 20 books every hour – filling the rustic shelves at Cambridge in under half a day! Today, the corridors of the University libraries are filled with the sounds of the clacking of keys and frantic mouse clicks rather than the rustling of pages. Even the cafeteria has not been spared, for a quick sandwich a bleary-eyed patron can choose between whole-wheat, bran, white-bloomer or rye, vegan, vegetarian, pescatarian or meat all emblazoned with their calorific values, nutritional content, color coded for convenience and when its time to pay – cash, contactless or credit. An economy of information this is not.

On the one hand, this means that from the most innocuous of choices – what to watch on Netflix – to the most profound decisions like choosing a partner or voting for Brexit, our environment is rife with signals. On the other, it means that we must contend with a wealth of information that is far beyond our capacity to attend. Simon (1971) reminds us of this fact:

> "In an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it" (Simon, 1971, pp. 40-41).

Ever since Simon's (1955, 1971, 1972) initial articulation of the concept of bounded rationality, decision making research has pivoted towards two extremes. On the one hand proposing an idealistic view of rational calculating organisms, acting in their best interest and (mostly) conforming to the provisions of utility maximization (Keeney & Raiffa, 1993; Morgenstern & Von Neumann, 1953) and on the other, proposing predictably irrational actors, driven by affect, intuition and 'animal spirits' (Ariely, 2008; Thaler & Sunstein, 2009; Tversky & Kahneman, 1974). In this thesis, we study a third way, one that attempts to somewhat reconcile these strands and proposes that decision making is best understood as a situated activity somewhere at the intersection of these seemingly divergent extremes (Gigerenzer, Todd, & ABC Research Group, 1999; Katsikopoulos, 2016). The basic building block to this approach is the proposition that good decision making – rather than in the conformity of behaviour with normatively prescribed models of rational action – should be assessed by evaluating the ability with which individuals can efficiently deploy their limited attentive and cognitive resources in a manner that is conducive to the demands of the task environments within which they operate.

The research presented in this volume thus, comprises of three essays on issues relating to limited attention in information-rich environments. The first, considers attention as a scarce resource in online contexts and presents an aggregate level analysis of consumer search behaviour. The second, considers the role of individual differences and attempts to investigate how decision makers that neglect their own cognitive limitations might, in a number of cases, suffer poorer qualitative decision outcomes. The third, synthesises these approaches and considers the interplay between individual cognitive abilities and task characteristics in aided decision making contexts highlighting that the (in)attentional costs of selective information processing are non-negligible.

Each essay can be read independently of the other since it proposes its own research questions, relies on separate methodological apparatus and forwards self-contained theses. At the same time, each essay follows a chronological development of ideas that reflect the core motivation behind the conduct of this research.

In the first essay, *The Attention Economy of Online Search*, we attempt to explain recent empirical discrepancies suggesting that despite low material costs, consumers continue to search for a very narrow number of alternatives in online contexts (Holland, Jacobs, & Klein, 2016; Johnson, Moe, Fader, Bellman, & Lohse, 2004; Zhang, Fang, & Liu Sheng, 2006). We appeal to Simon's (1971) idea of a general economy of attention and suggest that this discrepancy can be understood through the lens of a fundamental attention allocation problem. We build on empirical facts reported in the behavioural decision making and consumer research literatures – highlighting that individuals face upper bounds on their capacity for reasoning and decision making (Simon, 1955), search from a small consideration set of attended alternatives (Hauser & Wernerfelt, 1990) and are sensitive to the saliency of information in online contexts (Hefti & Heinke, 2015; Kahneman, 1973) – in order to develop an empirical model for the online search process. We demonstrate that limited online search can be explained due to an allocative trade-off between the number of alternatives consumers actively consider and the amount of time they can spend evaluating information on individual alternatives. Moreover, we show that the competitive intensity in online markets for attention, has significant implications on the strength and magnitude of this trade-off. For concentrated markets, where a fewer number of brands control a relatively larger proportion of the market, aggregate search time is reduced by nearly half while, for moderate levels of concentration, the rate at which search time declines with the inclusion of additional alternatives is significantly increased. Apart from demonstrating fundamentally asymmetric levels of competition in online markets (Peterson & Merino, 2003), these findings reinforce the importance of brand salience in online contexts. Our findings add to the growing consensus within the consumer behaviour literature suggesting that individuals use the consideration set as a heuristic strategy (Hauser, 2014) to limit the cognitive demands associated with a more extensive search process and suggest that at an aggregate level, individuals prefer to search more intensively for fewer brand alternatives rather than spread their search over a larger number of brands. We demonstrate the generality of this basic finding and show that while there is some heterogeneity in the extent of this trade-off between industries, the nature of this relationship is fairly robust across seven important US consumer markets.

The second essay, *Irrational Maximisers?* builds on this analysis and asks whether individuals that arbitrarily prioritise the expansion of alternatives in their decision making process suffer a decline in their ability to exercise deliberative judgement. A number of studies in the behavioural decision making literature have highlighted that a maximising decision orientation is associated with poorer affective outcomes and a generally pessimistic approach towards decision making (Polman, 2010; Roets, Schwartz, & Guan, 2012; Schwartz et al., 2002). Iyengar, Wells, & Schwartz (2006) initially suggested that even though maximisers make better choices than their satisficing counterparts, this negative affect is associated with their reliance on extensive alternative search as a fundamental feature of their decision process. Parker, De Bruin, & Fischhoff (2007) recently highlighted that a tendency to behaviourally maximise is negatively associated with general decision making competency. We draw on the psychological literature on heuristics and biases (Tversky & Kahneman, 1974), find support for Parker et al.'s (2007) findings and demonstrate that paradoxically, individuals that attempt to behaviourally maximise are more susceptible to rudimentary judgemental fallacies as compared to decision makers that directly confront their own cognitive limitations. Importantly however, we provide an explanation for the circumstances in which maximisers are prone to making poorer decisions by highlighting that they are susceptible to an overreliance on easily comparable attributes, arbitrary variety seeking and representativeness in circumstances where the task at hand exploits these biases. Moreover, rather than a matter of adaptively choosing such strategies (Gigerenzer et al., 1999), an overreliance on these approaches appears to be a systematic feature of the maximising decision orientation and persists even in cases when the task environment does not support their use.

The final essay *Inhibition, Integration and Selection*, draws on the learnings from the preceding studies and investigates the interplay between selective attention, enduring personal dispositions and task complexity on the ease with which individuals can deploy simplifying selection policies when choosing between items within a bundle. We build on the recent findings forwarded by decision scientists suggesting that simple heuristics that rely on selective processing rather than an integration of all information within decision environments can, in a number of circumstances, lead to good choices (Fasolo, McClelland, & Todd, 2007; Gigerenzer & Selten, 2001; Katsikopoulos, 2016). We show that when it comes to prescriptive applications of such strategies, enduring personal dispositions are related to general task performance and do not provide much discriminatory insight into strategy execution. On the other hand, our findings underline that the costs of ignoring available task information are non-negligible. We demonstrate that alongside the information structure within task environments, individuals' capacity to efficiently allocate attention has implications on their ability to simplify the problem space within contexts where multiple conflicting objectives need to be taken into account and counterbalanced.

1.2 Thesis Structure

This thesis is formatted in accordance with the guidelines outlined by the Management Sciences and Marketing department of the Alliance Manchester Business School at the University of Manchester. It comprises a collection of works presented in a manner suitable for publication and dissemination in peer-reviewed academic journals. In accordance with this format, this thesis is centred around three essays that report original research in Chapters 2, 3 and 4. Each chapter is self-contained and presents its own theoretical and conceptual framework, formulates and answers unique research questions and applies distinct analytical and empirical techniques. The sequence of the chapters corresponds to the order in which research has been undertaken and page numbers, sections, figures and tables follow a sequential order throughout the thesis.

The remainder of this thesis proceeds as follows. In Chapter 2, we evaluate "The Attention Economy of Online Search." In Chapter 3, we ask, "Irrational Maximisers?". In Chapter 4, we consider the interplay between "Inhibition, Integration and Selection". Finally, in Chapter 5, we summarise the main contributions from the preceding essays and provide some directions for further research.

2

The Attention Economy of Online Search: A natural experiment using clickstream data

Abstract

Traditional models of the economics of search suggest that as the material costs associated with searching for products and services are greatly reduced because of the Internet, consumers should search more extensively in online contexts. Recent empirical evidence strongly contradicts this hypothesis. In this paper, we address this discrepancy and situate the problem of limited search within an economy of attention. We conduct a natural experiment using a commercial panel of clickstream data to develop an empirical framework for the online search process based on the size of the consideration set, market concentration of attention and search time. Our results suggest that consumers are faced with a fundamental attention allocation problem characterised by a trade-off between the number of alternatives searched for and the time spent searching for information on individual alternatives. Furthermore, we find that the intensity of competition for attention in online markets affects both the magnitude and strength of this relationship. We discuss the theoretical and managerial implications from our findings and suggest some avenues for further research.

2.1 Introduction

The Internet provides an unprecedented resource for information search, unrestrained by the physical and opportunity costs that moderated consumer search behaviour in traditional retail environments. A recent survey conducted by Deloitte (2014) found that 86% of consumers research brands they are interested in online before shopping in a physical store while nearly two-thirds of consumers use the online medium to seek out store information (61%), prices (57%) and browse for products, services and special promotions (56%). Traditional models of the economics of information search suggest that consumer search behaviour is dependent on a trade-off between the utility gained through price reduction and the additional costs associated with further search, i.e. until marginal cost equals marginal benefit (Ratchford, Lee & Talukdar, 2003; Stigler, 1961; Weitzman, 1979). Building on this model of search behaviour, contemporary research has expanded Stigler's classic approach to include a number of qualitative factors such as product categories, brand recognition, online expertise and prior product experience as fundamental to the consumer search process (Huang, Lurie & Mitra 2009; Smith & Brynjolfsson, 2001). The expectation following this view is that the reduced costs associated with conducting product related search online are associated with a more extensive search process (Alba et al., 1997). With online markets becoming more mature however, a large body of empirical research suggests that this utility maximizing view of the consumer search process is inadequate in its explanation of actual search behaviour. While an increasing number of consumers have adopted the Internet as a tool for facilitating consumption decisions and carrying out pre-purchase search, this has not corresponded to an increase in the number of alternatives that consumers actively consider for purchase. Indeed, the extent of online search remains limited and comparable to search in offline contexts (Dawes, Mundt & Sharp, 2009 ; Holland & Jacobs, 2016; Johnson, Moe, Fader, Bellman & Lohse, 2000; Trinh 2015; Zhang, Fang & Liu-Sheng, 2006).

There are a number of reasons that have been offered for this discrepancy between expected and observed consumer behaviour. Early research looking at the use of the Internet for pre-purchase search suggested that the uncertainty associated with the quality of information available online resulted in the narrower search process.

Johnson et al. (2000) found evidence to suggest that over time, as consumers become more sophisticated in their use of the Internet, they tend to search for a marginally larger number of alternatives. Zhang et al. (2006) repeated Johnson et al.'s (2000) study to find a similarly narrow search process and attributed their findings to the relative infancy of the Internet in US markets at the time of their study. More recent research conducted by Holland, Jacobs & Klein (2016) however, suggests that even in mature online markets with high levels of Internet penetration – in particular they study the US and German markets – consumers continue to search for a rather narrow set of brand alternatives. Similar results have been found in a number of other studies that have focused on the extent of search that consumers conduct prior to making a purchase (Dawes et al., 2009; Trinh 2015).

An alternative stream of research suggests that the inability of information economics to account for a narrower than expected search process can be attributed to the fact that traditional economic models only account for the reduction in the external, physical search costs associated with the Internet while neglecting the cognitive and motivational costs that searching for product and service information online entails (Bettman, Johnson, Luce & Payne, 1993; Peterson & Merino, 2003). In other words, while the adoption of the Internet as a search tool minimises the costs associated with searching for products and services in physical stores, the most significant cost associated with conducting online search is the cognitive and attentive effort required in order to evaluate consumption decisions. This perspective would therefore suggest that while the Internet may make a much larger amount of information available to consumers, the limiting factor in determining the extent of search is the attentive capacity of searchers. While this aspect of consumer search behaviour has been analytically studied in the past, empirical evidence supporting this hypothesis is limited, particularly in the context of online search (Dommermuth & Cundiff, 1967; Hey, 1987; Saad & Russo, 1996; Sonnemans, 1998).

Our study attempts to bridge this gap in the literature by locating the search process within an economy of attention and constructing an empirical framework for the online search process based on the size of the consideration set, the level of concentration of attention within a market and attention as a function of the amount of time consumers spend over the course of a search session. Consequently, our research questions converge around the following stylised facts widely reported in the consumer behaviour and marketing literature (Hefti & Heinke, 2015; Hauser & Wernerfelt, 1990; Kahneman, 1973; Simon, 1971):

- Consumers face upper bounds on their capacity for reasoning and decision-making.

- Consumers search for a subset of brands (i.e. a consideration set) among a larger set of possible alternatives.

- Brand salience is an important determinant of search behaviour.

Following this line of reasoning, we aim to address three simple research questions:

1. Does the size of the consideration set affect the amount of time consumers spend on searching for information on a single alternative?

2. Does the level of concentration of attention in online markets affect the amount of time consumers spend on searching for information on a single alternative?

3. Does the level of concentration of attention moderate the relationship between the consideration set and the amount of time consumers spend searching for information on a single alternative?

In order to address these research questions, we contextualise search as a transaction involving the exchange of product or service related information for consumer attention (Simon, 1971). By conceptualising search as an attention intensive process, we demonstrate empirically that the narrow search patterns uncovered in the data can be explained due to a significant trade-off between the number of alternatives that consumers actively consider over the course of a search session and the amount of time they spend evaluating information on a single alternative. Providing empirical support for an attention economy of search, we suggest that consumers use the consideration set as a heuristic strategy to minimise the attentive effort associated with an extensive search process and that the strength and magnitude of this relationship is contingent on the competitive context of the online market.

2.2 Empirical Methodology

2.2.1 Data

To address our research questions, we use ComScore's disaggregate dataset of online clickstream data, representative of actual search behaviour from a panel of one-million consumers across 200,000 US households. Since many of the previous studies that report small consideration sets (Holland et al., 2016; Huang et al., 2009; Johnson et al., 2000; Zhang, 2006) have relied on this dataset, using ComScore's panel allows us to both, update existing literature with more recent data, as well as contrast our results with previous work. The data was acquired as part of a data sharing arrangement between the authour, the authour's research advisor and ComScore.[1] As the data is anonymised from the source, does not contain demographic or personal identifying information and was not post-processed in any way – apart from the computation of composite measures for market concentration as described in subsequent sections – no special ethical approval was sought for its use beyond general compliance with institutional ethical guidelines and ethical approvals for the conduct of the research reported in this thesis as a whole at the authour's host institution. Specifically, the dataset includes measures of the number of websites (domains) searched by each visitor, the number of pages searched within each domain, the time stamp for each visit and number of unique visitors to each website. We analyse data across seven industries, including air-travel, automotive, banking, insurance, hotels, telecommunications and groceries. The reasons we focus on these particular markets are two-fold. First, as the primary objective of this study is to investigate the trade-off between the number of brand alternatives that consumers search for and the attentive effort associated with searching for each alternative, it is important that the markets represent heterogeneous search contexts in order to minimise the occurrence of confounds due to industry specific and idiosyncratic search behaviours. Second, consideration sets for these industries have been reported in a number of studies considering search behaviour, allowing us to compare our findings with previous research (Dawes et al., 2009; Holland et al., 2016; Terech, Bucklin & Morrison, 2009; Zhang et al., 2006).

[1]The authour thanks ComScore, Prof. Christopher Holland and Dr. Julia Jacobs for providing access to the data. Any errors are the sole responsibility of the authour.

Our sample includes data for 16 airlines, 21 automotive brands, 15 banks, 11 grocery chains, 14 hotel brands, 13 insurance providers and 12 telecommunications operators in the US market and includes search data for each financial quarter, which resulted in 408 total observations. We focus on search session data over the annual reporting period of 2016-17 and define a single search session over a quarterly period, following previous research (Johnson et al. 2000; Zhang et al. 2006).

2.2.2 Search Time as a Measure of Attention

While the Internet has minimised the material costs associated with searching for product related information, the time and effort that consumers can spend evaluating this information is limited. This constraint on consumer attention means that consumers must rely on heuristics and prior knowledge to minimise the attentive effort associated with conducting an extensive amount of pre-purchase search online (Gigerenzer & Gaissmaier, 2011; Peterson & Merino, 2003). One of the principal tenets of an economy of attention is the zero-sum nature of the competition for attention as a resource (Davenport & Beck, 2001; Falkinger, 2007; Goldhaber, 1999; Hefti, 2011). We argue that the more brands consumers actively consider in making a purchasing decision, the less attention and time they can spend evaluating information on each brand alternative. While attention is an important concept for marketers, it has until recently been treated as either an implicit concept or, ignored altogether (Falkinger, 2007). One of the major reasons for this is the problem associated with the measurement of consumer attention that is often dependent on self-reported customer surveys or intrusive and/or highly clinical methods of measurement such as eye tracking and electroencephalograms (EEG's), limiting their ecological validity and applicability to more realistic consumer search contexts (Milosavljevic & Cerf 2008).

A number of studies that have investigated consumer search behaviour under the constraint of limited attention in the online context have been applied within the domains of online advertising and more specifically, search engine optimization (SEO) (Baye, Gatti, Kattuman,& Morgan, 2009; Smith & Brynjolfsson, 2004; Dreze & Zufryden, 2004; Ellison & Ellison, 2009; Pan, Hembrooke, Joachims, Lorigo, Gay, & Granka, 2007). Consequently, the tendency of such studies has been to quantify attention in the form of the number of clicks that a search result receives relative to its placement on a screen or list. There are a number of methodological issues with such an approach. First, while the number of "clicks" that a search result receives may highlight the relative salience of information within a list, it is an unreliable indicator of actual engagement as it does not encode any information on the quantity or quality of attention expended on an item of information (Chen, Lin, Yen, & Linn, 2011; Davenport & Beck, 2001). Second, the hypertext-based architecture of the World Wide Web means that the search process is often highly non-linear with consumers moving between multiple domains from within a single search query (Dodson, 2016). Third, as SEO techniques have become more sophisticated, rankings of search results are prone to manipulation (Anand, Chakraborty & Park, 2017; Potthast, Köpsel, Stein, & Hagen, 2016). One of the advantages of leveraging a large panel of Internet users is that it allows for a more appropriate measurement of attention by focusing on the time that a consumer spends during the course of a search session offering both, a broader scope than self-reported surveys and a more accurate representation of consumer attention in actual search contexts. While time may not be exactly synonymous with attentiveness (as any distracted student at a Monday morning lecture can attest to!), it can be argued that online search is an intentional and voluntary undertaking on the part of the consumer and involves a certain amount of *a-priori* attentiveness based on the expectation of accrued benefits from the undertaking (Beatty & Smith, 1987). Following this line of reasoning, we evaluate attention at the brand level and define our dependent variable search time per brand ($StpB_{ijk}$) as the amount of time a consumer spends searching for information within a single brand website, i within a market, j over a single search period, k.

2.2.3 Consideration Set

The notion that consumers search for a subset of brands from a larger set of available alternatives has a longstanding tradition in the marketing literature. Initially theorised by Howard (1963) and Howard and Sheth (1969) as the number of alternatives that a consumer considers to be 'adequate' prior to making a purchase, the concept was formally defined by Howard (1977) as an 'evoked set' or the subset of brands that a consumer actively considers during the pre-purchase stage from the larger number of alternatives that he/she is aware of. The 'evoked set' can therefore be understood as the brands that a consumer pays *attention* to as opposed those that he/she is aware of while making a decision. The implicit aspect of selectivity within this definition of the consideration set has a clear overlap with an understanding of attention as a selective filter that sorts salient items of information from multiple stimuli (Kahneman, 1973; Parkin, 2000). For instance, James's (1950) seminal definition for attention touches upon similar themes:

> "Millions of items of the outward order are present to my senses which never properly enter into my experience. Why? *Because they have no interest* for me. *My experience is what I agree to attend to.* Only those items which I *notice* shape my mind – without selective interest, experience is an utter chaos. Interest alone gives accent and emphasis, light and shade, background and foreground — intelligible perspective, in a word (James 1950, pp. 402, emphasis in original)".

More recently, Davenport and Beck (2001) distinguish between awareness and attention as a sequential process: "Items come into our awareness, we attend to a particular item, and then we decide whether to act (pp.20)."[2] Crucially, therefore, the

[2]It is important to note however that while Davenport and Beck's (2001) definition accounts for goal-directed and voluntary modes of attention, it does not consider bottom-up attentional processes that can often operate without the awareness stage depending on the signal to noise ratio of an environmental stimulus. Pinto et al. (2013) show that top-down and bottom-up attentional processes can be conceptually and empirically separated. Eysenck et al. (2007) suggest that automatic attentional biases towards certain types of stimuli can explain differences in performance on behavioural tasks that call for cognitive control in their *"Attentional Control Theory"*. In relation to the formation of consideration sets, it is possible that automatic bottom-up processes may result in hypersensitivity towards certain types of stimuli in online contexts. While not explicitly linking their work to the psychology of attention, Hauser (2014) presents a number of cases where automaticity may influence consumer search processes in laboratory contexts. Since we are mainly interested in assessing the role of the *size* of the consideration set – as opposed to its *contents* – on the amount of search consumers undertake, our motivating assumption is that at least to a certain extent, search is a voluntary and goal-directed process (Beatty & Smith, 1987) and as a result can be represented by a top-down framework. It is worth noting however that one of the main results emerging from our study suggests that concentration within a market – an endogenous indicator for the number of equally salient competitors – has a role to play in modulating the trade-off between the size of the consideration set and the amount of search undertaken per option. This result could be indicative

consideration set implies two fundamental prerequisites. First, a consumer must be aware of a set of brands from within the universal set of all available alternatives within a market and second, the brands that he/she actively considers is a subset of this awareness set.

While there are a number of pre-Internet studies documenting the size of consumers' consideration sets (see Hauser & Wernerfelt, 1990 for an authoritative review), there has been a recent resurgence in interest in the concept in online contexts. In general, average consideration sets fall within a very narrow range across disparate industries with consumers searching within a range of 1-6 brands (Trinh, 2015). Furthermore, while research has shown that the brands within consideration sets are affected as a result of in-store promotion and advertising, the size of the consideration set remains relatively constant (Fader & McAlister, 1990; Mitra, 1995). These findings run strongly contradictory to the traditional economics of search-based account that suggests that the extent of online search should increase as a result of the lowered search costs associated with searching online (Ratchford et al., 2003; Stigler, 1961). We argue that in light of the abundance of freely available and easily accessible information in online contexts, consumers face an attention allocation problem, i.e. consumers face a trade-off between the number of alternatives they can consider and the amount of time they can allocate to searching for information on the individual alternatives within their consideration sets.

Correspondingly, we define our first independent variable, $ConSet_{ijk}$ as the average number of retailer websites a consumer searching for information on brand i in industry j visits during the course of a single search session k. To observe online consideration sets across the seven industries, we use ComScore's audience duplication report detailing the total number of unique visitors to a retailer website and the number of visitors that visit two or more websites, i.e. search for multiple brands. Following Holland & Jacobs (2016) we exclude e-service users (i.e. customers that visit a website in order to

of the fact that consumers are highly sensitive towards environmental salience and allocate their attention in different ways depending on the distribution of market shares within an industry, an indication that bottom-up processes may be involved in the moderation of search effort. Owing to the practical difficulty of separating top-down and bottom-up processes in large-scale panel data, this result provides some promising avenues for further research on automaticity in online search using laboratory experiments and qualitative research frameworks.

manage an existing account) and focus exclusively on consumers in the pre-purchase stage to obtain a more robust measure for the observed consideration set sizes.

2.2.4 Concentration of Attention

As opposed to the consideration set that remains relatively constant, there is a large amount of literature that suggests that brand awareness and recall can be influenced. In particular, advertising, as well as the competitive context of markets have been shown to consistently affect the number of brands consumers are aware of (D'Souza & Rao, 1995; Lambert-Pandraud & Laurent, 2017; Nedungadi & Hutchinson, 1985; Oh, 2000). Some of the early optimism associated with the Internet as a decision support tool overstated its potential for an "ultimate consumer panacea" leading to near perfect price competition (see Peterson & Merino, 2003 for a detailed critique). Indeed, more recent evidence suggests that as the markets for Internet search mature and continue to grow economically and socially important, they are also becoming increasingly concentrated (Argenton & Prüfer, 2012). Furthermore, much like traditional retail environments, competition in online contexts is not immune to asymmetric information, first mover advantages and contextually grounded choice behaviour (Gandal, 2001; Lynch Jr & Ariely, 2000).

In light of this, we define our second independent variable $MktConc_{jk}$, as the level of concentration of attention within an industry j over a quarterly period k. One of the most commonly used metrics for assessing concentration within a market is the Herfindahl-Hirschman Index (HHI) (Liston-Heyes & Pilkington, 2004; Rhodes, 1993). The HHI is given by the squared sum of shares of all competitors within a market. We use the HHI as a direct measure of the level of concentration of attention in online markets across the seven industries in our dataset. Specifically, we calculate the concentration of attention in market j with N firms, each with a share of unique visitors, S_{ijk} as $\sum_i^N (S_{ijk})^2$. The HHI can take any value ranging from close to 0 to 1 representing a market with a huge number of equally sized competitors to a monopoly, respectively. In an industry with N equally sized competitors, the HHI is equivalent to $1/N$. As a result of feature, the inverse of the index is occasionally interpreted as the "number of equivalent competitors" within a market. For instance, a market with an HHI of 0.20 is indicative of a market with 5 equally sized competitors. Therefore, while an increase in the HHI is indicative of an increase in market concentration, an increase in its inverse is indicative of increasing competition. Since we formulated our research questions with respect to the concentration of attention within markets, we prefer the direct measure of the HHI. We use the specification outlined by the US department of justice and define an HHI value ≥ 0.25 as indicative of a highly concentrated market for attention, an HHI value between 0.15 and 0.25 as indicative of a moderately concentrated market and an HHI value ≤ 0.15 as a competitive market. Therefore, the independent variable measuring the industry concentration of attention ($MktConc_{jk}$) is measured at three levels Competitive (HHI $\leq$ 0.15), Moderate (0.15 $<$ HHI $<$ 0.25) and Concentrated (HHI $\geq$ 0.25).

We argue that since consumers search from within a subset of a larger awareness set, markets where there is a high level of competition for attention will correspond to the largest awareness sets. That is, if competitors within a market are relatively similar sized, consumers will face higher levels of uncertainty with respect to their consideration sets representing the best (or most satisfactory) alternatives (Simon, 1955). Alternatively, an inverse effect would be expected in the case of highly concentrated markets, i.e. where a relatively small number of competitors control a proportionally large amount of attention. Therefore, following the rationale from information theory, as higher levels of uncertainty are directly related to the effort that needs to be expended on an information-processing task, we expect Search Time per Brand ($StpB_{ijk}$) to fall as the level of concentration of attention increases (Shannon & Weaver, 1998).

2.2.5 Modelling Approach

We measure search time per brand ($StpB_{ijk}$) and consideration set sizes ($ConSet_{ijk}$) at the brand level with 408 observations for each variable and market concentration of attention ($MarkCon_{jk}$) at the industry level with 103, 180 and 125 observations in the *Competitive*, *Moderate* and *Concentrated* conditions. As our data contains observations from a disparate set of industries with differing baseline levels of search, it is important to control for similarities of consumer search behaviour within industries. To address this issue, we use a linear mixed effects model (LMEM), in order to account for industry specific idiosyncrasies as these models allow for implicit controls for random factors without the problems associated with multiple levels of data aggregation (Gelman & Hill, 2006).

We include our measure for the online consideration set ($ConSet_{ijk}$), the level of concentration of attention in the market ($MarkConc_{jk}$) and the interaction between $ConSet_{ijk}$ and $MarkConc_{jk}$ as fixed effects in our model and treat $MarkConc_{jk}$ as a factor nested within the different industries in our dataset. As random effects, we include the intercepts for each Industry as well as a by-industry random slope for the effect of the online consideration set ($ConSet_{ijk}$) within the industry at each time period in order to account for the variability of the fixed effects in our model within the different industries and quarters. As our research questions are primarily concerned with the population level effects (i.e. fixed effects), we use maximum likelihood estimation (ML) to obtain our model coefficients as it provides consistent and unbiased estimates for fixed effects in LMEMs (Baayen, Davidson & Bates, 2008). As opposed to alternative panel data models such as standard pooled ordinary least squares (pOLS), fixed effects (FE) and random effects (RE), mixed effect models (LMEMs) offer a number of advantages, the most salient of which to our approach, is their ability to estimate unbiased coefficients for panels with an unbalanced number of observations for grouping variables (see Baayen, Davidson & Bates, 2008; Gelman & Hill, 2006 for a general overview; Chapman & Feit, 2015 provide an introduction in the context of behavioural applications; Allenby & Rossi, 1999 address the relevance of LMEMs in marketing research; Kapstein & Eckles, 2012 for an application). Our regression model is therefore specified as:

$$\begin{aligned} log(\widehat{StpB}_{ijk}) =& \beta_0 + a_{1,Industry_j,Q_k} + (\beta_1 + a_{2,Industry_j,Q_k})ConSet_{ijk} + \\ & \beta_2 MarkConc_{jk}(level = Moderate) + \\ & \beta_3 MarkConc_{jk}(level = High) + \\ & \beta_4 ConSet_{ijk} \times MarkConc_{jk}(level = Moderate) + \\ & \beta_5 ConSet_{ijk} \times MarkConc_{jk}(level = High) \end{aligned} \tag{2.1}$$

$$log(StpB_{ijk}) \sim Norm(\widehat{StpB}_{ijk}, \sigma^2) \tag{2.2}$$

$$\boldsymbol{a}_{1:2,Industry_j,Q_k} \sim MVNorm(0, \boldsymbol{\Sigma}) \tag{2.3}$$

We use the notation where $\boldsymbol{a}_{1:2,Industry_j,Q_k}$ is a vector containing our random effects terms for the intercept ($a_{1,Industry_j,Q_k}$) and slope ($a_{2,Industry_j,Q_k}$) parameters for industry

j in quarter k and $\boldsymbol{\Sigma}$ contains the covariance structure (i.e. the intra-class correlation to control for the heterogeneity of search behaviour across different industries) for the slope and intercept. Since we do not assume a linear relationship between our dependent and independent variables, we apply a log transformation to the response variable $StpB_{ijk}$ in order to account for the positive skewness of the distribution (Keene, 1995; Lütkepohl & Xu, 2012). $ConSet_{ijk}$ is a continuous covariate representing the absolute size of the online consideration sets. Finally, we enter two separate indicator variables for $MarkConc_{jk}$ coded as 1 for $Moderate$ and $Concentrated$ markets with $Competitive$ as the reference category.

2.3 Results

Descriptive statistics. Table 1 summarises the descriptive statistics for the key variables across the seven industries in our dataset.

In support of previous research, our findings suggest that consumers search for a relatively few number of brand alternatives with average consideration sets ranging from 2.42 in the Insurance market and 3.13 in the Automotive sector. The consideration sets uncovered in our data are comparable to online consideration sets reported in recent studies. For instance, the average online consideration sets for the air-travel industry (i.e. between 2.44 to 3.18) in the present study are comparable to Zhang et al.'s (2006) consideration set of 3.31 once differences in methodology are taken into account while, Ratchford et al. (2003) in a twelve-year-old study reported a consideration set of 3.04 for the US automotive industry, compared to 3.13 reported here. Our findings are also similar to previously reported consideration set sizes for the US groceries, banking and telecommunications sectors (Dawes et al., 2009; Trinh, 2015). Furthermore, we find that the time and effort associated with conducting online search is relatively more extensive however, varies significantly between different industries. The banking industry is the most search intensive in our dataset with consumers searching on average for a consideration set of 2.55 brands however, spending an average of 28.27 minutes for information on a single brand. Conversely, consumers searching for hotels spent the least amount of time searching for information on individual alternatives, on average spending 7.08 minutes.

TABLE 2.1: Means for key variables across industries

Industry	Search Time per Brand[a] ($StpB_{ijk}$)				Consideration Set ($ConSet_{ijk}$)				Concentration[b] ($MarkConc_{jk}$)			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Air-travel	13.77	13.55	16.13	12.75	3.18	2.44	3.00	2.63	.14	.17	.15	.15
Automotive	7.40	7.87	8.62	7.81	3.33	3.62	2.52	3.05	.13	.14	.16	.25
Banking	30.15	29.86	27.94	30.80	2.73	2.00	2.87	2.60	.15	.18	.14	.16
Groceries	7.46	7.26	7.33	7.76	2.46	2.73	2.36	2.18	.18	.19	.19	.18
Hotels	6.52	6.86	8.02	6.93	2.64	2.43	3.07	2.79	.29	.28	.26	.26
Insurance	14.63	13.63	18.18	13.15	2.13	3.00	2.23	2.23	.16	.18	.17	.19
Telecom	11.25	14.78	13.07	12.25	2.67	2.92	3.00	2.83	.30	.26	.29	.25

[a]Search time is in minutes.
[b]HHI values were grouped into Competitive (HHI $<$ .15), Moderate (.15 $\leq$ HHI $\leq$ .25) and highly Concentrated (HHI $>$ .25) markets for each of k quarters.

Qualitatively, the level of concentration of attention appears to have some effect on the amount of time consumers spend on search for each alternative both within and between the different industries in our dataset. In order to quantify this effect, we estimate our regression model as specified in the previous section. Table 2 summarises the results from our model. In the subsequent sections, we directly address the research questions posed at the outset and report the findings from our analysis.

Does the size of the consideration set affect the amount of time consumers spend on searching for information on a single alternative? In our LMEM, the coefficient for the effect of $ConSet_{ijk}$ ($\beta_1 = -.24, se = .04$) was negative on $StpB_{ijk}$ and dropping $ConSet_{ijk}$ from our model reduced goodness of fit significantly, as demonstrated by a likelihood ratio test ($ConSet_{ijk} : \chi^2(1) = 39.38, p < 0.001$). We estimated a standard deviation in search time per brand of 5.38 minutes across all industries in our dataset along with a residual variance of 5.91 minutes resulting in a moderate intra-class correlation of 0.43 capturing the industry specific heterogeneity of the consumer search process. We are not concerned in the heterogeneity across different markets in itself, as this has been well documented in the literature (Beatty et al., 1987; Huang et al., 2009) rather, we find that even after accounting for differing patterns of consumer

TABLE 2.2: LMER FIXED EFFECTS ESTIMATES PREDICTING SEARCH TIME PER BRAND

	Log Search Time per Brand ($StpB_{ijk}$)	
Variables	Estimate (β_x)	Std. Error (SE)
Constant	3.15***	.18
Main Effects		
Consideration Set ($ConSet_{ijk}$)	-.24***	.04
Market Concentration (ref = *Competitive*) ($MarkConc_{jk}$)		
Moderate ($.15 < HHI < .25$)	.13	.15
Concentrated ($HHI \geq .25$)	-.41*	.17
Interaction Effects		
$ConSet_{ijk} \times MarkConc_{jk}(level = Moderate)$	-.11**	.04
$ConSet_{ijk} \times MarkConc_{jk}(level = Concentrated)$	-.01	.04
Fit Statistics		
Model $\chi^2(df)$	23.91(5), p < .001	
Log Likelihood	-186.7	
AIC	407.3	
Pseudo R^2	.78	

$***p < .001, **p < .01, *p < .05$, β = Unstandardised regression coefficient. VIFs ranged from 1.57 - 1.86 and did not indicate any issues with multicollinearity.

search across markets, as consideration set sizes increase, the amount of time consumers spend on searching for information on a single brand alternative consistently reduces. Specifically, we find that a unit increase in the size of the consideration set leads to a reduction in search time per brand by 22% even after accounting for heterogeneity in different market contexts.

Does the level of concentration of attention in online markets affect the amount of time consumers spend on searching for information on a single alternative? In order to test the effect of the level of concentration of attention in a market ($MarkConc_{jk}$) on the amount of time consumers spend on searching for information on a single brand, we enter our indicator variables for $MarkConc_{jk}$ for the $Moderate$ and $Concentrated$ market conditions with $Competitive$ as the reference category. Our LMEM estimated a large negative coefficient for markets at the $Concentrated$ ($\beta_3 = -.41, se = .17$) and a marginal positive coefficient at the $Moderate$ ($\beta_2 = .13, se = .15$) levels. Likelihood ratio tests demonstrated that in $Concentrated$ markets, consumers consistently spent less time searching for information on a single brand ($Concentrated : \chi^2(1) = 5.57, p = .018$). Conversely, we do not find evidence to suggest that search time per brand differs in $Competitive$ and $Moderate$ market contexts ($Moderate : \chi^2(1) = .78, p = .377$). Therefore, while we find that the amount of time consumers spend searching for information on a single brand is similar for competitive and moderately concentrated attention markets, in highly concentrated market contexts, search time per brand was 34% lower.

Does the level of concentration of attention moderate the relationship between the consideration set and the amount of time consumers spend searching for information on a single alternative? While we did not find any differences in the baseline search levels between Competitive and Moderate market contexts, our LMEM recovered a significant estimate for the interaction term $ConSet_{ijk} \times Moderate(\beta_4 = -.11, se = .03)$ as demonstrated by a likelihood-ratio test ($ConSet_{ijk} \times Moderate : \chi^2(1) = 8.19, p = .004$). Therefore, we find that under the condition of moderate concentration of attention within an industry, the strength of the negative relationship was increased proportionally by a further 10%. The interaction term for $ConSet_{ijk} \times Concentrated(\beta_5 =$

$-.01, se = .04$) was not statistically significant ($\chi^2(1) = .07, p = .791$). These results suggest that while a unit change in the size of the online consideration set reduces search time per brand by 22% in competitive and concentrated attention markets, under moderate levels of concentration, the same change in the size of the consideration set leads to a corresponding reduction in search time per brand of 32%.

Figure 2.1 provides a visualization of the results from our mixed model. Figure 2.1(a) illustrates the population level effects for the relationship between the size of the online consideration set and search time per brand as well as the fitted regression lines for the competitive, moderate and concentrated market contexts. Figure 2.1(b) is a visual representation of the higher order clustering of effects within the different industries in our data and illustrates that while there is a substantial amount of heterogeneity of search time per brand across industries, the relationship between the size of the consideration set and search time per brand as well as the effects associated with the levels of concentration of attention within the different markets in our data remain consistent. Figure 2.1(c) is a visualisation of the population level interaction between search time per brand and market concentration in minutes. Figure 2.1(d) presents the absolute effect of the level of competition of attention in a market and mean search time per brand. Note that Figures 1(a) and (b) are plotted on the transformed scale for $StpB_{ijk}$ whereas Figures 1(c) and (d) illustrate the absolute effect size in minutes.

2.4 Discussion and Conclusions

Despite the low costs of information acquisition in online contexts, we find that consumers are fundamentally constrained by their capacity to attend to a limited amount of information over the course of a search session. Consequently, our results demonstrate that a limited search process can be understood through the lens of an attention allocation problem typified by a trade-off between the number of alternatives for which search is undertaken and the amount of time consumers can spend evaluating information on individual alternatives. Our findings extend traditional models of consumer search behaviour that suggest that as the costs associated with information acquisition are reduced in online contexts, the differences in consumer search in different market contexts is eroded (Ratchford et al., 2003; Stigler, 1961). Instead, we find that search

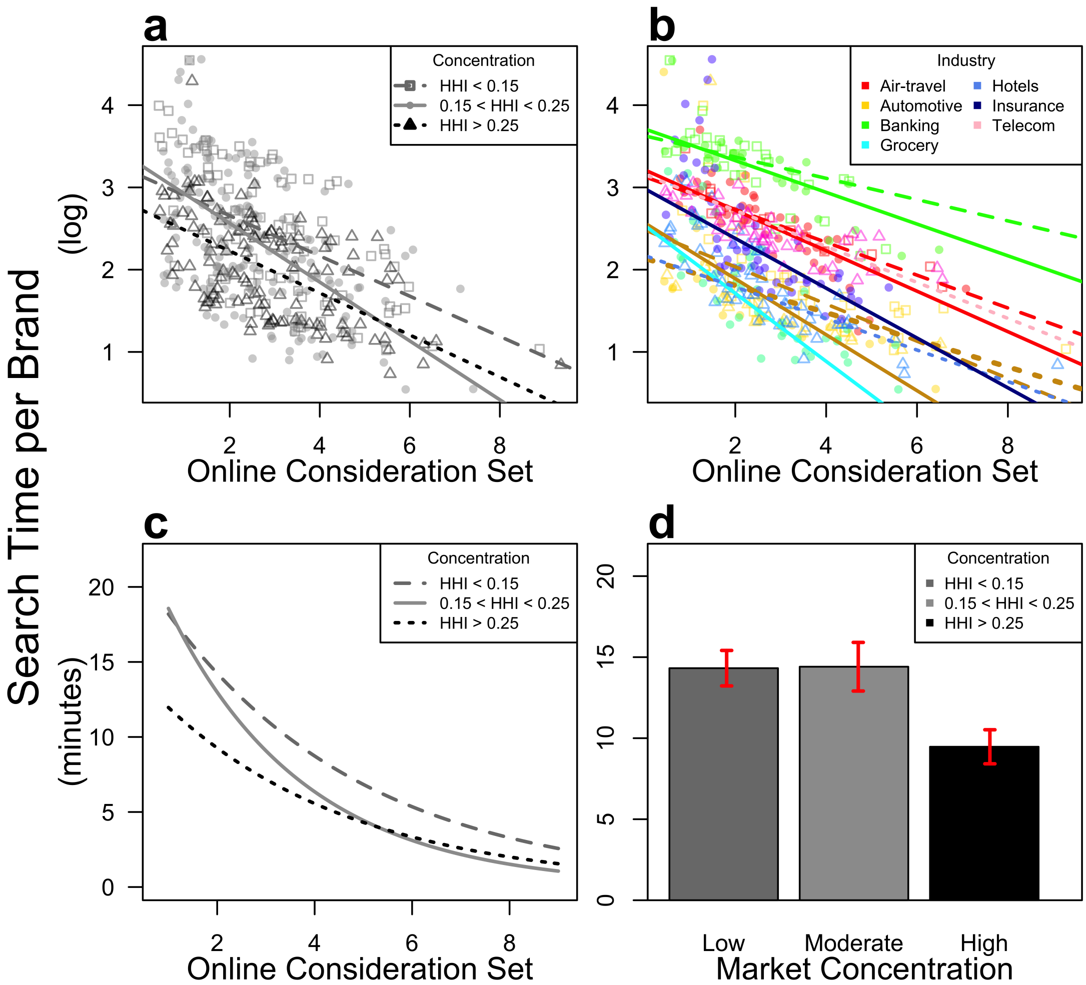


Figure 2.1: (a) Fitted population regression lines for competitive (dashed line), moderate (solid line) and concentrated (dash-dotted line) attention markets; (b) Industry specific regression lines; (c) Population level effect of interaction between concentration and consideration set sizes in minutes (d) Effect size of the level of market concentration on mean search time per brand in minutes, concentration increases along the x-axis (std. error given by the red bars)

patterns vary significantly across different industries and the intensity of competition for consumer attention within online markets intensifies both the magnitude and the strength of the relationship between the size of a consumer's consideration set and the amount of time he/she spends seeking out information on individual alternatives. Notably, our results suggest that online markets are dynamically competitive, and even short-term changes in market concentration can have significant implications for how consumers allocate their attention to alternatives within their consideration sets.

Our findings provide a number of novel theoretical avenues and demonstrate how the insights from behavioural research can inform our understanding about online search processes. Our results clearly illustrate that consumers prefer searching longer for fewer alternatives rather than spreading their search effort across a larger set of considered alternatives. This finding supports previous work in the consumer behaviour literature proposing that consumers may use consideration sets as a heuristic information handling strategy in online contexts (Mitra, 1995). While this aspect has been theorised in the past (Hauser, 2014), to the best of our knowledge, our results provide the first empirical evidence of this phenomenon in naturalistic online search contexts. A second important contribution from our analysis sheds light on the role of market concentration on the online search process. In highly concentrated markets, consumers search nearly a third as long as in moderate or competitive environments. This is strongly suggestive of the fact that under high levels of concentration – i.e. where only 1-4 competitors are equally salient[3] – consumers may view equally salient alternatives as 'satisficing' substitutes. Furthermore, under moderate levels of concentration, while search per alternative is higher on average than concentrated markets and comparable with competitive markets, the magnitude by which consumers reduce search for every addition into the consideration set 10% higher. Paradoxically, this result suggests that in cases where there are between 4-7 equally salient competitors within a market, consumers search significantly less per alternative for every additional

[3]As discussed in section **2.2.4** the inverse of the HHI can be interpreted as the number of equally salient competitors within a market. This corresponds to approximately: < 4 equivalent competitors in concentrated markets, between 4 and 7 equivalent competitors in moderately concentrated markets, and > 7 competitors in highly competitive markets.

option for which search is undertaken. While our analysis does not offer precise insights about why consumers might actively discount their search time for information on equally competitive alternatives in such a manner, we speculate that this result may be indicative of consumers' desire to avoid conflicts arising from the increased uncertainty associated with considered alternatives representing satisfactory choices under moderate levels of market concentration. Such an interpretation would correspond to emerging literatures on the role of uncertainty in information avoidance (e.g. Golman et al., 2017). What is clear from our analysis however, is that under moderate levels of concentration, online search is particularly elastic – i.e. a small change in the size of the online consideration set results in a much steeper decline in attention to each considered alternative as compared to competitive and concentrated environments.

Our findings provide three broad practical insights of interest to brand managers and organisational actors. First, the narrow consideration sets uncovered in our data, underline the importance of brand salience in the online context. Since consumers search for a narrow set of alternatives, it is important for marketers and brand builders to be included within the consumer's consideration set rather than rely on discovery through search. Second, brand managers should remain cognizant of changes in the competitive structure of online markets, particularly as even short-term changes in the concentration of attention within a market can have significant implications for how consumers allocate their time between competing alternatives. Third, while the online medium is an important avenue for consumer engagement and marketing activities, smaller competitors in highly concentrated markets should supplement their marketing efforts with traditional media-mix strategies as they stand to gain very little from too strong an emphasis on direct search.

2.5 Limitations and Further Research

While incorporating a large panel of Internet users to study patterns of search behaviour provides a better representation of actual consumer search processes and increases the external validity and generalizability of our results, there are a number of important caveats that must be underlined. Panel data are non-probabilistic in nature and can often comprise of individuals from similar socio-economic status and backgrounds that may bias statistical results if such aspects are not explicitly controlled for (for a survey see, Callegaro et al., 2014). Even large scale panel-data – such as the ComScore dataset used in this study – that does not rely on self-reports from surveys can have relatively homogeneous participants meaning that along with the instrumental variables under study, the results also describe the particular composition of the panel itself. Large-scale panel data do not provide much insight into how individual factors and demographic variables affect online search processes. More importantly, while data aggregated at the brand and industry levels provide valuable insights into consumer behaviour on average, it also introduces the issue of 'ecological fallacy' arising from ascribing aggregate patterns of behaviour to the behaviour of individual consumers (Gelman & Hill, 2006). Since the data is collected in the field, it is a challenging task to isolate instrumental variables that relate to the structure, style and presentation of information with the same level of control afforded in the laboratory.

A number of studies in process tracing research and decision making have highlighted that structural components with respect to how information is presented on a website can have consequences for the speed and accuracy of information processing tasks (Lurie, 2004; Currim, Mintz & Siddarth, 2015; Wilson, 2014). Since our data are measured at the domain level, it does not include any information on the qualitative aspects of the information that consumers engage with over a single search session. As these elements are likely to vary across industries as well as individual websites, they may provide further insight into the consumer search process in online markets. Furthermore, we do not differentiate between consumer search styles. For instance, experiential versus goal-driven search behaviours may vary considerably and consequently moderate the trade-off between the number of alternatives consumers search for and the extent of search they undertake on individual alternatives (Karimi, Papamichail & Holland, 2015; Peterson, Balasubramanian & Bronnenberg, 1997; Weathers & Makienko, 2006). Similar differences would be expected for hedonic versus utilitarian search contexts (Bridges & Florsheim, 2007; Khan & Dhar, 2010; Micu & Coulter, 2012). While we have attempted to address a number of these limitations through a careful selection of our modelling approach that allows us to control for some of these differences across markets, we are unable to investigate why these differences arise in a substantive and qualitative manner. Using extensive web tracking data to study these behaviours present both ethical as well as practical challenges. Future research could address these aspects by incorporating qualitative and experimental research designs to study these issues in detail. As our study has focused on a mature online market, the search behaviours that we have observed are perhaps also related to the extent of Internet adoption in the US. Additional analysis needs to be conducted to assess if our results are scalable across geographical markets with asymmetric levels of Internet adoption. Finally, while our results provide compelling evidence to suggest that on aggregate, consumers are faced with an attention allocation problem, a future line of inquiry may investigate the question of whether some individuals are more adept at responding to this challenge than others.

3

Irrational Maximisers? When maximisers are more prone to biased judgements than their satisficing counterparts

Abstract

We investigate the central question of whether in certain circumstances, behavioural maximisers are in fact poorer decision makers compared to their satisficing counterparts. We draw on behavioural decision theory and the dual system paradigm to suggest that maximisers' denial of their bounded-rationality leads them to arbitrarily expand choice even when normatively preferable alternatives are available. We test our hypothesis in a series of experiments and our findings provide support for this claim. Specifically, we show that, a) maximisers demonstrate a lower preference for analytical information processing, b) in absolute terms, maximisers are more likely to adhere to a number of behavioural biases than their satisficing counterparts, c) their adherence to these biases is due to a reliance on easily comparable criteria, variety seeking and representativeness as non-compensatory information handling heuristics, and d) their adherence to biased responses persist even in situations where a biased alternative is dominated by an objectively superior choice or a normative choice is inaccessible. We discuss our findings with respect to their implications for a boundedly-rational view of unaided decision processes and suggest that the very behavioural strategies that

maximisers adopt in their quest for the "best" alternative, predispose them to errors in judgement in a number of cases.

3.1 Introduction

Behavioural decision theory has traditionally been focussed on demonstrating that decision makers systematically deviate from normative expectations of the axioms of expected utility maximisation under well-defined conditions (e.g., Ayal and Zakay, 2009; Bonner and Newell, 2008; Kahneman and Tversky, 1972; Slovic, Finucane, Peters, and MacGregor, 2007; Todd, 2007). Over half a century ago, Simon (1955, 1956, 1983) suggested that in many choice contexts, particularly those encountered in complex environments where information is abundant, choosing the "good-enough" option or "satisficing" may be a more realistic representation of a sophisticated decision maker. Simon's central argument was based on the notion that in practice, maximising a decision outcome is impractical and difficult to implement owing to the cognitive and information processing costs that evaluating perfect information under the rational choice assumption entail. Simon (1971) saw information as something that consumed the time and attentive resources of its recipients and as intrinsically effortful to evaluate. In doing so, he demonstrated that a satisficing decision strategy may be more beneficial in cases where losses in an expected payoff can be justified by reducing the requisite cognitive effort from maximising a decision outcome.

Increasingly, decision making research has begun to turn its attention towards individual differences between decision-makers, investigating whether individuals make decisions in consistent ways across tasks (Ayal, Hochman, and Zakay, 2011; Bromiley and Curley, 1992), the importance of preferences, ability and demographic characteristics in explaining decision making competence (Bruine de Bruin, Parker, and Fischhoff, 2007; Parker, De Bruin, and Fischhoff, 2007), the role of individual differences in the perception of risk and risk judgments (Weber, Blais, and Betz, 2002) and more broadly in experimental studies across a number aided decision making contexts (O'Keefe, 2016). Following this shift in emphasis from aggregate to individually specific facets of decision making, Schwartz et al. (2002) built on Simon's initial work in order to develop a scale measuring the extent to which individuals adopt maximising or satisficing orientations in general decision contexts. Indeed, in many ways, Schwartz et al.'s (2002) scale is a measure of maximising even when satisficing is a sufficient strategy (for instance, items on this scale include "When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program" and "When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to."). As a result, it is not surprising that in Schwartz et al.'s (2002) own research – as well as a number of other studies (Iyengar, Wells, and Schwartz, 2006; Parker et al., 2007; Polman, 2010; Roets, Schwartz, and Guan, 2012) – a maximising orientation is generally negatively related to subjective measures of happiness, satisfaction, self-esteem and general well-being.

While Simon (1971) and Schwartz et al. (2002) share a common intuition – that an abundance of choice places cognitive strains on decision makers – they present two related but disconnected accounts of this phenomenon. Where Simon (1972) limited his analysis to demonstrating the cognitive intractability of maximising in actual decision contexts and the universality of the satisficing orientation, Schwartz et al.'s (2002) efforts are directed at evaluating the affective outcomes that adopting a maximising orientation entail. While both perspectives provide crucial insights into the problem of choice in information-rich contexts, a central question remains rather nebulous- are behavioural maximisers actually poorer decision makers compared to their satisficing counterparts?

In a number of studies, an *a-priori* assumption regarding decision maker orientation is that behavioural maximisers should tend to be more deliberative and rational decision makers (Lai, 2010; Purvis, Howell, and Iyer, 2011). Many of these studies point to the research conducted by Iyengar et al. (2006) that found that whilst college graduates who tended to maximise during their job search ended up with 20% higher salaries when compared to satisficers, they also reported lower levels of satisfaction during and after their job search. In stark opposition, other studies have shown that maximisers underperform in decision making tasks such as forecasting (Jain, Bearden, and Filipowicz, 2013) and score less well on decision making competence measures (Bruine de Bruin et al., 2007). In a comparison of a number of decision making styles, Parker et al. (2007) found that a maximising orientation is negatively related to composite measures of decision maker competence and positively related to maladaptive behavioural outcomes such as a higher reliance on others, behavioural coping, impulsivity and an avoidant attitude towards decision making. These perspectives would suggest that the apparent better performance of maximisers in Iyengar et al.'s (2006) study may be a result of maximisers' ability to focus on relatively easily comparable criteria as opposed to other important determinants of job satisfaction (Parker et al., 2007). While we tend to agree with this latter perspective for its compatibility with Simon's initial motivations for suggesting satisficing as a more pragmatic decision strategy, it is quite likely that maximisers have no other alternative but to focus on relatively easily comparable criteria, especially as a function of the number of options they consider over the course of their search process (the upper bound for the number of jobs considered by maximisers in Iyengar et al., 2006 was one-thousand!). Surely if Simon's intuition is correct, a decision-making orientation that prioritises the expansion of choices in already choice-rich environments is exactly the kind of impracticality that leads to the advisability of satisficing in the first place.

In this paper, we address precisely this aspect of the maximisers problem and argue that maximising and deliberative judgement can often be conflicting goals. Specifically, we suggest that in a number of situations, maximisers value the expansion of choice at the expense of normatively superior alternatives, a tendency that results in poorer decisions that significantly deviate from normatively expected choice behaviour. We start by asking whether self-reported maximisers express a lower preference for analytical information processing. Subsequently, we assess for a number of specific situations, if information processing preferences are held constant, whether maximisers are more prone to adhering to behavioural biases and deviations from normatively expected choice behaviour. After a brief review of the relevant literature, we present our hypotheses and structure our study in four parts. In study 1, we investigate if maximisers are less likely to adopt an analytical information processing preference. In study 2(a), we demonstrate that maximisers are more prone to exhibiting deviations from normatively expected choice behaviour in absolute terms, even after controlling for the effects of information processing preferences. In study 2(b), we further explore maximisers' deviations from normative choice outcomes and show that the direction of bias adherence in specific instances, is predicated on maximisers' reliance on relatively easily comparable criteria, variety seeking behaviour and a desire for representativeness. Finally, in study 3, we replicate our findings and show that even in cases where a biased choice is dominated by an objectively superior alternative or a normative alternative is unavailable, maximisers' adherence to biased outcomes persist.

3.2 Review of Previous Research and Hypotheses Development

In the previous section, we suggested that maximising and deliberative judgement may be inherently conflicting decision styles. In order to expand on this claim, we draw on the dual system hypothesis. Popularised as system 1 and system 2 thinking by Kahneman (2003, 2011) in what are perhaps his most widely read works, the dual system approach is a long-established paradigm in behavioural decision research (Epstein, 1994; Sloman, 1996; Stanovich and West, 2000). Proponents of this view suggest that individual decision making is related to a psychological preference for analytical (system 2) and intuitive (system 1) information processing styles. This paradigm has been widely applied to a number of assessments of individual decision making and is consistently able to make predictions relating to both affective and deliberative decision-making processes. Studies seem to unanimously suggest for instance, that individuals that express preferences for higher analytical judgement perform better in a number of cognitive tasks and are less prone to adhering to biased judgements and deviations from more rational, normatively consistent behavioural outcomes (Ayal et al., 2011; Ayal, Rusou, Zakay, and Hochman, 2015; Kahneman and Egan, 2011; Kahneman and Frederick, 2002; Pacini and Epstein, 1999; Shiloh, Salton, and Sharabi, 2002). In contrast, research considering the role of intuitive information processing on decision outcomes is considerably more mixed. While a number of studies have demonstrated that intuitive decisions makers are often prone to making errors in judgement as a result of an over-reliance on affective mechanisms (Kahneman and Frederick, 2002; Shiloh et al., 2002), recent research has shown that under certain circumstances – in particular, where decisions may call for affect-based evaluations – more intuitive decision makers may outperform their analytical counterparts (Ayal et al., 2015).

While maximising and the dual-system approach are somewhat interrelated concepts, a major point of difference between these two notions is that where the former articulates a general decision maker orientation that specifically considers the propensity of decision makers to expand choice through information search, the latter considers individual preferences for information processing. In plainer terms, while maximising relates to the question of how much information to consider, the dual system paradigm considers how this information is evaluated. This insight is central to the distinction between Simon's (1955), scepticism of the veracity of maximising as a viable decision strategy and Schwartz et al.'s (2002) trait-based account of maximising tendency. Simon's (1971) main contention was directed precisely at the issue that maximising is rendered problematic due to an insurmountable cognitive burden placed on maximisers, resulting in a suboptimal allocation of scarce cognitive resources towards the resolution of decision problems. Thus, while it may at first seem a counter-intuitive claim that a desire to acquire more information should negatively relate to a preference for deliberative evaluation, a number of plausible explanations can be found within recent advances in economic theory, the information overload paradigm and in the internal logic of the behavioural maximising construct itself.

3.2.1 Are Maximising and analytical information processing antithetical?

The view that individuals possess scarce cognitive resources that are selectively deployed towards information processing is long held in cognitive psychology (Broadbent, 1954; Shiffrin and Schneider, 1977; Simon, 1990). Economic analysis has built on these insights and suggested that as a result of this inherent scarcity, cognitive and attentive resources ought to be allocated efficiently in order to facilitate better decision making and in order to do so optimally, ignoring irrelevant, invalid or excessive information may be necessary (Caplin and Dean, 2015; Gabaix, Laibson, Moloche, and Weinberg, 2006; Sims, 2003). The standard economic analysis of decision making holds that information is valuable only to the extent to which it aids in better decision making (Golman, Hagmann, and Loewenstein, 2017; Stigler, 1961). Again, a straightforward corollary from this is that in circumstances where additional information is irrelevant to the task at hand or does not improve decision quality it should be avoided. Information is thus, a costly resource that incurs both cognitive and opportunity costs of its recipients and enters a decision maker's utility function directly (Stigler, 1961). A number of studies have shown that in many cases decision makers do not conform to this expectation and engage in wasteful or irrational information acquisition (Eliaz, Offerman, and Schotter, 2008; Loewenstein, 1994; Powdthavee and Riyanto, 2015; Todd, 2007). For instance, in an experimental setting, Eliaz et al. (2008) show that some individuals are willing to incur monetary losses in order to acquire non-instrumental and worthless information due to a desire for a greater sense of confidence, early uncertainty resolution and *ex-post* predictions of the odds of success. Powdthavee and Riyanto (2015) show that even when subjects were aware of the exact level of uncertainty associated with competing outcomes, they were likely to give up monetary payoffs in exchange for random predictions as function of their desire to avoid regret and delegate decision making to an external source. These findings relate directly to findings in Parker et al. (2007) which suggest that behavioural maximisers are more regretful, more likely to delegate decision making and more avoidant towards decision-making than their satisficing counterparts.

Relatedly, a large body of literature emerging under the consumer information overload paradigm suggests that not only can individuals engage in inefficient information search but they are also faced with an allocative trade-off between the amount of information they consider and the extent of analytical evaluation that can be deployed to make more effective decisions (Jacoby, Speller, and Berning, 1974; Jacoby, Speller, and Kohn, 1974). Keller and Staelin (1987) for instance demonstrate in a job selection experiment with a sample of MBA students that as the number of decision attributes increased, motivated participants performed poorly on measures of decision effectiveness. Moreover, as Siebert and Kunz (2016) suggest, while searching for information and alternatives in a systematic manner is an important element of proactive decision making, it is the quality and not the quantity of information that matters (Korhonen et al., 2018), since individuals conduct simple computations to process information and often fail to use all information available to them (Keller and Katsikopoulos, 2016). When cast in the light of the findings from Parker et al. (2007), these studies lend credence to the view that as decisions become more complex and require assessments of competing criteria, maximisers may resort to evaluations of relatively easy to compare criteria as a function of the size of their consideration sets. A question that emerges from these considerations is – could maximisers' reliance on relatively straightforward comparisons, variety seeking and extensive information acquisition predispose them to behavioural biases in situations where an emphasis on such features may result in suboptimal decisions? In the next sections, we present a number of cases where this type of tendency may be operative.

3.2.2 The Ratio Bias

We begin this section by reiterating two explicit assertions in Schwartz et al.'s (2002) conceptualisation of behavioural maximising. First, in contrast to Simon's (1955) arguments in support of the universality of satisficing as a decision strategy, Schwartz et al. (2002) view maximising and satisficing as unidimensional behavioural traits, with the implication that individuals cannot simultaneously be maximisers and satisficers (see also Schwartz, 2004a, 2004b and for a critique, Diab, Gillespie, and Highhouse, 2008). Second, while the maximising construct measures the extent to which decision makers expand their choice sets, undertake information search and are less steadfast in their decisions, it does not contain any actual measure of decision quality or effectiveness (Schwartz et al., 2002). This would suggest that any inferences about maximising being related to universally better decision outcomes may be premature, particularly given the dearth of empirical evidence testing this hypothesis (noting the few exceptions from the studies that we have already cited). Indeed, as we have suggested in previous sections, a number of studies point to cases where an emphasis on expanding choice can lead to suboptimal decision outcomes (e.g., Eliaz and Schotter, 2007; Keller and Staelin, 1987; Powdthavee and Riyanto, 2015). Moreover, if we accept the contention that an extensive expansion of choices would confer additional cognitive burdens on maximisers, leading them to prioritise relatively easy to compare criteria, does this in turn imply that maximisers would be more prone to making errors in judgement in cases where such criteria are salient over other normatively more relevant ones?

The most widely known assessment of this latter effect at an aggregate level can be found in Denes-Raj and Epstein's (1994) exploration of the ratio-bias. The ratio bias relates to individuals' evaluations of low probability outcomes as more likely when presented in the form of large numbered ratios as opposed to equally likely lower numbered ones. For instance, in a number of applications decision makers assign higher probabilities to drawing a red marble from an urn containing for example, 100/1000 red marbles than 1/10, even though the odds of success are identical in both cases (e.g., Ayal et al., 2011; Denes-Raj and Epstein, 1994; Denes-Raj, Epstein, and Cole, 1995). These findings have largely been explained as emerging from a reliance on more easily comparable criteria such as the frequency of the numerator at the expense of the normatively relevant attribute (i.e. the overall proportion) (Kirkpatrick and Epstein, 1992; Piaget and Inhelder, 1975) and are thus, compatible with the analysis we have presented. Recent investigations of this effect have begun to take into account the role of individual differences in explaining adherence to this kind of bias. Ayal et al. (2015) for instance show that information processing preference can have effects on the extent to which individuals conform to ratio-biases – specifically, individuals reporting a high preference for analytical information processing were less likely to respond based on the frequency of the numerator. Bonner and Newell (2008) tested the ratio-bias with the presence of temporal frames and found that individuals consistently conformed to Denes-Raj and Epstein's (1994) predictions relating to deviations from normative choice behaviour. Overall, there is broad evidence in support of the generality of the ratio-bias (Denes-Raj, Epstein and Cole, 1995). If our assertion that Iyengar et al.'s (2006) findings may emerge from the relatively parsimonious comparability of salaries at the expense of other important decision attributes, maximisers should exhibit a higher level of conformity with the ratio-bias as compared to their satisficing counterparts. In other words, maximisers should exhibit a preference towards an easily accessible attribute (i.e. the frequency of the numerator) over a cognitively more demanding judgement (i.e. evaluating the overall proportion) as a result of an inherent or adaptive behavioural inclination to maximise choice sets.

3.2.3 Pseudo Diversification

We have argued that maximisers susceptibility to biased judgements in situations calling for the evaluation of competing attributes results from a reliance on easily compared attributes at the expense of normatively more relevant ones, another important aspect, perhaps even more central to the internal logic of the maximising behavioural orientation, relates to maximisers' desire to expand choice and seek a more diverse set of options. Indeed, in general terms, variety seeking and the diversification of options while making decisions is a strong human tendency. The literature on these subjects is extensive and discussed by psychologists (e.g., Ayal and Zakay, 2009; Driver and Streufert, 1969; Fisk and Maddi, 1961), economists (e.g., Benartzi and Thaler, 2007; DeMiguel, Garlappi, and Uppal, 2007; French and Poterba, 1991), decision scientists (e.g., Galak, Kruger, and Loewenstein, 2011) and consumer researchers (e.g., Simonson, 1990; Van Trijp, Hoyer, and Inman, 1996). As a result, a number of explanations for this phenomenon have been offered ranging from suggestions of novelty and complexity as inherently satisfying human desires (McAlister and Pessemier, 1982; Simonson, 1990), a desire for change as a result of decreased satiation from repeated consumption (McAlister, 1982; McAlister and Pessemier, 1982), temporal effects of sequential or simultaneous decisions (Simonson, 1990), reductions in uncertainty through diversification and bundling (Ayal and Zakay, 2009; Simonson, 1990) and as Shwartz et al. (2002) suggest, to a general proliferation of choice. The fact that variety seeking is ubiquitous however, does not preclude that diversification can often be a naïve choice heuristic. In a number of applications, particularly in the context of studies that investigate financial decision making where the diversification of portfolios is a common investment strategy, experiments and field research has shown that in many cases variety seeking can lead to poorer decision outcomes (Ayal and Zakay, 2009; Baltussen and Post, 2011; Benartzi and Thaler, 2001).

While seeking a diversified choice set is central to the maximisers' decision making orientation – studies have shown for instance that maximisers search for more job opportunities (Iyengar et al., 2006), seek more variety when making material purchases (Carter and Gilovich, 2010), search longer and more extensively while making purchases online (Karimi, Papamichail, and Holland, 2015) and engage in more extensive upward social comparisons to differentiate themselves from their peers (Weaver, Daniloski, Schwarz, and Cottone, 2015) – to date, no studies directly address if maximisers' emphasis on engaging in variety seeking predisposes them to adhering to the behavioural biases associated with pseudo-diversity and poorly or over diversified options (see for instance, Benartzi and Thaler, 2007, 2001; Hedesström, Svedsäter, and

Gärling, 2009). Perhaps the closest indirect investigation of such an effect can be found in Polman's (2010) experiments on maximisers' variety seeking behaviour. In particular, study 2 in Polman's (2010) analysis leads to some notable results. The set-up was as follows: subjects are asked to perform Bechara, Damasio, Tranel, and Damasio's (1997) Iowa gambling task where they aim to win money by choosing cards from four separate decks. While two decks represent relatively large gains but larger losses, another two represent small gains but even smaller losses, such that an optimal decision strategy should converge towards choices from the deck guaranteeing small gains. Contrary to the expectation that maximisers would be more likely to conform with the strategy with better odds of success, Polman's (2010) analysis showed that not only did maximisers exhibit higher levels of variety seeking, drawing more cards from both sets of decks, but they also on average ended up with lower overall payoffs than their satisficing counterparts. This analysis would suggest therefore, that there are at least some circumstances in which maximisers' desire to seek variety predisposes them to judgements that neglect salient features of a decision problem that would lead to, normatively speaking, better outcomes. As a result, this raises the question of whether maximisers would be predisposed to preferring apparently diversified choices over less-diversified ones if the resulting payoffs are equivalent and, more importantly, would this preference extend to cases where the diversified option is the normatively inferior choice?

3.2.4 Representativeness

An important rationale for maximisers to seek out much larger choice sets over their decision process relates to their desire for representativeness. Dar-Nimrod et al. (2009) succinctly summarise this tendency – "more options to choose are perceived as better than are fewer options because, logically, the larger set is more likely to yield a desirable option (pp. 635, Dar-Nimrod, Rawn, Lehman, and Schwartz, 2009)." Indeed, it is precisely this mechanism that seems to rationalise maximisers' expectations that extending and conducting a more expansive search would lead to surprising alternatives that would have otherwise been left unattended, or excluded from consideration (Schwartz et al., 2002; Sparks, Ehrlinger, and Eibach, 2012). Dar-Nimrod et al. (2009) for instance show, that this kind of assessment influences maximisers' decisions to bear additional cognitive, affectual and material costs in order to seek a more exhaustive set of choices. Sparks et al. (2012) build on this analysis and suggest that this tendency in turn, corresponds to lowered levels of commitment towards decisions by hampering maximisers' ability to suppress thoughts about potentially forgone alternatives after a choice has already been made. At the same time, in their search for representativeness, maximisers seem to demonstrate problematic perceptions of temporal events. Besharat, Ladik, and Carrillat (2014), in a study based on a probabilistic sample of the US population, suggest that maximisers are more pessimistic towards past experiences, dissatisfied in the present, and overly optimistic about the availability of time and other resources in the future, comparative to their satisficing counterparts.

An implication from these findings relates to the way in which maximisers make evaluations based on already available information. For instance, in cases where maximisers need to assess the likelihood of encountering a superior alternative amongst an unattended set, when the current set is known, they may express a preference for the unattended set as a result of their reluctance to accept available information as sufficiently representative. In plainer terms, maximisers may be less likely to settle on a "good-enough" choice amongst an available set of alternatives as a result of an expectation that a better unattended alternative may still be available elsewhere and become accessible in the future (Shwartz et al., 2002; Schwartz, 2004a). A bias of this form, where decision makers take a series of past observations as evidence that the next iteration would lead to a contrary outcome is often referred to as *negative recency.* The prototypical demonstration of this phenomenon is encountered in the gambler's fallacy where individuals often make corrective adjustments in locally observed outcomes of chance events, in order to reflect the underlying randomness of the process (Tversky and Kahneman, 1971). On the other hand, when the mechanisms that generate the outcomes of such processes are seen to be dependent on past outcomes, decision makers can often exhibit a bias in the opposite direction or exhibit positive recency. For instance, while a coin toss may be viewed as an inherently random event with each outcome being representative of the underlying chance mechanism that generates it, when outcomes are perceived as being dependent on individual skill, decision makers often assess individual observations as being representative of an overall underlying pattern, even when this may not necessarily be the case. Gilovich, Vallone and Tversky (1985) demonstrated this type of bias in cases where individuals assessed positive player streaks in basketball games as evidence for a "hot-hand effect". Thus, the way in which individuals respond to sequences of previously observed outcomes often depends on the way in which they represent the mechanisms producing them. As maximisers' desire for representative sets of choices is a core definitional feature of the maximising behavioural orientation (Schwartz, 2004a; Schwartz et al., 2002), we expect maximising tendency to be positively associated with a higher adherence to both these biases. In other words, we expect maximisers to exhibit increased negative recency on the gambler's fallacy and increased positive recency on the hot hand effect as a result of their desire to seek representativeness from an available set of choices.

3.2.5 Hypotheses

In the previous sections, we have presented a number of arguments to suggest that the tendency of behavioural maximisers to seek a large amount of information, more diverse alternatives and representative sets of choices are central to their decision-making orientation. At the same time, we have suggested that these tendencies in turn, may be antithetical to their ability to engage in deliberative information processing, which predisposes them to behavioural biases and significant deviations from normatively expected decision making. Based on these considerations we formulate our first two hypotheses:

Hypothesis 1 (H1): *A preference for analytical information processing will be negatively related to maximising tendency.*

Hypothesis 2 (H2): *Maximising tendency will be positively correlated to deviations from normatively expected choices.*

Furthermore, based on our considerations of the literature on the individual behavioural biases, we formulate the expectation that for each of the behavioural biases we have discussed, maximisers will be more prone to adhering to the prescriptive bias as compared to their satisficing counterparts. Following the recommendations in Ayal et al. (2011), we do not hypothesise simply that a bias exists, but instead specify the precise direction in which the bias emerges. More specifically, since any deviation from a normatively appropriate alternative can be attributed to the presence of a bias, it is important to state *a-priori* how an assessment of a bias can be distinguished from non-systematic errors. As a result, we distinguish between the prescriptive bias – i.e. the direction in which extant literature suggests that a response will tend towards, if a bias is to be detected – versus a non-systematic error – i.e. the tendency to diverge from both the normative solution and the prescriptive bias. Formulating our hypotheses in this manner has two main advantages. First, this allows us to make explicit what we mean by bias adherence and second, it affords added statistical power as we can conduct one-tailed significance tests which are more robust and informative about deviations from mean adherence rates. Based on this line of reasoning, we propose the following hypotheses:

Hypothesis 3 (H3): *Maximising tendency will be positively correlated to an adherence to the ratio bias.*

Hypothesis 3a (H3a): *Maximisers will prefer the larger numerator over the normative choice.*

Hypothesis 3b (H3b): *Maximisers will prefer the larger numerator over the smaller numerator.*

Hypothesis 4 (H4): *Maximising tendency will be positively correlated to adherence to pseudo-diversification.*

Hypothesis 4a (H4a): *Maximisers will prefer the diversified choice over the normative choice.*

Hypothesis 4b (H4b): *Maximisers will prefer the diversified choice over the non-diversified choice.*

Hypothesis 5 (H5): *Maximising tendency will be positively correlated to adherence to the gambler's fallacy.*

Hypothesis 5a (H5a): *Maximisers will exhibit increased negative recency over a normative choice.*

Hypothesis 5b (H5b): *Maximisers will exhibit increased negative recency over positive recency.*

Hypothesis 6 (H6): *Maximising tendency will be positively correlated to adherence to the hot-hand effect.*

Hypothesis 6a (H6a): *Maximisers will exhibit increased positive recency over a normative choice.*

Hypothesis 6b (H6b): *Maximisers will exhibit increased positive recency over negative recency.*

3.3 Study 1

3.3.1 Method

In study 1 our goal was to assess whether maximisers express a lowered preference for an analytical information processing style. Three hundred and fifty participants from Amazon MTurk completed the study in exchange for a nominal monetary compensation (see Buhrmester, Kwang, and Gosling, 2011 and Desai and Kouchaki, 2017 for surveys of MTurk data quality). All participants were told that they would be expected to respond to a series of questions relating to choices and decisions in daily life and were otherwise naïve to the objectives of the study. After providing electronic consent and agreeing to participate in the study, respondents were directed to questionnaires measuring maximising orientation and information processing preferences interspersed with a number of filler items and demographic questions. Questionnaires were presented in randomised and counterbalanced blocks to minimise order effects within our sample. We implemented three attention check questions over the course of the entire survey and removed four participants that failed to respond appropriately (n = 4). Our final sample included three hundred and forty-six participants (49% female, n = 169). The largest age-group in our sample was 26-35 years (43.6%, n = 151). Highest level of education was 1.2% no degree, 17.1% high-school degree, 7.8% professional diploma, 48.8% undergraduate degree, 24.6% master's degree, 0.5% doctorate.

3.3.2 Measures

Self-reported maximising. In order to measure decision maker orientation to maximise or satisfice, we used Schwartz et al.'s (2002) thirteen-item scale (e.g. "When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program") anchored at 1 (=completely disagree) and 7 (=completely agree). The scale is formulated as a bi-polar construct suggesting a propensity to adopt a maximising orientation at the higher end of the scale and to satisfice at the lower end. A full list of items from the maximising scale can be found in Appendix A (section 3.8.2).

Information processing preference. We used Pacini and Epstein's (1999) revised version of the 40-item Rational and Experiential information processing styles Inventory (REI). Participants were asked indicate how true each of the scale items was for them anchored at 1 (=Definitely False) and 7 (=Definitely True). The REI consists of two unipolar scales (20-items each) assessing the extent to which individuals are likely to adopt either of the dual information processing styles. The first scale assesses favourableness towards cognitively demanding activities from participants and relates to a preference for analytical information processing (e.g. "I usually have clear explainable reasons for my decisions"). The second relates to attitudes towards experiential activities and corresponds to the intuitive information processing preference (e.g. "I often go by my instincts when deciding on a course of action"). As opposed to the maximising inventory that measures satisficing/maximising on a single continuum, the REI conceptualises analytical and intuitive information processing preferences as orthogonally related constructs, i.e., a strong preference towards analytical information processing does not necessarily preclude a high preference for intuitive information processing. Appendix A (section 3.8.1) provides a full list of the REI items.

3.3.3 Results and Discussion

Before testing our hypothesis, we assessed the internal consistency of the three scales employed in our study by computing Cronbach's alpha coefficients for each. Consistent with previous applications of these measures, we found high internal consistency for all three scales ($\alpha_{maximising} = .87$; $\alpha_{analytical} = .86$; $\alpha_{intuitive} = .89$). Next, we computed composite scores for each of the three scales by averaging across individual items. Overall, average scores for maximising tendency ($M = 4.52, SD = 1.16$) and preference for analytical ($M = 4.79, SD = .87$) or intuitive ($M = 4.47, SD = .93$) information processing styles in our sample were comparable to previous applications (Dar-Nimrod et al., 2009; Iyengar et al., 2006; Schwartz et al., 2002). In our sample, a preference for analytical information processing was weakly positively correlated to a preference for an intuitive information processing style ($r = .16, p < .001$) and there was no significant correlation between maximising and intuitive information processing ($r = .16, p = .24, ns$). As expected we found a negative correlation between maximising and analytical information processing preferences ($r = -.17, p < .01$). In order scrutinise our correlational analysis by controlling for demographic differences between maximisers and test our hypothesis that there would be a negative relationship between a tendency to maximise and a preference for analytical information processing, we conducted a multiple regression analysis on the composite measure of maximising tendency. We entered composite scores for preference for analytical and intuitive information processing as covariates in the model along with continuous controls for age and highest level of education and an indicator variable for gender, coded to 1 (=female) and 0 (=male). Our overall model was significant ($F(5, 340) = 11.74, p < .001$) and able to explain 14.7% of the variability in maximising scores. Our dependent variable for maximising orientation was approximately normally distributed across the mean ($M = 4.52, Mdn = 4.46, skew = -.11, kurtosis < .001$) and visual assessments of residuals plotted against fitted values and qq-plots from our model did not suggest any significant deviations from the assumption of normally distributed errors. While we did not expect to encounter problems associated with multicollinearity owing to the relative parsimony of the estimated model, since our covariates were marginally correlated, we computed variance inflation factors (VIFs) for all variables. VIFs ranged from 1.04 to 1.09, well below recommended threshold values, suggesting multicollinearity was not an issue with our model (Hair, Black, Babin, Anderson, and Tatham, 2014).

As expected, we estimated a significant negative main effect of a preference for an analytical information processing style on maximising tendency ($\beta = -.18, p < .01$) and the effect was near identical to the Pearson correlation coefficient, suggesting

TABLE 3.1: Multiple regression results for study 1 estimating the relationship between analytical information processing preference and maximising tendency

	Estimate for maximising tendency	Collinearity statistics	
	B (SE)	VIF	TOL
Information processing preference			
Analytical	-.18 (.07)**	1.06	.94
Intuitive	-.03 (.07)	1.09	.91
Demographic controls			
Age	-.27 (.05)***	1.05	.95
Education	.19 (.06)***	1.04	.96
Gender (male=0, female=1)	.00 (.12)	1.06	.95
Constant	5.48 (.48)***		
R^2	.15		

$***p < .001, **p < .01, *p < .05$
B = unstandardised regression coefficient, SE = standard error, VIF = variance inflation factor, TOL = Tolerance (1/VIF).

that after controlling for differences in age, highest level of education, gender and a preference for intuitive information processing, there was a consistent negative relationship between maximising and analytical information processing preferences. The coefficient for intuitive information processing was marginally negative, lower than the Pearson coefficient and non-significant ($\beta = -.03, p = .62, ns$). We find similar positive and negative coefficients for education ($\beta = .19, p < .001$) and age ($\beta = -.27, p < .001$) respectively, as reported in Parker et al. (2007), supporting their view that demographic characteristics may have some bearing on individual maximising tendencies. In order to assess model-fit and test for any interactions between our covariates we also fit an alternative model including a term for the interaction between the two REI measures. There was no significant effect of the interaction between intuitive and analytical information processing preferences on maximising tendency ($\beta = .08, p = .10, ns$) and the coefficients for other parameters remained largely unchanged. The model including the interaction term was a poorer fit to the data and did not explain a significantly larger proportion of variance than our more parsimonious model ($F(1) = 2.70, p = .10, SS = 3.12$) and as a result we do not discuss it further. Table 3.1 shows the complete results from our analysis. Overall, the results from our analysis provide support for our hypothesis (H1) and suggest that a preference for analytical information processing is negatively related to maximising tendency.

3.4 Study 2

3.4.1 Method

In study 2, our goal was to address H2 (study 2a) and H3 - H6 (study 2b). We recruited five hundred and fifty participants from MTurk of which twelve did not complete the survey as a result of failing an attention check question. Our final sample included five hundred and thirty-eight participants (56% female, n = 300). The largest age group was 26-35 years (46.7%, n = 251). Highest level of education was 0.01% no degree, 18.6% high-school degree, 10.6% professional diploma, 44.8% undergraduate degree, 24.2% master's degree, 0.01% doctorate. The experimental procedure was comprised of two stages. First, similar to study 1, subjects completed the maximising and rational-experiential information processing (REI) inventories presented in randomised order and were asked to provide standard demographic information. After completing this section, all subjects received an identical set of instructions as follows: "In the next section of this survey, you will be presented with a number of scenarios and asked to make a choice or prediction based on these. Please try and think carefully about your responses and be as accurate as possible." In the second stage, subjects were presented with four prototypical questions used to examine adherence to biased thinking. The questions used in this stage of the study were adapted from previous applications and presented in a randomised order (ratio-bias, Denes-Raj and Epstein, 1994; pseudo-diversification, Ayal and Zakay, 2009; gambler's fallacy, Kahneman and Tversky, 1972; hot hand effect, Ayal et al., 2015). We framed questions so that subjects were presented with a normatively expected choice along with two biased choices in either direction. For instance, to assess adherence to the ratio-bias we asked participants to assess the likelihood of drawing a red marble from either one of two urns, A or B, containing 100/1000 and 1/10 red marbles respectively, participants could choose between urn

A, urn B, or indicate an indifference between both options. In this case therefore, the indifferent choice would be the normatively expected outcome, selecting urn A would correspond to the predicted direction of the ratio-bias and selecting urn-B would represent a biased response in the other direction. A complete list of questions used as stimuli for this stage of the experiment can be found in Appendix B.

3.4.2 Reliability and Manipulation Check

Based on Cronbach's alpha coefficients, all three scales employed in our analysis demonstrated high internal consistency ($\alpha_{maximising} = .85; \alpha_{analytical} = .85; \alpha_{intuitive} = .88$). The mean score for maximising tendency was 4.60 ($SD = 1.09$), analytical information processing preference was 4.77 ($SD = .87$) and intuitive information processing preference was 4.60 ($SD = .91$). Next, to establish if the questions intended to assess biased responses represented deviations from normatively expected choices, we evaluated the overall and individual frequencies of bias adherence in our sample across all tasks. In order to do this, we coded a selection of a biased response in either direction as "1" and the corresponding normatively expected choice as "0" for each of the four examined biases. Across all four tasks, the proportion of subjects adhering to biased responses was 77.5%. Adherence rates for individual instances were, 84.6% for the ratio bias, 88.3% for pseudo-diversification, 45.5% for the gambler's fallacy and 84.4% for the hot hand effect. Thus, save for the gambler's fallacy, we find a large proportion of our sample presenting instances of bias adherence, suggesting that our manipulation of questions attempting to induce deviations from normatively expected choice behaviour was successful.

3.4.3 Study 2(a): Examining overall bias adherence

In study 2(a), our aim was to assess the relationship between maximising tendency and overall adherence to biased thinking. Specifically, we wanted to test our hypothesis (H2) that maximisers would present more deviations from normatively expected choice behaviour across all four tasks as compared to their satisficing counterparts. In order to do this, we estimated a binomial logistic model predicting the number of times a biased choice was selected across the four tasks based on maximising scores, information processing preference and demographic characteristics. Our outcome variable is therefore a count of the number of instances subjects present of adhering to a biased response in either direction (=1) as opposed to the normatively expected choice (=0), across all tasks. As both analytical and intuitive information processing have been shown to affect adherence to biased judgements in previous research, we enter these variables as covariates in the model along with controls for gender (1=female, 0=male), age and highest level of education. Our main focus however was to test, holding these variables constant, if a tendency to maximise was positively related to bias adherence.

Results and Discussion

Before making any inferences from our model, we conducted tests to detect overdispersion and poor-fit. The ratio of residual deviance to degrees of freedom from our model was sufficiently close to 1 ($\sigma_p = 1.09$) and did not suggest any significant issues with overdispersion (Payne et al., 2017, have suggested a threshold for preferring overdispersed models in cases where $\sigma_p \geq 1.50$). A likelihood ratio test confirmed that our model fit significantly better than a null model ($\chi^2(6) = 40.87, p < .001$) and a Hosmer-Lemeshow test for the alternate hypothesis of a poorly fit model did not provide any evidence to suggest calibration errors ($\chi^2(7) = 10.02, p = .187$). Overall, these tests suggest that the coefficients and standard errors estimated by our model are robust and representative of the underlining data.

None of the demographic variables in our model predicted an adherence to biased responses and as a result, we do not discuss these any further. In line with our expectations, our analysis revealed a significant effect of maximising tendency on bias adherence ($\chi^2(1) = 13.12, p < .001$). Specifically, we found that a one unit increase in maximising tendency increased the log odds of deviating from a normatively expected choice by 19.8%. We computed an odds ratio of 1.21 ($95\%CI = 1.08, 1.33$) with the inference that for every one unit increase in maximising tendency, the probability of selecting a biased response increased by 3.5%. These findings suggest that on average, compared to their satisficing counterparts, maximisers are more likely to deviate from normatively expected choices. The comparative results based on mean bias adherence rates for maximisers and satisficers are plotted in Figure 1. We were also

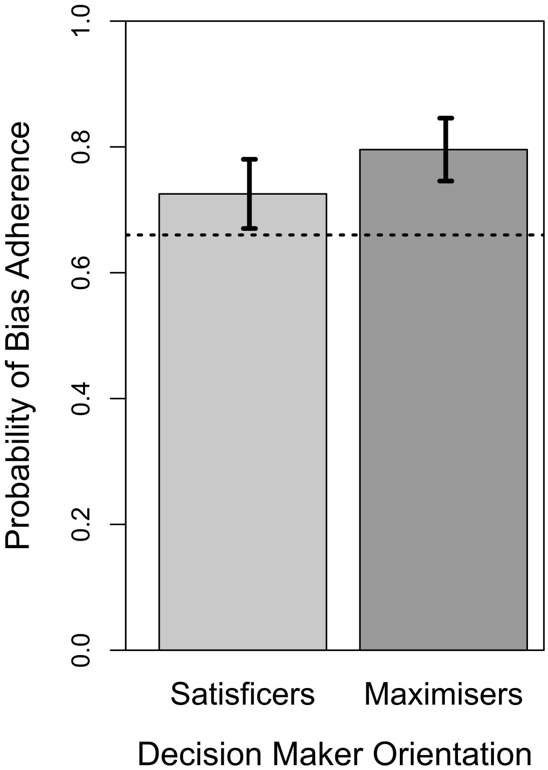


Figure 3.1: Mean bias adherence rates for maximisers and satisficers. Maximisers and satisficers are grouped via median split. The error bars show the 95% confidence interval. The dotted line represents chance performance.

TABLE 3.2: BINOMIAL LOGISTIC REGRESSION RESULTS FROM STUDY 2(A) PREDICTING BIAS ADHERENCE ACROSS ALL TASKS

	Estimates for rate of overall bias adherence			Collinearity statistics	
	B (SE)	OR	95% CI	VIF	TOL
Focal predictor					
Maximising	.19 (.05)***	**.21**	**[1.08, 1.33]**	1.15	.87
Information processing preference					
Analytical	-.18 (.06)**	**.84**	**[.74, .95]**	1.09	.92
Intuitive	.15 (.06) **	**1.16**	**[1.04, 1.30]**	1.09	.92
Demographic controls					
Age	.05 (.05)	1.05	[.95, 1.16]	1.12	.90
Education	-.01 (.05)	.98	[.89, 1.08]	1.03	.97
Gender (male=0, female=1)	.01 (.05)	1.01	[.82, 1.25]	1.03	.97
Constant	.49 (.49)				
Model fit					
Model $\chi^2(df)$	29.27 (6), p <.001				
H-L $\chi^2(df)$	10.02(7), p = .187, ns				
$R^2(McFadden)$	.03				
$R^2(Nagelkerke)$	.08				

$***p < .001, *p < .05$

B = unstandardised regression coefficient, SE = standard error, OR = odds ratio, 95% CI = confidence interval for OR, VIF = variance inflation factor, TOL = Tolerance (1/VIF), Model $\chi^2(df)$= Likelihood-ratio test, H-L $\chi^2(df)$= Hosmer-Lemeshow test, $R^2(McFadden)$ = McFadden pseudo-R^2, $R^2(Nagelkerke)$ = Nagelkerke pseudo-R^2.

Note. Significant odds-ratios are in **bold-face.**

able to replicate recent findings with respect to the effect of analytical and intuitive information processing on biased thinking. We found a significant negative effect of a preference for analytical information processing ($\beta = -.18, OR = .84, \chi^2(1) = 8.18, p = .004$) and a positive effect for intuitive information processing ($\beta = .15, OR = 1.16, \chi^2(1) = 6.78, p = .009$) on adherence to biased responses. Taken together, our analysis provides support for our hypothesis (H2) that on average, maximisers are more susceptible to conforming to behavioural biases across all tasks compared to their satisficing counterparts. The overall results from our analysis are presented in Table 3.2.

3.4.4 Study 2(b): Examining the directionality of biased responses

While we were interested in examining the overall level of bias adherence in study 2(a), in study 2(b), we evaluated the directionality of the responses on individual tasks. Specifically, we test H3-H6. We conducted separate multinomial logistic regressions to estimate the probabilities associated with each of the responses across all four tasks. Since response variables in all four cases could take on one of three possible values (i.e. selecting a biased response in either direction or a normatively expected response, see Appendix B), multinomial logistic regression was determined to be a suitable analytical approach as it extends logit models to such cases, without the assumption of independent samples involved in repeated logistic regression (Agresti, 2003). In order to provide a consistent basis of comparison across all four models, we used the prescriptive direction of the bias (i.e. exhibiting a bias in the expected direction) as a reference against which to compare the probabilities of selecting the normatively expected choice or exhibiting a bias in a direction other than that suggested by our hypotheses. To assess model fit, we employed similar procedures as in study 2(a), compared the fitted models against intercept-only models, conducted Hosmer-Lemeshow tests and computed pseudo R^2 statistics for each of our multinomial models. The results from these are presented in Table 3.3. Overall, all four models were significant and did not indicate any evidence to suggest poor model fit.

TABLE 3.3: FIT STATISTICS FOR MULTINOMIAL LOGISTIC REGRESSIONS CONDUCTED IN STUDY 2(B)

	(a) Ratio-bias	(b) Pseudo Diversification	(c) Gambler's Fallacy	(d) Hot Hand Effect
Model $\chi^2(df)$	44.31(12), $p <.001$	79.53(12), $p <.001$	36.87(12), $p <.001$	45.29(12) $p <.001$
H-L $\chi^2(df)$	15.43(16), $p = .494, ns$	9.75(16), $p = .879, ns$	13.60(16), $p = .629, ns$	19.62(16), $p = .238, ns$
$R^2(McFadden)$	0.05	0.08	0.04	0.05
$R^2(Nagelkerke)$	0.09	0.16	0.08	0.09

Model $\chi^2(df)$= Likelihood-ratio test, H-L $\chi^2(df)$= Hosmer-Lemeshow test, $R^2(McFadden)$ = McFadden pseudo-R^2, $R^2(Nagelkerke)$ = Nagelkerke pseudo-R^2.
p = p-value, ns = not significant.

Results and Discussion

a) Ratio Bias

To evaluate whether maximising tendency predicted a higher adherence to the ratio bias, we estimated a multinomial logistic model to predict the odds of choosing the normatively expected choice (n = 83) or the smaller numerator (n = 116), compared to the reference category of choosing the larger numerator (n = 339) as a function of maximising tendency. We controlled for analytical and intuitive information processing preferences, age, highest level of education and gender. In support of our hypothesis, our analysis revealed significantly lower odds of selecting the normatively expected choice as compared to the biased outcome as maximising tendency increased ($\beta = -.37, \chi^2(1) = 8.70, p = .003$). Specifically, we found for every one unit increase in maximising tendency, the relative likelihood of selecting the normatively expected choice over the biased outcome was reduced by 3.2% ($OR = .68, 95\%CI = .53, .88$). We recovered significant estimates for analytical ($\beta = .47, \chi^2(1) = 9.11, p = .003, OR = 1.61$) and intuitive ($\beta = .47, \chi^2(1) = 9.11, p = .003, OR = 1.61$) information processing preferences, suggesting that a higher preference for analytical (intuitive) information processing was associated with increased (decreased) odds of choosing the normatively expected choice. In contrast, we did not find any significant effects of maximising tendency or information processing preferences on choosing the smaller numerator compared to the larger numerator. The estimate for maximising tendency was negative however not significant at the 95% confidence level ($\beta = -.19, \chi^2(1) = 2.99, p = .084$). Taken together our analysis suggests that maximisers are more likely to adhere to the ratio bias as compared to their satisficing counterparts however, maximising tendency does not affect the probability of exhibiting a bias in the opposite direction. Thus, while our analysis provides support for H3a, we were unable to support H3b. The overall results from our analysis are summarised in the left-most panel in Table 3.4.

b) Pseudo Diversification

Next, we employed the same procedure in order to assess the relationship between maximising tendency and adherence to the pseudo-diversification bias. We used the diversified choice ($n = 309$) as the baseline against which to compare the odds of selecting the normatively expected ($n = 63$) and non-diversified ($n = 166$) choices. Maximising tendency was the sole significant predictor of choosing in either direction. As tendency to maximise increased, subjects were less likely to select both the normatively expected ($\beta = -.63, \chi^2(1) = 17.34, p < .001$) and the non-diversified choice ($\beta = -.75, \chi^2(1) = 44.73, p < .001$). For every one unit increase in maximising tendency, the relative odds of selecting the normatively expected choice compared to the diversified choice reduced by 4.2% ($OR = .53, 95\%CI = .39, .71$). The relative odds of selecting the non-diversified choice reduced by 5.3% ($OR = .47, 95\%CI = .38, .59$). The results from our analysis are summarised in panel b in Table 3.4. Overall, in support of H4a and H4b, our analysis suggests that maximisers exhibit a preference for an apparently diversified option over both, the normatively expected choice as well as the non-diversified option.

c) Gambler's Fallacy

For the gambler's fallacy task, we asked subjects to predict the probability of the next outcome of a (fair) coin toss after three successive tails outcomes. We coded a response of heads $> 50\%$ as a negative recency ($n = 171$), heads $< 50\%$ as a positive recency

($n = 74$) and heads = tails = 50% as the normatively expected choice ($n = 293$). In order to assess whether maximising tendency was associated with an increased likelihood of exhibiting negative recency on the gambler's fallacy task, we compared the odds of choosing the normative and positive recency choices against the negative recency outcome. Our analysis revealed a significant negative effect of maximising tendency on selecting both the normatively expected ($\beta = -.23, \chi^2(1) = 7.38, p = .007$) and positive recency ($\beta = -.41, \chi^2(1) = 8.47, p = .004$) outcomes. Specifically, we found that comparative to the negative recency choice, for every one unit increase in maximising tendency, the odds of choosing the normatively expected outcome fell by 2.3% ($OR = .77, 95\%CI = .64, .93$) whereas the odds of exhibiting a positive recency fell by 3.4% ($OR = .66, 95\%CI = .50, .87$). A preference for analytical information processing predicted an increased likelihood of selecting the normatively expected choice ($\beta = -.23, \chi^2(1) = 7.38, p = .007, OR = 1.33$) and decreased likelihood of a positive recency ($\beta = -.23, \chi^2(1) = 7.38, p = .007$) as compared to a negative recency. We did not find any effect of a preference for intuitive information processing on choosing in either direction (see Table 3.4, panel c). Taken together, our results support H5a and b, suggesting that maximisers are more likely to adhere to the gambler's fallacy than their satisficing counterparts and maximisers are more likely to exhibit negative as opposed to positive recency.

TABLE 3.4: Multinomial logistic regression results from study 2(b). Models (a)-(d) predict odds of picking the normatively expected choice or exhibiting a bias in the opposite direction compared to the reference category.

	(a) Ratio Bias				(b) Pseudo Diversification				(c) Gambler's Fallacy				(d) Hot Hand Effect			
Reference category:	Larger numerator (n = 339)				Diversified choice (n = 309)				Negative recency (n = 171)				Positive recency (n = 290)			
	Normative choice (n = 83)		Smaller numerator (n = 116)		Normative choice (n = 63)		Non-diversified choice (n = 166)		Normative choice (n = 293)		Positive recency (n = 74)		Normative choice (n = 84)		Negative recency (n = 164)	
	B (SE)	OR	B (SE)	OR	B (SE)	OR	B (SE)	OR	B (SE)	OR	B (SE)	OR	B (SE)	OR	B (SE)	OR
Focal Predictor																
Maximising	-.37** (.13)	**.68**	-.19 (.12)	.83	-.63*** (.15)	**.53**	-.75*** (.11)	**.47**	-.26** (.10)	**.77**	-.41** (.14)	**.66**	-.34** (.13)	**.71**	-.22* (.10)	**.80**
Information processing preference																
Analytical	.47** (.16)	**1.61**	-.10 (.13)	.90	.02 (.16)	0.98	-.19 (.12)	.82	.29* (.12)	**1.33**	-.39* (.17)	**.68**	.29 (.16)	1.34	.39** (.12)	**1.48**
Intuitive	-.38* (.14)	**.68**	.08 (.13)	1.09	-.24 (.16)	.79	-.21 (.12)	.81	-.11 (.12)	1.11	.20 (.17)	1.22	-.19 (.15)	.83	-.10 (.11)	.91
Demographic controls																
Age	.09 (.12)	1.10	.09 (.11)	.87	.05 (.13)	1.05	-.13 (.10)	.88	-.14 (.10)	.87	-.06 (.14)	.95	-.29* (.13)	**.75**	.07 (.10)	1.07
Education	-.03 (.11)	.97	.10 (.10)	.90	-.09 (.13)	1.09	.15 (.10)	.61	.05 (.09)	1.05	.04 (.13)	1.09	-.25* (.12)	**.78**	-.25** (.09)	**.78**
Gender	-.10 (.26)	.91	-.56* (.22)	**.57**	-.02 (.29)	1.02	-.49* (.21)	**.86**	-.06 (.20)	.94	.08 (.29)	1.04	-.36 (.26)	.70	-.36 (.21)	1.03
Constant	-.34 (1.20)		.87 (1.02)		2.06 (1.42)		5.78*** (1.04)		.10 (.95)		1.85 (1.31)		1.57 (1.18)		-.19 (.96)	

***p < .001, **p < .01, *p < .05. B = unstandardised regression coefficient, SE = standard error, OR = odds ratio.
Note. Significant odds-ratios are in **bold-face**.

d) Hot Hand Effect

Finally, we assess whether maximisers are more likely to exhibit higher positive recency in the hot hand effect. Similar to the procedure employed in the gambler's fallacy task, we coded responses (see Appendix B) as representing positive (Ace > 45%) and negative (Ace < 45%) recency or the normatively expected choice (Ace = 45%, Not Ace = 55%). We used the positive recency (n = 290) choice as the reference against which to compare the normative ($n = 84$) and negative recency outcomes (n = 164). Our analysis revealed a significant negative effect of maximising tendency on selecting the normative ($\beta = -.34, \chi^2(1) = 7.12, p = .008$) and negative recency ($\beta = -.22, \chi^2(1) = 4.98, p = .026$) outcomes. Compared to the positive recency, a unit increase in maximising tendency reduced the odds of selecting the normative outcome by 2.9% ($OR = .71, 95\%CI = .55, .91$) and negative recency by 2% ($OR = .80, 95\%CI = .66, .97$). Our results support H6a and H6b and suggest that maximisers are more likely to exhibit positive recency over a negative recency, or selecting the normatively expected choice and are more susceptible to the hot hand effect as compared to their satisficing counterparts. The results from our analysis are summarised in panel d in Table 3.4.

We plot our results from study 2(b) in Figure 3.2. Our results suggest that maximising tendency is positively related to an adherence to each of the biases we have investigated. Furthermore, in three of the cases (pseudo-diversification, gambler's fallacy and hot-hand effect), we find that while maximising is positively related to selecting the prescriptive biased outcome, it is negatively related to exhibiting biases in the opposite direction. In figure 2, we visualise this effect by plotting the relative change in the odds of selecting in the predicted direction of the bias (the light grey region under the curve) against exhibiting a bias in the opposite direction (the dark grey region under the curve). Interestingly, this effect was most pronounced in the pseudo-diversification task. One of the major implications of this result relates to a core definitional distinction between maximisers and satisficers with respect to their orientations towards variety seeking. Specifically, since a preference (or aversion) to variety seeking is a central distinction between Schwartz et al.'s (2002) operationalisation of the maximising (satisficing) construct, this pattern of results suggests that

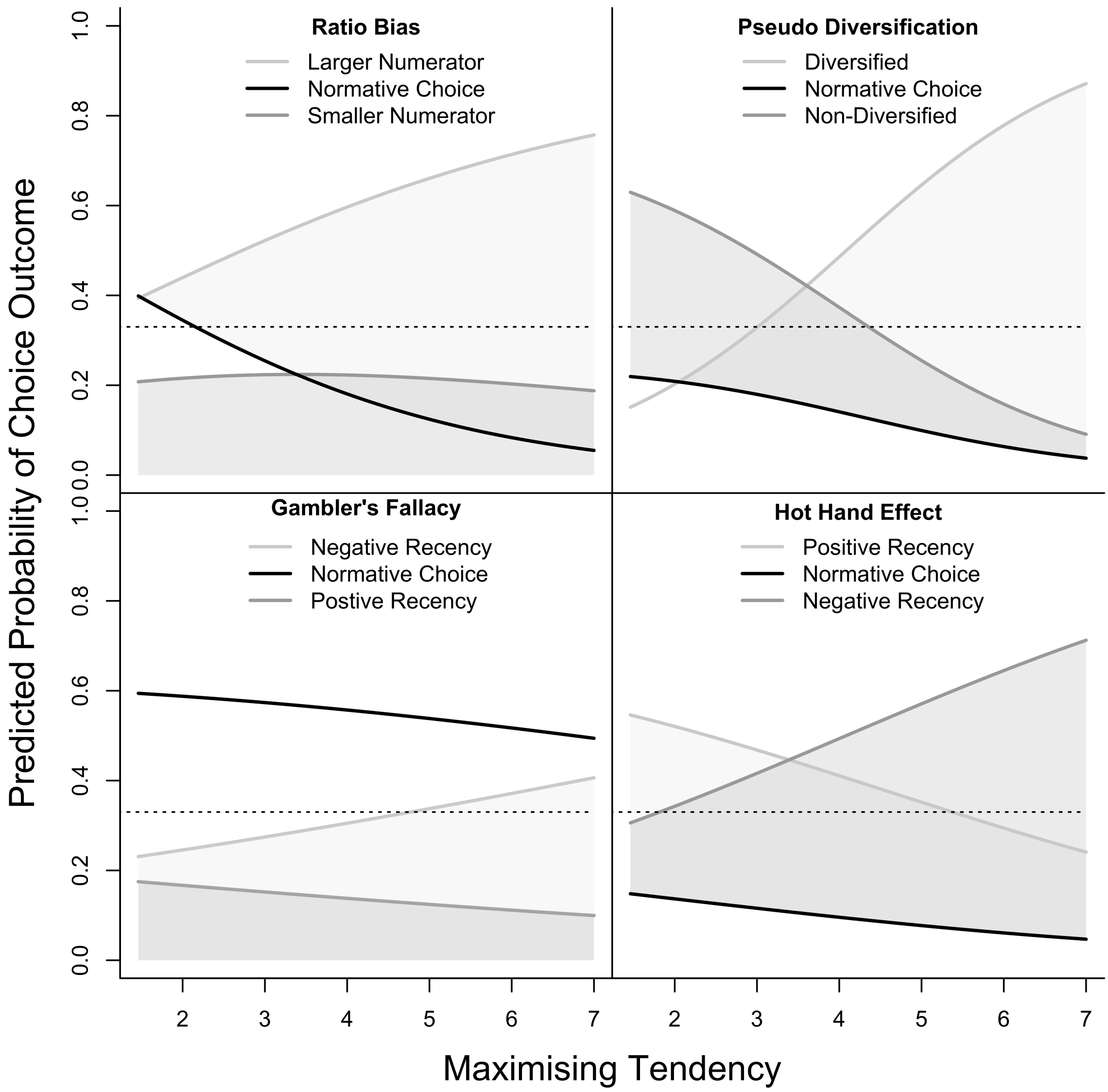


Figure 3.2: Fitted multinomial regression plots from study 2(b). The solid lines represent probabilities for each of the three choice outcomes as a function of maximising tendency. The shaded areas under the curve show the relative change in odds of choosing the prescriptive biased option (light grey) compared to choosing a biased option in the other direction (dark grey). The dotted line represents chance performance.

while maximisers are more prone to exhibiting a bias towards an apparently diversified choice, satisficers are likely to exhibit a bias in the opposite direction. We also found this effect in both the gambler's fallacy and hot-hand tasks. Notably, lower maximising scores resulted in similar responses for both positive or negative recencies in either case, however as maximising tendency increased, subjects were more likely to respond in accordance with the direction predicted by both biases. That is, as maximising tendency increased, subjects exhibited negative recency in the gambler's fallacy task and positive recency in the hot hand effect task. Our results therefore, provide support for all but one of our hypotheses (i.e. H3b). In H3b, we expected that maximisers would exhibit a lower preference for the smaller numerator however, our results were unable to provide support for this proposition. One of the reasons for this discrepancy could relate to the larger than average adherence to the ratio-bias across our sample. Indeed, as we initially suggested, the ratio-bias has variously been demonstrated to be a fairly general phenomenon with a high level of adherence at the aggregate level (Denes-Raj et al., 1995). Thus, while we were not able to establish any relationship between maximising tendency and an aversion towards the smaller numbered proportion, we did find that as maximising tendency increased, subjects were more likely to select the prescriptive bias as opposed to the normatively expected choice.

One of the major limitations in study 2 is related to the construction of the tasks that were employed. Specifically, in the ratio bias and pseudo-diversification tasks, we asked subjects to select between choices with equivalent odds of success. While operationalising our study in this manner allowed us to test our directional hypotheses, we were unable to infer from these results if maximisers would continue to exhibit these preferences for choices with unequal outcomes. Furthermore, with respect to the gambler's fallacy task in particular, a large number of subjects responded in the normatively expected manner. As a result, we were unable to say if the pattern suggested by our results would extend to cases where subjects are required to make predictions while explicitly ignoring base rates. In other words, we were unable to establish if maximisers that selected the normatively expected choice would be more likely to exhibit recency biases in cases where the indifferent outcome is unavailable. This latter limitation is equally applicable to our investigation of the hot hand effect.

We address these limitations in study 3.

3.5 Study 3

3.5.1 Method

In study 3, we were mainly interested in investigating if our findings from study 2 were replicable in contexts where a biased outcome is dominated by a normatively superior choice or a normative choice is inaccessible. We test the former aspect for the ratio-bias and pseudo-diversification cases and the latter, in the context of the gambler's fallacy and hot hand effect. We recruited two hundred and sixty participants from MTurk for this study and dropped one respondent that failed to respond correctly to an attention check question. Our final sample included two hundred and fifty-nine participants ($49.8\% female, n = 129$). The largest age group was 26-35 years ($40.9\%, n = 106$). Highest level of education was 1.2% no degree, 19.7% high-school degree, 7.3% professional diploma, 49.4% undergraduate degree, 22% master's degree and 1 respondent reported holding a doctorate. We employed a near identical research design as in study 2 however, altered the questions presented in the second stage of the experiment, so choices reflected either unequal odds of success or elicited preferences based on recency judgements disregarding base rates. For instance, in the ratio-bias example, we altered the proportions of the two urns (Urn A = 99/1000 and Urn B = 1/10) so that subjects were presented with a dominating choice (Urn B) and a biased choice (Urn A). We employed a similar format in the pseudo-diversification task. For the gambler's fallacy and hot hand effects, we framed questions so that subjects were asked to offer a preference for a biased choice exhibiting either negative or positive recency. For instance, we framed the gambler's fallacy task as follows: "A fair coin has equal probabilities of 50% for a heads or tails outcome (H = 50% and T = 50%). Imagine that you have just witnessed three tosses of a fair coin and the outcome was tails all three times (i.e. T-T-T). Even though you know that the probability of a heads or tails outcome on the next (i.e. fourth) toss are identical, you may have a preference for one or the other outcome given your observations. Considering this, which do you think may be the more likely outcome on the next toss?" The adjusted questions for all four tasks in study 3 can be found in Appendix B.

3.5.2 Reliability and Manipulation Check

All three scales used in our analysis demonstrated high internal consistency ($\alpha_{maximising} = .82; \alpha_{analytical} = .88; \alpha_{intuitive} = .91$) and composite means for maximising tendency ($M = 4.32, SD = 1.02$), analytical ($M = 4.93, SD = .88$) and intuitive ($M = 4.32, SD = 1.02$) information processing preferences were comparable to studies 1 and 2. For each of the four biases, we coded a choice corresponding to the prescriptive bias as "1" and the normatively expected alternative as "0" (note that for the gambler's fallacy and hot-hand effect, we coded the positive and negative recency responses as 0 respectively, since the basis of comparison was to assess whether the directionality of the recency biases uncovered in study 2(b) persist in cases where the normative choice is unavailable). Overall bias adherence was significantly lower than in study 2, with 55.99% of subjects exhibiting biased thinking averaged across all four tasks (ratio bias = 51.35%, pseudo-diversification = 55.60%, gambler's fallacy = 59.46%, hot hand effect = 57.53%).

3.5.3 Results and Discussion

Similar to study 2, we assessed goodness of fit for all of the models that were estimated and did not find any evidence to suggest poor model fit. The analytical strategy employed to assess overall bias adherence was identical to study 2(a) however, in order to assess individual instances, we conducted binary logistic regressions on the dichotomous outcomes for each of the individual biases. The complete results from our analysis along with goodness of fit tests are reported in Table 3.5.

We were able to replicate our results from study 2(a) and found that maximising tendency was positively correlated to overall bias adherence across all four tasks ($\beta = .52, \chi^2(1) = 69.48, p < .001$), with a one unit increase in maximising tendency increasing the probability of selecting a biased choice by 11.8% ($OR = 1.69, 95\%CI = 1.47, 1.95$). We also found similar negative and positive effects of preference for analytical ($OR = .67, 95\%CI = .57, .79$) and intuitive ($OR = 1.22, 95\%CI = 1.06, 1.41$) information processing styles on bias adherence. Next, we assessed whether maximising tendency was positively associated with bias adherence in the individual tasks.

For the ratio-bias, we found that as maximising tendency increased, subjects were

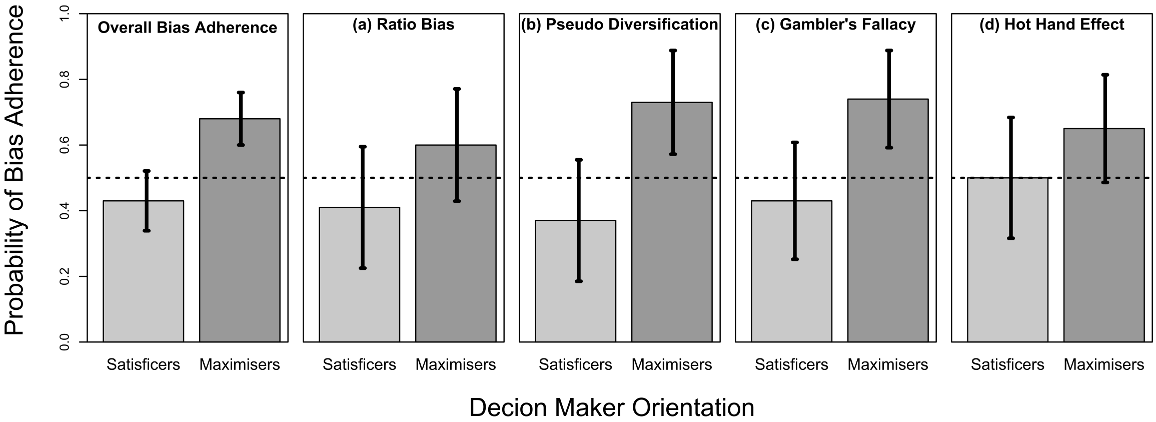


Figure 3.3: Overall and task specific mean bias adherence rates grouped by decision making orientation from study 3. Maximisers and satisficers are grouped by median split. Error bars represent 95% confidence intervals and were computed via separate regressions carried out using the median grouped maximising/satisficing factor. Panels (a) - (d) represent individual binary logistic regressions carried out for each of the four tasks.

more likely to select the biased choice as opposed to the normatively expected outcome ($\beta = .44, \chi^2(1) = 9.63, p = .002$). Specifically, a unit increase in maximising tendency was associated with a 9.9% increase in the probability of selecting the larger numerator over a dominating outcome ($OR = 1.56, 95\% CI = 1.18, 2.06$). Similarly, for the pseudo-diversification bias, every unit increase in maximising tendency was associated with an 8.9% increase in the probability of picking a poorer diversified option over a dominating non-diversified one ($\beta = .74, \chi^2(1) = 29.39, p < .001, OR = 2.09, 95\% CI = 1.55, 2.83$). Finally, we tested the recency biases exhibited on the gambler's fallacy and hot hand tasks. In line with our previous findings, our analysis revealed that maximising tendency was positively related to exhibiting increased negative recency on the gambler's fallacy ($\beta = .63, \chi^2(1) = 26.84, p < .001, OR = 1.89, 95\% CI = 1.40, 2.55$) and positive recency on the hot hand effect ($\beta = .39, \chi^2(1) = 9.45, p = .002, OR = 1.48, 95\% CI = 1.13, 1.95$). Comparative mean bias adherence rates for maximisers and satisficers are plotted in Figure 3.3.

Taken together, our findings from study 3 provide further support for our central claim that maximising tendency is associated with significant deviations from normatively expected behavioural outcomes for the specific instances that we have discussed. Furthermore, our results show that maximisers' adherence to biased judgements with respect to evaluations of proportions and diversified choices persist in cases where a biased choice is dominated by a normatively superior alternative. With respect to recency based judgements, our results support findings reported in study 2 and suggest that maximisers are more prone to exhibiting adherence to biases in judgements associated with assessing representativeness. Overall, our results suggest that compared to their satisficing counterparts, maximisers are significantly more likely to exhibit behavioural biases in the cases that we have investigated.

3.6 General Discussion

A number of studies have analysed how human behaviour and behavioural factors affect the modelling aspects of problem-solving (Hämäläinen, Luoma, and Saarinen, 2013). Exploring how individuals apply decision rules and heuristics is particularly useful in multiple criteria decision analysis interventions (Morton and Fasolo, 2009) and parameter elicitation settings (Montibeller and Von Winterfeldt, 2015). Our main intention in conducting the research presented in this paper was to address the inherent contradiction between maximisers' desire to achieve the "best" decision outcomes and the strategies that they employ in order to meet this expectation. Our central contention related to the denial of bounded rationality and scarcity of available cognitive resources that is a fundamental feature of the maximiser's decision making orientation (Schwartz et al., 2002; Simon, 1955). In study 1, we demonstrated, in accordance with Simon's (1971) original conceptualisation of the practical rationality offered by a satisficing decision orientation, that maximising and analytical information processing are at least somewhat conflicting preferences. We hypothesised that this conflict arises from maximisers' tendencies to rely on extensive information acquisition, variety seeking and representativeness at the expense of other, normatively more salient features when faced with a decision problem. We tested these hypotheses in study 2 and found, in accordance with behavioural research on biases associated with heuristic judgements (Ayal and Zakay, 2009; Denes-Raj and Epstein, 1994; Gilovich et al., 1985; Tversky and Kahneman, 1971), that maximisers systematically conformed to predictable deviations from normatively expected choice behaviour. We extended our analysis in study 3 to situations where biased outcomes were dominated by objectively better alternatives or normative choices were entirely inaccessible and found that even in such cases, maximisers reliably presented a higher tendency to resort to heuristic evaluations and responded in accordance with known behavioural biases. Our results therefore, provide compelling evidence to suggest that an assumption that a maximising orientation results in better decision making at the expense of poor affective outcomes may be an insufficient explanation for the maximiser's predicament (Iyengar et al., 2006). Instead, our analyses suggest that while maximisers may hope for better decision making, the very mechanisms they employ to attain this objective are often cognitively intractable and problematize their judgements in cases where a higher reliance on non-compensatory heuristics leads them towards making poorer choices.

Our study provides two main contributions to the behavioural decision-making literature. First, we have shown at least certain circumstances where a maximising decision orientation is a relatively poor decision-making strategy in terms of qualitative decision outcomes. This finding stands apart from previous research on behavioural maximising that has traditionally been focussed on the negative affective outcomes associated with a maximising decision-making orientation (Dar-Nimrod et al., 2009; Roets et al., 2012; Schwartz et al., 2002). Contrary to a widely purported belief that maximisers are more rational and deliberative, we find that maximising tendency is positively associated with an increased tendency to deviate from normative decision outcomes and negatively associated with a preference for deliberative judgement. Second, while much of the behavioural research investigating the implications of individual differences on sub optimal decision making has emphasised factors such as demographic characteristics (Bruine de Bruin et al., 2007), information processing preferences (Ayal et al., 2011), affect (Slovic et al., 2007) and orientations towards risk (Bromiley and Curley, 1992; Weber et al., 2002), to the best of our knowledge, our study presents some of the first evidence to suggest that a general subjective orientation towards choice may be an important and as yet, neglected behavioural and individually specific determinant of deviations from the axioms of prescriptive choice theories.

TABLE 3.5: Logistic regressions predicting overall and individual bias adherence for study 3.

	Overall Bias Adherence		(a) Ratio Bias		(b) Pseudo Diversification		(c) Gambler's Fallacy		(d) Hot Hand Effect	
	B (SE)	OR [95% CI]	B (SE)	OR [95% CI]	B (SE)	OR [95% CI]	B (SE)	OR [95% CI]	B (SE)	OR [95% CI]
Focal predictor										
Maximising	.53***	**1.69**	.44***	**1.56**	.63***	**1.89**	.74***	**2.09**	.39**	**1.48**
	(.07)	**[1.47, 1.95]**	(.14)	**[1.18, 2.06]**	(.15)	**[1.40, 2.55]**	(.15)	**[1.55, 2.83]**	(.14)	**[1.13, 1.95]**
Information processing preference										
Analytical	-.40***	**.67**	-.44**	**.64**	-.82***	**.44**	.03	1.03	-.48**	**.62**
	(.08)	**[.57, .79]**	(.17)	**[.47, .89]**	(.19)	**[.30, .64]**	(.16)	[.75, 1.40]	(.16)	**[.45, .85]**
Intuitive	.20**	**1.22**	.40**	**1.49**	.42**	**1.53**	-.07	.94	.13	1.13
	(,07)	**[1.06, 1.41]**	(.15)	**[1.11, 2.01]**	(.16)	**[1.11, 2.10]**	(.14)	[.71, 1.24]	(.14)	[.86, 1.50]
Demographic controls										
Age	.06	1.06	.29**	**1.34**	-.14	.87	.02	1.02	.04	1.04
	(.06)	[.94, 1.19]	(.12)	**[1.06, 1.69]**	(-.12)	[.68, 1.11]	(.12)	[.81, 1.28]	(.12)	[.83, 1.31]
Education	.09	1.09	.25*	1.29	.19	1.21	.04	1.04	-.12	.89
	(.06)	[.96, 1.23]	(.13)	[1.00, 1.66]	(.13)	[.93, 1.57]	(.13)	[.81, 1.34]	(.13)	[.69, 1.14]
Sex[1]	.05	1.06	.17*	1.18	-.13	.88	.16	1.17	.01	1.01
	(.14)	[.81, 1.38]	(.13)	[.69, 2.01]	(.29)	[.50, 1.55]	(.28)	[.68, 2.02]	(.27)	[.69, 1.14]
Constant	-1.48*		-.3.37*		-.66		2.89*		.74	
	(.64)		(1.32)		(1.35)		(1.35)		(1.26)	
Model fit										
Model $\chi^2(df)$	100.67 (6), p <.001		30.47 (6), p <.001		54.77 (6), p <.001		30.01 (6), p <.001		20.87 (6), p = .002	
H-L $\chi^2(df)$	10.16 (7), p = .180, ns		10.25 (7), p = .175, ns		6.17 (7), p = .520, ns		5.15 (7), p = .642, ns		7.99 (7), p = .334, ns	
$R^2(McFadden)$	.07		.08		.15		.09		.06	
$R^2(Nagelkerke)$	.12		.15		.26		.15		.10	

[1]male = 0, female = 1.

B = unstandardised regression coefficient, SE = standard error, OR = odds ratio, 95% CI = 95% confidence interval for OR. Model $\chi^2(df)$ = Likelihood-ratio test, H-L $\chi^2(df)$ = Hosmer-Lemeshow test, $R^2(McFadden)$ = McFadden pseudo-R^2, $R^2(Nagelkerke)$ = Nagelkerke pseudo-R^2.

$***p < .001, **p < .01, *p < .05, ns = notsignificant.Note.$ Significant odds-ratios are in **bold-face**.

In addition, our results also present some practical guidelines for decision scientists and operational researchers interested in behavioural issues in the application of decision analysis or model supported decision processes. Our results suggest that maximisers may over-weigh easily available information, variety and representativeness as part of their decision making process. For one-off strategic decisions, problem-structuring methods and facilitated modelling may be particularly adept at identifying and minimising the role that these factors play in the model development stage (Franco & Mintibeller, 2010). The task of de-biasing may be more challenging in the case of repeated and tactical decisions. A stark result from our analysis suggests that maximisers are susceptible to some biases even in cases where there is a clearly dominating option within a decision environment, this result provides empirical evidence for Parker et al.'s (2007) proposition that a maximising decision style may be maladaptive. As an important aspect of adaptivity in decision making relates to individuals' ability to recognise dominance in a decision environment (Goldstein & Gigerenzer, 2002), the ability to do so well, corresponds with decision making in dynamic operational environments. A potential way forward could be to equip maximisers with a broader range of choice heuristics through training and application however, the question of whether adaptivity in decision making can be trained and improved in a sustained manner remains an important open challenge for behavioural operational researchers.

3.7 Limitations and Further Research

An important caveat for our work is related to the range of tasks that we examined in studies 2 and 3. In order to facilitate internal validity and consistency across our analyses, we limited our stimuli to well-known hypothetical decision problems. As a result, our results must be interpreted with caution in terms of their applicability to other decision contexts. Future researchers should attempt to build on the analyses we have presented here and test these hypotheses in field settings involving decision making in natural contexts. Furthermore, we must stress on the fact that our intention is not to suggest that maximisers are universally poor decision makers. Rather, in the present context, we were mainly interested in demonstrating some specific behavioural features of the maximising orientation that predispose behavioural maximisers to the kinds of biases that we have discussed. Further research is required to assess whether these instances arise from these specific features or are a general aspect of the maximising decision orientation.

An additional limitation that can be raised about our analyses relates to the choice of the measure we have adopted to assess maximising tendency. Schwartz et al.'s (2002) operationalisation of the thirteen-item maximising inventory is a controversial issue within the behavioural decision making community with many alternative measures having been proposed in the literature (e.g. Diab et al., 2008; Weaver et al., 2015). At the same time, on the point of measurement, we firmly agree with Misuraca and Fasolo's (2018) assertion that the proliferation of maximising scales – rather than leading to a coherent body of work of conceptual relevance to the study of such a decision style – has lead to an approach of fit-for-purpose scale development, resulting in disjoint scales and a lack of substantive theoretical and conceptual progress. Our main motivation in conducting this research was to address the surprising results in Iyengar et al. (2006) – incorporating the identical measure for maximising tendency as adopted in our studies – that suggest maximisers choose better but feel worse about their choices. Our findings highlight at least some circumstances where maximisers choose poorly both in terms of assessments against normative standards as well as in comparison to their satisficing counterparts. An important extension of this work is therefore, to investigate whether other measures for a maximising decision style converge with the results that we have reported here. We hope that along with Misuraca and Fasolo's (2018) call to caution, our results help stimulate further conceptual development in this area that promises significant insights about the nature of behavioural rationality.

3.8 APPENDIX A: Supplementary Information on Experimental Materials

3.8.1 Rational and Experiential information processing styles Inventory (reproduced from Pacini and Epstein, 1999)

%% The REI was coded on a 7-point Likert scale anchored at 1 (= definitely false) and 7 (= definitely true). The scale consists of 40 items with 20 items corresponding to a rational information processing style and 20 items corresponding to an experiential (intuitive) information processing style. Both scales are orthogonally related and treated as separate constructs. In other words, a high score on the rational style inventory does not preclude a high score on the experiential style inventory. %%

%% Reverse coded items are indicated with (R) and were recoded for the analysis. %%

%% Instructions %%

On the next few pages, you will need to provide responses to a number of statements describing your assessment of your own way of approaching decisions.

PLEASE INDICATE THE EXTENT TO WHICH THE FOLLOWING STATEMENTS DESCRIBE YOU.

%% Rational Scale %%

1. I try to avoid situations that require thinking in depth about something. (R)
2. I'm not that good at figuring out complicated problems. (R)
3. In enjoy intellectual challenges.
4. I am not very good at solving problems that require careful logical analysis. (R)
5. I don't like to have to do a lot of thinking. (R)
6. I enjoy solving problems that require hard thinking.

7. Thinking is not my idea of an enjoyable activity. (R)
8. I am not a very analytical thinker. (R)
9. Reasoning things out carefully is not one of my strong points. (R)
10. I prefer complex problems to simple problems.

%% New Page %%

%% Rational Scale %%

PLEASE INDICATE THE EXTENT TO WHICH THE FOLLOWING STATEMENTS DESCRIBE YOU.

11. Thinking hard and for a long time about something gives me little satisfaction. (R)
12. I don't reason well under pressure.
13. I am much better at figuring things out than most people.
14. I have a logical mind.
15. I enjoy thinking in abstract terms.
16. I have no problem thinking things through carefully.
17. Using logic usually works well for me in figuring out problems in my life.
18. Knowing the answer without having to understand the reasoning behind it is good enough for me. (R)
19. I usually have clear, explainable reasons for my decisions.
20. Learning new ways to think would be very appealing to me.

%% New Page %%

%% Experientiality Scale %%

PLEASE INDICATE THE EXTENT TO WHICH THE FOLLOWING STATEMENTS DESCRIBE YOU.

1. I like to rely on my intuitive impressions.
2. I don't have a very good sense of intuition. (R)
3. Using my gut feelings usually works well for me in figuring out problems in my life.
4. I believe in trusting my hunches.
5. Intuition can be a very useful way to solve problems.
6. I often go by my instincts when deciding on a course of action.
7. I trust my initial feelings about people.
8. When it comes to trusting people, I can usually rely on my gut feelings.
9. If I were to rely on my gut feelings, I would often make mistakes. (R)
10. I don't like situations in which I have to rely on intuition. (R)

    %% New Page %%

    %% Experientiality Scale %%

    PLEASE INDICATE THE EXTENT TO WHICH THE FOLLOWING STATEMENTS DESCRIBE YOU.

11. I think there are times when one should rely on one's intuition.
12. I think it is foolish to make important decisions based on feelings. (R)

13. I don't think it is a good idea to rely on one's intuition for important decisions. (R)

14. I generally don't depend on my feelings to help me make decisions. (R)

15. I hardly ever go wrong when I listen to my deepest gut feelings to find an answer.

16. I would not want to depend on anyone who described himself or herself as intuitive. (R)

17. My snap judgements are probably not as good as most people's. (R)

18. I tend to use my heart as a guide for my actions.

19. I can usually feel when a person is right or wrong, even if I can't explain how I know.

20. I suspect my hunches are inaccurate as often as they are accurate. (R)

3.8.2 Behavioural Maximising Scale (reproduced from Schwartz et al., 2002)

%% The maximising scale was coded on a 7-point Likert scale anchored at 1 (= strongly disagree) and 7 (= strongly agree). %%

%% Instructions %%

Choices can be difficult. Please select the point on the scale that indicates how far you agree or disagree with the following statements.

1. When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program.

2. When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to.

3. I treat relationships like clothing: I expect to try a lot on before I get the perfect fit.
4. No matter how satisfied I am with my job, it's only right for me to be on the lookout for better opportunities.
5. I often fantasize about living in ways that are quite different from my actual life.
6. I'm a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.).
7. I often find it difficult to shop for a gift for a friend.
8. When shopping, I have a hard time finding clothing that I really love.
9. Deciding what to watch on TV is really difficult. I'm always struggling to pick the best choice.
10. I find that writing is very difficult, even if it's just writing a letter to a friend, because it's so hard to word things just right. I often do several drafts of even simple things.
11. No matter what I do, I have the highest standards for myself.
12. I never settle for second best.
13. Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment.

3.9 APPENDIX B: Choice Problems in studies 2 and 3

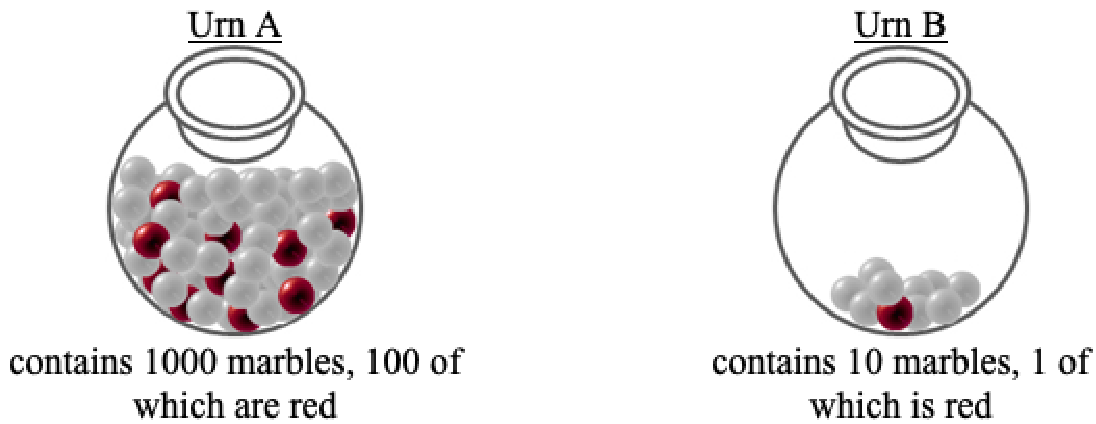
3.9.1 Study 2

%% The following questions were presented to participants in study 2 . We adapted all questions from previous applications and presented them in counterbalanced blocks. %%

%% The normatively expected response in indicated in bold-face. %%

Ratio Bias (Denes-Raj et al., 1995)

Imagine that you are a participant in a gameshow. You are presented with two urns, filled with red and grey marbles. While one urn contains one-thousand marbles of which one-hundred are red, another contains ten marbles of which one is red. The gameshow host asks you to select one of the urns to choose from. If a red marble is drawn, you win a cash prize. Which of the urns do you choose?



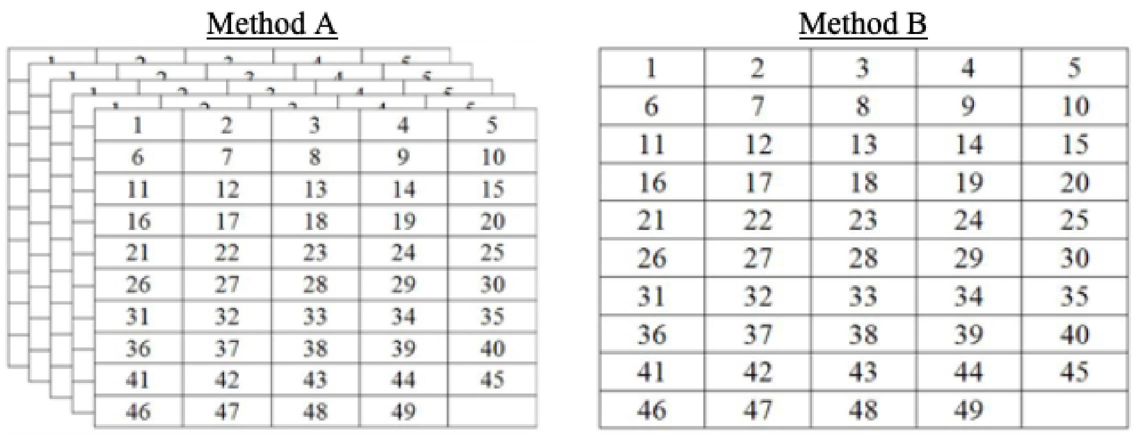
1. Urn A - 100/1000 red marbles

2. Urn B - 1/10 red marbles

3. **Either one - it doesn't matter**

Pseudo Diversification (Ayal & Zakay, 2009)

A friend of yours has five stacks of lottery tickets. Each ticket has the numbers 1 to 49. To decide the winner of the lottery, a computer will randomly generate five different numbers from this range. To win the lottery you must guess all five numbers. Your friend is willing to let you try your luck but insists that you pick from one of two strategies. In the first, you can pick five tickets and mark six numbers on each of them. If you mark at least one of your tickets with all five numbers that the computer picks, you win. In the second method, you can pick one lottery ticket and mark six numbers on it. If you mark all five of the randomly chosen numbers you win. Which of these strategies do you pick?



1. Method A – Pick five tickets and mark six numbers on each of them

2. Method B – Pick one ticket and mark six numbers on it

3. **Either one – it doesn't matter**

Gambler's Fallacy (Kahneman & Tversky, 1972)

A fair coin has equal probabilities of 50% for a Heads or Tails outcome (H = 50% and T = 50%). Imagine that you have just observed three tosses of a fair coin and the outcome was Tails all three times (i.e. T-T-T). Given your observations, how likely do you think that the next outcome will be:

1. Heads (0-100) % = **50**
2. Tails (0-100) % = **50**

Hot hand effect (Ayal et al., 2015)

In tennis, an ace is a point winning legal serve that is untouched by the receiver. Maria is well known for her excellent serves and on a regular day, she hits an ace 45% of the time. Imagine that in the game that she is currently playing, she just hit two aces in a row. How likely do you think her next serve will be an ace?

1. Ace (0-100) % = **45**
2. Not Ace (0-100) % = **65**

3.9.2 Study 3

%% The questions were similar to those presented in study 2 however, for ratio-bias and pseudo diversification examples a dominating alternative was added while in the gambler's fallacy and hot-hand effect tasks, participants were asked to provide a prediction disregarding base-rates. %%

%% The figures shown above were used after making the relevant alternations, not shown here to conserve space. %%

Ratio Bias (Denes-Raj et al., 1995)

Imagine that you are a participant in a gameshow. You are presented with two urns, filled with red and grey marbles. While one urn contains one-thousand marbles of which ninety-nine are red, another contains ten marbles of which one is red. The gameshow host asks you to select one of the urns to choose from. If a red marble is drawn, you win a cash prize. Which of the urns do you choose?

1. Urn A - 99/1000 red marbles
2. Urn B - 1/10 red marbles

Pseudo Diversification (Ayal & Zakay, 2009)

A friend of yours has five stacks of lottery tickets. Each ticket has the numbers 1 to 49. To decide the winner of the lottery, a computer will randomly generate five different numbers from this range. To win the lottery you must guess all five numbers. Your friend is willing to let you try your luck but insists that you pick from one of two strategies. In the first, you can pick five tickets and mark five numbers on each of them. If you mark at least one of your tickets with all five numbers that the computer picks, you win. In the second method, you can pick one lottery ticket and mark six numbers on it. If you mark all five of the randomly chosen numbers you win. Which of these strategies do you pick?

1. Method A – Pick five tickets and mark five numbers on each of them
2. Method B – Pick one ticket and mark six numbers on it

Gambler's Fallacy (Kahneman & Tversky, 1972)

A fair coin has equal probabilities of 50% for a heads or tails outcome (H = 50% and T = 50%). Imagine that you have just witnessed three tosses of a fair coin and the outcome was tails all three times (i.e. T-T-T). Even though you know that the probability of a heads or tails outcome on the next (i.e. fourth) toss are identical, you may have a preference for one or the other outcome given your observations. Considering this, what do you think the outcome will be on the next toss?

1. Heads
2. Tails

Hot hand effect (Ayal et al., 2015)

In tennis, an ace is a point winning legal serve that is untouched by the receiver. Maria is well known for her excellent serves and on a regular day, she hits an ace 45% of the time. Imagine that in the game that she is currently playing, she just hit two aces in a row. Even though you know that the probability of her hitting another ace is 45%, given her performance, how do you think her next serve will play out?

1. Ace

2. Not Ace

4

Inhibition, Integration and Selection: Compatibility effects in multiple-criteria strategy execution

Abstract

A number of recent studies have proposed the use of "fast and frugal" decision aids as viable alternatives to support decision processes in cases where time or other operational concerns preclude the application of more standard decision analytic methods. While a growing body of evidence shows that such procedures – which are mostly non-compensatory – can be surprisingly accurate, very little research has evaluated how well decision makers can execute the prescriptive recommendations of aids based on such decision strategies in practice. This is a significant omission as unlike standard decision analytic approaches, "fast and frugal" heuristics heavily rely on core cognitive competencies – such as executive function and general decision making ability – of human decision makers (DMs) and can often be developed without much feedback from the aids' end users themselves. In this study, our primary motivation was to investigate the conditions in which synergies between individual, model and task features can improve prescriptive strategy execution in multiple-criteria decision making (MCDM) contexts. Drawing on the behavioural, neuropsychological and decision analytic literatures, we propose that compatibility effects will influence the effectiveness with which DMs can execute decision strategies that draw on prescriptive psychological heuristics – "fast and frugal" or otherwise. We report results from an experiment investigating

aided strategy execution. The main findings suggest that strategy execution is highly sensitive to task characteristics however, the effects of the number of alternatives and attributes on choice quality differ in magnitude and direction depending on which decision strategy is prescribed. Subjective decision style was found to affect overall task performance, but did not support the hypothesised relationship derived from the literature. Subjects' ability to regulate inhibitory control was found to positively affect non-compensatory strategy execution, suggesting compatibility effects between executive function and strategy execution. These findings are discussed in light of recent calls from OR scholars for the development and application of decision aids that draw on prescriptive "fast and frugal" principles.

4.1 Introduction

One of the central findings from behavioural decision research over the past two decades suggests that decision makers often shift to "fast and frugal" choice heuristics depending on task contingencies (Gigerenzer, Todd, & ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993). This framework proposes that rather than integrating all available information in the resolution of a decision problem, decision makers are highly selective in what pieces of discriminatory information they attend to and what they ignore. For instance, while normatively held decision-theoretic models such as the weighted additive difference rule (WADD, Keeney & Raiffa, 1993) assumes that decision makers assign weights to each decision attribute and compute the product sums for each available alternative until arriving at a final choice, lexicographic models suggest that in order to reach a decision, individuals may only attend to a single (subset) of highly salient attribute(s), ignoring all other problem information within the choice domain (e.g. Fishburn, 1974; Gigerenzer, Hoffrage, & Kleinbölting, 1991; Tversky, 1969). As a result, these latter classes of models, said to comprise the mind's "adaptive toolbox" are frugal – in that they dispense with the notion of optimization and often even probabilities and utility computations – and therefore are assumed to be faster as decisions can be based on highly intuitive search, stopping and decision rules (Gigerenzer & Selten, 2001). Even though the applicability of such approaches to general decision making contexts remains highly contested (see for instance Bröder & Newell, 2008; Hilbig, 2010), the "fast and frugal" framework provides three basic insights into unaided decision processes. (1) That decision makers are parsimonious in their expenditure of scarce cognitive resources, (2) That the decision strategy applied depends on the task in question, and (3) That decisions are often based on the relative salience rather than the integration of information within the task domain. These strategies are therefore termed *non-compensatory*, as they do not involve adjustments for explicit trade-offs between alternative and attribute values – i.e. high values on one criterion do not compensate for low values on others – as would be the case under the axioms of expected value and utility maximization frameworks. Instead, the "fast and frugal" framework takes a more boundedly rational position on human decision processes and suggests that individuals often formulate aspirational thresholds (e.g. satisfice, Simon, 1955) or a hierarchical ordering of attributes (e.g. eliminations by aspects, Tversky, 1972) in order to reduce the amount of cognitive effort that needs to be expended on the resolution of a decision problem. Non-compensatory strategies are thus, often conceptualised as an adaptive behavioural response to increasing complexity within a decision environment.

At the same time, as these strategies involve less-consistent processing of information across alternative and criterion values, they are often assumed to be more error-prone and susceptible to decreases in choice performance as compared to compensatory selection procedures. Payne et al. (1993) for instance, in what they term an "effort-accuracy trade-off", suggest that individuals may favour easier to apply decision rules as a function of increasing task complexity, even though non-compensatory approaches may result in decisions less consistent with decision makers' underlying preferences. An important contribution of Gigerenzer et al.'s (1999) research programme however, was to draw attention to the fact that in a number of circumstances, simple non-compensatory heuristics could perform comparably – and in some cases, even outperform – more complex and computationally expensive compensatory selection rules. This basic finding has since been replicated both in simulation and behavioural contexts (Baucells & Carrasco, 2006; Borges, Goldstein, Ortmann, & Gigerenzer, 1999; Hogarth & Karelaia, 2005; Katsikopoulos, 2016). Indeed, a growing body of evidence suggests that simple lexicographic or conjunctive rules can be effective information handling tools for unaided decision making, as they allow individuals to construct dominance structures in environments where either a strictly dominating alternative is absent or, information is too voluminous to feasibly apply expected value-based computations.

Despite the apparent success of the adaptive toolbox metaphor in demonstrating the flexible and contingent nature of human decision processes, what has not been seen in the psychological literature is an explicit focus on the antecedents of strategy execution. This latter aspect remains contested within the behavioural decision making community with some suggesting that simple non-compensatory strategies may not be particularly effortless to execute as a result of the extensive amount of pre-computation involved in establishing a prescriptive hierarchy of preferences (e.g. how hierarchies for discriminatory information or stopping rules are established in the first place, Juslin & Persson, 2002; Marttunen, Haag, Belton, Mustajoki, & Lienert, 2019). On the other hand, there is evidence to suggest that compensatory strategies may not be as difficult to apply to a decision problem if the decision maker is familiarised with the underlying intuition behind the model. Experimental investigations for instance, have highlighted that while decision makers may not necessarily assign differential weights to decision attributes, simpler compensatory procedures such as an equal weights strategy or frequency-based heuristics are fairly prevalent and often able to approximate the variance in the choice data (Alba & Marmorstein, 1987; Glöckner & Herbold, 2011; Pachur & Forrer, 2013).

With the growing interest in behavioural OR, a number of researchers have suggested the development and application of decision aids and support tools based on non-compensatory principles (Keller & Katsikopoulos, 2016; Kottemann & Davis, 1991; Vansnick, 1986). As a result, the facility with which individuals can execute these strategies becomes an important area that needs to be investigated in a systematic manner within the OR community. Indeed, one of the principle objectives of behavioural operational research is to investigate how individual and task features influence model use amongst decision makers (Franco & Hamalainen, 2015; Katsikopoulos, 2016; O'Keefe, 2016). While the circumstances in which individuals self-select or switch decision strategies is an important open question in the behavioural decision theory and OR literatures, the question of how well individuals can execute indicative strategies is arguably of much greater importance in contexts where model-based interventions may be appropriate.

In this study, we therefore direct our efforts towards interrogating the differences between simple compensatory and non-compensatory strategies from the perspective of strategy execution. We conduct an experimental investigation in order to evaluate how task complexity (i.e. the number of alternatives and decision criteria) and individual characteristics influence performance in a hypothetical multiple-criteria decision task. Drawing on the behavioural, psychological and OR literatures, we derive a set of compatibility hypotheses that suggest synergies between individual, model and task characteristics may play a role in facilitating strategy execution. Our findings highlight four core features relating to aided strategy execution in multiple criteria decision making contexts. 1) The differences in the performance of compensatory and non-compensatory heuristics can be fully explained as a function of task characteristics. 2) The number of alternatives and decision criteria under consideration affect the performance of compensatory and non-compensatory strategies in a distinct manner, such that increasing the number of attributes actually improves the accuracy of prescribed non-compensatory procedures. 3) The facility with which individuals can regulate selective attention and inhibit non-instrumental information improves task performance in non-compensatory contexts while not affecting performance on comparable compensatory tasks. 4) While subjective dispositions towards compensatory or non-compensatory decision making affect overall task performance, this basic tendency does not provide much discriminatory insight relating to actual strategy execution.

We position these findings within the context of the broader behavioural OR literature and discuss their relevance in informing the design of decision aids and support tools that draw on non-compensatory principles. In the following sections, we review previous work on decision strategies, particularly highlighting the gaps in the extant literature relating to prescriptive strategy execution. Subsequently, we present our theoretical framework and hypotheses before culminating with sections presenting the analysis and discussion of our main results.

4.2 Previous Research

4.2.1 From Descriptive to Prescriptive Approaches to Non-Compensatory Decision Making

In the preceding section, we indicated that despite the wide-spread discussions on strategy shifting and adaptive strategy selection in the behavioural and psychological literatures, the issue of strategy execution has received comparatively less attention. An important reason for this is that traditionally, decision research has held the view of non-compensatory strategy use as inferior and suboptimal deviations from normative decision making, a tendency which decision analysts could alleviate by supporting decision makers with tools and procedures to encourage their adoption of more rational models based on the principles of subjective expected utility maximisation (Keeney & Raiffa, 1993; Von Winterfeldt & Edwards, 1986). In multiple criteria decision making contexts – i.e. situations where multiple conflicting objectives need to be taken into account and counterbalanced – the weighted additive difference (WADD) model has often served as a benchmark for a normative basis towards effective decision making. In their seminal paper on strategy selection, Beach and Mitchell (1978) echo this sentiment and propose an intuitive argument suggesting that the selection of a decision strategy is often contingent on the demands of a task and a trade-off between the accuracy and decision effort required in arriving at a final course of action. They classify strategies as "aided-analytic or unaided-analytic" and "non-analytic", referring to compensatory and non-compensatory decision making respectively. Despite their view that what is 'optimal' in a given decision context depends on the specific requirements of the task, Beach and Mitchell's (1978) contingency model takes a rather pessimistic position on non-compensatory strategy use suggesting that such strategies may disproportionately lead to erroneous judgements.

As is now well known, this latter assertion does not necessarily seem to be the case and in a number of circumstances – particularly when information acquisition costs are high (Bröder, 2000), decisions are made under extreme time pressures (Payne et al., 1993; Rieskamp & Hoffrage, 1999) or, when criterion information is obfuscated and must be retrieved from memory (Bröder & Schiffer, 2006) – non-compensatory heuristics can lead to decisions that converge towards choices predicted by more complex weighted linear additive models. While early behavioural decision research in the vein of Tversky and Kahneman's (1974) heuristics and biases programme refrained from providing a formal prescriptive basis for strategies that deviated from other expectancy-based models, decision theorists have increasingly turned their focus towards formalising these aspects of behaviour, either as mathematical models (e.g. eliminations by aspects, Tversky, 1972; satisficing, Simon, 1955) or as a set of explicit verbal protocols following a sequential series of instructions (e.g., frequency of good and bad dimensions, Alba & Marmorstein, 1987; majority of confirming dimensions, Russo & Dosher, 1983). Indeed, this distinction is a core point of departure between the "fast and frugal" framework proposed by Gigerenzer et al. (1999), the standard decision analytic approach (Von Winterfeldt & Edwards, 1986) and the heuristics and biases program (Tversky & Kahneman, 1974).

Instead of viewing strategies that rely on the maximisation of expected utility by integrating all relevant problem information as the normative ideal, Gigerenzer and Todd (1999) suggest that in many cases formal non-compensatory procedures can be viewed not just as descriptions of human behaviour but as a prescriptive basis for guiding action if certain task requirements are satisfied. Keller and Katsikopoulos (2016) provide an overview of circumstances when non-compensatory decision aids may be appropriate and an illuminating demonstration within the context of decisions made by ground troops relating to the escalation of force in military stability operations. Similarly, Katsikopoulos, Durbach and Stewart (2018) integrate the behavioural, psychological and OR literatures and propose a decision aid to evaluate when simple decision models may be appropriate. Although there is still a clear lack of consensus regarding the precise conditions under which non-compensatory models may be applied as prescriptive decision aids – French, Maule, and Papamichail (2009) for instance suggest that such procedures may not be particularly useful in situations where an optimal course of action is unknown – proponents of the "fast and frugal" view have cited the simplicity and transparency associated with non-compensatory strategies as salient benefits to their applicability for a range of decision problems. At the same time, while non-compensatory strategies may better correspond with decision makers intuitions, the assertion that they are necessarily simpler to execute as compared to more compensatory approaches seems to rest on the belief that the latter set of models "assume the human mind has essentially unlimited demonic or supernatural reasoning power (Gigerenzer & Todd, 1999, pp. 7)" – a contention that must be sufficiently qualified within the context of operational decisions.

4.2.2 Simple or Non-Compensatory?

An important point to note at this juncture is that just because a strategy is compensatory does not imply that it is also complicated to apply. Indeed, in contrast to the view that compensatory decision models assume unbounded rationality on the part of the decision maker, the limits of optimization are not only well known (Ackoff, 1979; Simon, 1955), but one of the principle arguments supporting the use of soft OR techniques in conjunction with optimization methods in decision analysis (Franco & Montibeller, 2010; Mingers, 2011). To a large extent, this latter insight has prompted the development of special cases of the WADD framework and resulted in the proposal of a number of simpler heuristics that are compensatory – i.e. still depend on the integration of all available task information – but relatively more accommodating of a decision maker's limited cognitive resources. For instance, while a compensatory strategy that ignores attribute weights (e.g. equal weighted rule, Einhorn & Hogarth, 1975) is relatively trivial to execute compared to a weighted additive difference strategy (i.e. where individuals are assumed to have fully formed preferential weights for all decision attributes, including single attribute utility functions that prohibit interactions between different criteria), by the same token, non-compensatory strategies like eliminations by aspects that assume decision makers can construct a probabilistic ranking of attributes, attend to only those attributes and inhibit all other problem information can be far more involved than simpler one-reason-based decision rules (Goldstein & Gigerenzer, 2002). This latter point is particularly relevant when decision aids that draw on prescriptive "fast and frugal" principles place requirements on decision makers' abilities to apply such strategies in an error free manner – often assuming that individuals can execute such approaches with perfect attention and recognition memory.

In their systematic study of a number of decision strategies, Bettman, Johnson and Payne (1990) attempted to develop a measure for decision effort based on the basic cognitive operations that need to be applied in order to execute a particular strategy. They count what they term "elementary information processes (EIPs)"– e.g. products, additions, eliminations etc. – that a particular strategy calls for and suggest that the difficulty of executing any given strategy is the weighted sum of these procedures. For instance, they suggest that since computing the product for attribute values against decision weights is more effortful than summing un-weighted attribute values across alternatives, the former consideration should play a larger role in informing which strategy is executed as the complexity of the task increases. In many respects, Bettman et al.'s (1990) view on contingent strategy selection is similar to the model proposed by Beach and Mitchell (1978), however as a result it suffers from its limitations as well. Most importantly, while Bettman et al. (1990) convincingly demonstrate that the number of EIPs involved in executing a particular strategy affects the time and self-reported decision effort in preferential choice problems, their results highlight large individual differences with respect to the consistency with which decision makers apply prescribed decision strategies as well as their sensitivity to task characteristics. A fairly obvious consideration in implementing a prescriptive decision aid, particularly where the goal is to simplify strategy execution, is that the prescribed selection rule should be applied by a decision maker in a manner that is consistent with the decision aid's recommendations. Indeed, this consistency argument is one of the prominent reasons that decision analysts have traditionally focused their efforts on refining compensatory decision making procedures as these are often assumed to be more robust to differences in individuals decision styles, information processing preferences and personal characteristics (Von Winterfeldt & Edwards, 1986). If as some have suggested, behavioural operational research is to serve as a bridge between soft and hard OR (Keller & Katsikopoulos, 2016; Morton & Fasolo, 2009), it is precisely these latter aspects of strategy execution that require systematic evaluation, particularly with respect to how such characteristics interact with task features in determining the effectiveness with which a particular decision strategy can be employed towards the resolution of a decision problem.

4.2.3 Task Environments

In line with the view that individuals are equipped with a 'toolbox' of a diverse range of strategies, research has attempted to evaluate the conditions under which decision makers might adopt simpler non-compensatory approaches to contend with increasing complexity in task environments. Early work building on Beach and Mitchell (1976) and subsequently Payne et al.'s (1999) "effort-accuracy framework" suggested that, rather than being a property of the difficulty associated with executing a particular decision rule, complexity should instead be conceptualised as a feature of the task in question. The information overload paradigm for instance, has long held that as the number of alternatives and criteria actively considered over the course of making a decision are increased, choice quality can become adversely affected as a result of individual cognitive and motivational limitations (Iyengar & Lepper, 2000; Jacoby, Speller, & Kohn, 1974). While the initial results from Jacoby et al. (1974) have been heavily criticised on both theoretical and methodological grounds (e.g. see for instance Russo, 1974), there appears to be an emerging consensus that information overload is both plausible and a relevant phenomenon in multi-criteria decision problems, even if the precise conditions under which this becomes observable remain contested (Jacoby, 1984; Korhonen et al., 2018; Malhotra, 1984; Scheibehenne, Greifeneder, & Todd, 2010). Payne et al. (1999) appeal to precisely this logic in suggesting that as the number of alternatives and criteria under consideration increase, decision makers are more likely to make errors as a result of their need to apply non-compensatory decision rules in order to reduce the processing requirements associated with compensatory procedures. Both Jacoby et al. (1974) and Payne et al. (1999) however, assess errors in terms of a choice being consistent with the predictions of benchmark models such as the WADD rule, an assumption that may not be appropriate in a number of situations (e.g. see for instance Malhotra, 1982).

Indeed, in addition to strong behavioural evidence in favour of the prevalence of non-compensatory decision making, a growing body of literature has emerged to highlight that rather than instances of irrationality, non-compensatory decision strategies can in many cases be highly effective and accurate in determining an optimal course of action. Hogarth and Karelaia (2005) for instance, compare the performance of deterministic eliminations by aspects models (DEBA) and other compensatory decision strategies in multi-attribute choice problems and demonstrate that non-compensatory selection procedures out-perform models that explicitly confront trade-offs between alternative and attribute values. Similarly, Fasolo, McClelland and Todd (2007) argue that in cases where information on attributes is abundant – for example searching for products on the Internet – basing a decision on only a subset of available criteria can result in good choices, particularly when criterion weights are unequally distributed (i.e. some attributes are considered to be significantly more important than others).

Along with the early studies documenting the surprising accuracy of simple non-compensatory decision strategies (e.g. Borges, Goldstein, Ortmann & Gigerenzer, 1999; Gigerenzer & Goldstein, 1996), there is now a considerable body of evidence converging around the finding that simple non-compensatory heuristics can lead to effective decision making and in some cases, even optimal choices (Baucells & Carrasco, 2006; Brighton, 2006; Hogarth & Karelaia, 2006; Karelaia, 2006; Katsikopoulos & Martignon, 2006). As a result of the relative simplicity coupled with the surprisingly effective performance of non-compensatory heuristics, drawing on the prescriptive foundations of these strategies can be an appealing prospect for decision analysts, particularly in contexts where time pressures or an abundance of information preclude the systematic integration of all relevant criteria within the task domain. At the same time, due to the sensitivity of such decision rules to seemingly minor changes in task environments and individual characteristics, investigating the conditions where individuals can apply these strategies more effectively becomes a pressing concern in evaluating their performance as prescriptive decision aids.

4.2.4 Executive Function and Capacity Constraints

Ever since the initial articulation of adaptive decision making and subsequently, with the introduction of Gigerenzer et al.'s (1991) "adaptive toolbox", a number of researchers have attempted to study the individual sources of variation in the selection and use of different decision strategies. Traditionally, this strain of research investigated the role of higher order cognitive functions such as fluid intelligence, working memory capacity and task interference as possible determinants of adaptive strategy use. Lee and Cummins (2004) for instance, contrast the predictive accuracy of a lexicographic heuristic – which bases decisions only on a single highly discriminatory criterion – against a linear additive model to find that at the intra-individual level, there was a strong preference for either the compensatory or non-compensatory strategy with large between individual differences in which strategy best explained individual choices in the experimental task. Even though in their task, the emphasis was on examining adaptive strategy selection rather than strategy execution, their results suggest at least some evidence that individual differences in cognitive styles and information processing preferences may have a role to play in strategy execution as well, however they do not elaborate on what these factors might be.

Payne et al. (1993) conceptualised a similar tentative explanation to contend with the individual differences in adaptive strategy use in their own experiments, suggesting that strategy shifting may be associated with differences in individuals information processing capacities – specifically, they suggested that as the complexity of the task environment increases, decision makers with lower cognitive capacity should be more likely to employ simpler non-compensatory selection procedures. Bröder and Eichler (2001, c.f. Bröder & Newell, 2008) attempted to test this hypothesis in an experimental task and to surprising effect, discovered that individuals that were more intelligent tended to favour non-compensatory strategies if the task environment supported their use – a finding that was replicated in additional studies (Bröder, 2003). In other experiments, when an exogenous cognitive load was placed on participants – subjects were asked to retain a running count of the occurrence of the number nine in memory while performing a behavioural task – Bröder and Schiffer (2006) demonstrated that rather than shifting to non-compensatory strategies as a function of higher cognitive load, subjects were *more* likely to apply compensatory selection procedures in the high cognitive load condition.

These findings suggest that the difficulty associated with the execution of compensatory strategies may have initially been overstated – indeed, task interference and added cognitive load seemed to restrict non-compensatory decision making rather than facilitate it. Bröder and Newell (2008) interpret these results as suggestive of the fact that rather than strategy execution, cognitive capacity is more instrumental in the meta-cognitive judgement responsible for determining which strategy is appropriate for a particular task environment. In contexts where decision aids draw on prescriptive "fast and frugal" principles, the question of whether a particular environment is conducive to non-compensatory processing is often determined by the analyst in conjunction with various stakeholders (e.g. Keller & Katsikopoulos, 2016). As a result, this means that the effectiveness of such interventions depends not only whether a particular task environment supports the use of such strategies, but also the facility with which individuals can execute the recommendations of the decision aid in practice – an area that still remains largely under researched.

4.2.5 Cognitive Styles

A related but conceptually distinct approach towards evaluating the role of individual differences in adaptive strategy execution draws on psychometric and trait-based notions, appealing to presumably stable individual orientations in explaining decision making outcomes. A number of studies have demonstrated the relevance of stable personality traits in general decision making contexts (Pacini & Epstein, 1999; Schwartz et al., 2002; Weber & Milliman, 1997), however the extent to which these characteristics are applicable to aided decision making remains unclear. Bröder (2012) summarises a number of experiments attempting to establish the individual determinants of adaptive strategy execution based on a broad range of decision maker characteristics – e.g. impulsivity, need for cognition, action orientation along with the "Big Five" personality traits, often considered to be fundamental personality dimensions – however their results remained inconclusive and did not indicate any discernible influence of such characteristics in strategy selection or execution.

In an early observational study, Zakay (1990) conceptualised the reliance on a particular decision strategy as an individual preference to use either a predominantly compensatory or non-compensatory decision style. In contrast to Bröder (2012), Zakay's (1990) approach was more granular in that their instrument was conceptualised as a specific bi-polar construct measuring subjects self-reported reliance on primarily compensatory (or non-compensatory) decision making. Their initial results suggested a correlation between subjective decision styles and actual strategy use on a subsequent decision making task. Shiloh, Koren and Zakay (2001) extended these findings and demonstrated that a basic orientation towards compensatory decision making may influence subjective assessments of decision complexity and conclude by calling for a systematic investigation of the "basic tendencies" that may affect adaptive strategy use.

Both these studies however do not cast any light on whether such decision styles have any qualitative impact on decision making – indeed, while they demonstrate that self-reported decision styles may correspond to strategy use, the assertion that individuals apply these strategies with any consistency or accuracy does not follow from these findings. In cases where model use has been considered in other OR contexts – for instance in the use of visualisations and information displays – while individual differences have been consistently reported, personality correlates are for the most part, weakly – if at all – related to task performance (O'Keefe, 2016).

4.3 The Compatibility Hypothesis

As is apparent from our review of the literature, research on non-compensatory decision strategies has disproportionately been focussed on adaptive strategy selection, with the issue of how these approaches can serve as prescriptive aids in guiding decision makers towards an appropriate course of action being largely overlooked. As the support for the effectiveness and precision of non-compensatory strategies suggests, far from being instances of irrational decision making, these strategies may be particularly well suited to a number of task environments. Calls from OR scholars for decision aids and support tools drawing on these principles reinforces the success of the "fast and frugal" framework not just as a description of behaviour but a potentially vast source for decision analysts to draw on in supporting individual decision processes. At the same time, the complex assemblages of individual and environmental features means that it can often be difficult and perhaps, inappropriate to study these issues in isolation from one another. These considerations, coupled with the lack of a systematic analysis of the interactions between individual, model and task characteristics investigating aided strategy execution in multiple-criteria contexts, led to the conception of our *compatibility hypotheses.*

Broadly stated, the compatibility hypothesis suggests that an alignment between the inputs and outputs within a decision context influences the quality of decision outcomes. Initially proposed by Slovic, Griffin and Tversky (1990) in order to explain why normatively equivalent methods of elicitation could sometimes give rise to systematically different responses, this hypothesis has since been applied to a range of decision problems investigating compatibility between broad stimulus and response characteristics (Kornblum, Hasbroucq, & Osman, 1990), decision styles and situational factors (Ayal, Rusou, Zakay, & Hochman, 2015), as well as state variables and task requirements (Kruglanski & Gigerenzer, 2011). In aided multiple criteria decision making contexts, compatibility effects may manifest as a result of synergies between decision maker characteristics and the features of the decision model in question, as well as those between the model and task environment. We conceptualise three such sources: (1) the compatibility between the prescribed decision strategy and task complexity, (2) the compatibility between individuals' preferred decision style and the prescribed decision strategy, and (3) the compatibility between decision makers' ability to inhibit non-instrumental information and the prescribed decision strategy. We draw on these aspects to address two simple research questions contrasting between compensatory and non-compensatory strategy execution in aided multiple criteria decision making contexts.

1. Does the complexity of a decision task, indexed by the number of alternatives and criteria under consideration, affect the accuracy with which individuals can execute prescribed decision strategies?

2. Do individual characteristics affect the accuracy with which decision makers can execute prescribed decision strategies over and above the effects of task features?

4.3.1 Decision Model and Task Complexity

As we discussed in the previous sections, the work of Payne et al. (1993) has demonstrated that as the complexity of a decision environment increases, decision making behaviour is more compatible with non-compensatory strategy execution. While Payne et al. (1993) initially conceptualised such strategies as being inferior to more compensatory decision models, there is ample evidence suggesting their suitability in a number of circumstances. The most salient to our approach is Fasolo, McClelland

and Todd's (2007) suggestion that in cases where criterion weights are unequally distributed, non-compensatory procedures can lead to decisions that are consistent with decision makers' "true" preferences. This is a rather intuitive argument as it speaks to one of the core distinctions between compensatory and non-compensatory strategies. More precisely, while compensatory decision models take into account all attributes for all alternatives – for instance, less important attributes may be represented by lower criterion weights but are still taken into consideration – non-compensatory decision rules simply disregard non-instrumental features, basing the ultimate course of action on only the most salient attribute(s). This means that compensatory decision models become objectively more difficult to execute as more criteria are added to a choice problem, regardless of their relative importance. As a result, we argue that in cases where underlying preferences remain unaffected by the inclusion of additional criteria, prescribed non-compensatory decision strategies will be less susceptible to decreases in choice performance than comparable compensatory strategies as the number of decision criteria increase.

Similarly, the role of the number of alternatives in a choice set can have implications on the quality of choices made by decision makers. This aspect has been extensively studied within the psychological and marketing literatures under the banner of information or choice overload (Iyengar & Lepper, 2000; Jacoby et al., 1974; Malhotra, 1984). It is fairly obvious that increasing the number of alternatives that a decision maker must actively consider in determining a suitable course of action will increase the search space within the problem context. At the same time the extent to which this affects individuals' ability to execute simplifying strategies remains largely contested (Russo, 1974). Gigerenzer and Todd (1999) suggest that non-compensatory strategies can be effective information handling tools for situations where decisions are characterised by an abundance of information, however they do not explicitly disentangle the role of attributes and alternatives. This may be a problematic omission as the number of alternatives and criteria can affect choice quality in distinct and seemingly unrelated ways (e.g. Malhotra, 1984). At the same time, based on the weight of arguments from Payne et al. (1993) as well as Gigerenzer et al. (1999) that non-compensatory strategies are universally less involved and can be executed with relative ease, we formulate the expectation that as the number of alternatives increases, prescribed non-compensatory strategies will be less susceptible to decreases in performance as compared to compensatory strategies.

Hypothesis 1a (H1a): *Prescribed non-compensatory (compensatory) strategies will be less (more) susceptible to decreases in choice accuracy as the number of decision criteria increase.*

Hypothesis 1b (H1b): *Prescribed non-compensatory (compensatory) strategies will be less (more) susceptible to decreases in choice accuracy as the number of alternatives increase.*

4.3.2 Decision Style and Decision Model

Another important aspect that may influence task performance is the compatibility between individual traits and the requirements of the task at hand. McMackin and Slovic (2000) for instance, demonstrated compatibility effects between a deliberative mode of thought and deliberative judgements. Their main results suggested that while deliberation improved performance on a task explicitly calling for analytical processing – i.e. subjects were asked to make numerical estimations – a deliberative mode of thought degraded performance on a task that required affect-based judgements. In a similar investigation based on a measure for rational or experiential information processing styles (see for example, Pacini & Epstein, 1999), Ayal, Rusou, Zakay, and Hochman (2015) demonstrated that individuals with an intuitive style performed better on an intuitive task – demonstrating fewer intransitive preferences – whereas those with a more analytical style performed better on an analytical task. While Gigerenzer and Todd (1999) propose that the selection of a strategy can be inferred solely from the structure of the decision environment, others have argued for the importance of basic individual dispositions in determining the effectiveness with which these can be executed. Zakay (1990) for instance, conceptualises a preference for a predominantly compensatory or non-compensatory decision strategy as a relatively stable individual characteristic, arguing that a basic tendency towards a particular decision style may have implications for which strategies an individual employs in practice (Shiloh et al., 2001). If this is indeed the case, then it should be possible to observe similar compatibility effects between decision style and strategy execution as reported in other studies (Ayal et al., 2015; McMackin & Slovic, 2000). In other words, a more compensatory decision style should correspond to relatively better performance on tasks calling for the execution of compensatory strategies as compared to those calling for non-compensatory strategies.

Hypothesis 2 (H2): *A higher subjective preference for a compensatory decision style will be positively related to individuals' abilities to execute prescribed compensatory strategies.*

4.3.3 Inhibitory Control and Decision Model

The relationship between cognitive ability and the facility with which decision makers can apply various decision rules has been of interest ever since the early work of Beach and Mitchell (1978). At the same time, while the relationships between executive function and adaptive strategy use have been widely hypothesised (e.g. Payne et al., 1993; Simon, 1971), they have rarely been the subject of empirical examination. Traditionally, these aspects have been studied under the premise of broad capacity constraints, and their specific components – attentional shifting, inhibitory control and working memory capacity – have often been treated synonymously in the rare studies that have attempted to investigate their role in adaptive strategy selection (Bröder, 2003). More recently, primarily in the neuropsychological literature, research has attempted to identify and disentangle the precise cognitive determinants of strategy execution. Del Missier, Mäntylä and Bruine de Bruin (2010) – in what to our knowledge is the first study considering the role of executive functions on strategy execution – examined the relationship of working memory capacity, inhibition and attentional shifting on downstream measures of decision maker competency. Their results suggested that while attentional shifting was associated with stable risk perceptions, inhibitory attentional control was positively related to individuals' abilities to accurately apply a variety of decision rules (see also, Del Missier, Mäntylä, & De Bruin, 2012; Rosi, Bruine de Bruin, Del Missier, Cavallini, & Russo, 2019). In interpreting this latter finding, Del Missier et al. (2010) suggest that "the successful application of decision rules requires the capacity to selectively focus attention and inhibit irrelevant (or no

TABLE 4.1: HYPOTHESISED RELATIONSHIPS OF TASK AND INDIVIDUAL VARIABLES ON THE CONSISTENCY WITH WHICH PRESCRIBED DECISION RULES CAN BE EXECUTED CONTRASTED BETWEEN COMPENSATORY AND NON-COMPENSATORY DECISION STRATEGIES.

	Compensatory	Non-Compensatory	Overall
Task Level			
No. of Alternatives	– – –	(–)	– –
No. of Attributes	– –	(–)	–
Individual Level			
Decision Style	(+)	NH	NH
Inhibitory Control	NH	(+)	+

Note. The negative sign implies a negative relationship between the variable and strategy execution and a positive sign indicates a positive effect. NH = No *a-priori* hypothesis.

more relevant) stimuli (pp. 69)." While they do not distinguish between compensatory and non-compensatory strategy execution, the substance of their conclusions seem to cohere to the fundamental conception of non-compensatory decision rules as highly selective when contrasted against more integrative compensatory procedures. In simpler terms, inhibitory attentional control is the ability of individuals to regulate what they pay attention to and what they ignore. Thus, it is often conceptualised as the component of the greater attentional system responsible for goal-directed and selective attentional processes (for an overview see Diamond, 2013). When extending this to the domain of prescribed strategy execution, while both compensatory and non-compensatory strategies are goal-directed in nature, only the latter are highly selective. As a result, we argue that more selective non-compensatory strategies are more compatible with individuals' abilities to regulate inhibitory attentional control. Based on this line of reasoning, we expect that higher inhibitory control will correspond with relatively better performance on tasks calling for the execution of non-compensatory strategies as compared to those calling for compensatory strategies.

Hypothesis 3 (H3): *Better inhibitory control will be positively related to individuals' ability to execute prescribed non-compensatory strategies.*

4.3.4 Summary

Table 4.1 summarises the hypothesised relationships between the variables within our framework. The parenthesised relationships refer to the compatibility hypotheses under investigation in our study while the un-parenthesised effects refer to known relationships between variables derived from the studies discussed in previous sections. The number of operators (i.e. minus/plus signs) indicate the amount of previous evidence supporting the relationship. Relationships for which there is a lack of extant findings and where we do not specify *a-priori* hypotheses, are denoted 'NH' and are estimated directly from the data.

4.4 Experimental Method

4.4.1 Design

In a $2 \times 2 \times 2$ within-subjects design, we manipulated the prescribed decision strategy (compensatory or non-compensatory), number of alternatives (3 or 5) and number of criteria (5 or 9). In addition to the experimentally manipulated variables, we included between-subjects measures for decision style and inhibitory control.

4.4.2 Participants

Forty-eight individuals (35.42% female, $n = 17$) were recruited through Amazon MTurk's online subject pool. Samples drawn MTurk are often used in behavioural studies and have been shown to perform on-par when compared to both student and expert samples (for a overview on MTurk data see Buhrmester, Kwang, & Gosling, 2011). Mean participant age was 36.77 years ($SD = 12.43$). Highest level of education was, 22.92% high-school ($n = 8$) or professional diploma ($n = 3$), 45.83% undergraduate degree ($n = 22$) and 31.25% master's degree ($n = 13$) or doctorate ($n = 2$).

4.4.3 Materials and Measures

All experimental materials and data collection procedures were programmed in the software package outlined in Stoet (2010).

Compensatory Style Questionnaire

In order to measure self-reported decision style, we employed Zakay's (1990) forty-item compensatory style questionnaire (CSQ). The CSQ is formulated as a bi-polar construct suggesting a subjective preference for compensatory decision making at the higher end of the scale and non-compensatory decision making at the lower end. Subjects were asked to indicate their agreement with items (e.g. "The correct manner to reach a decision is to treat the advantages and disadvantages of different alternatives as counterbalancing each other.") on a Likert-scale anchored at 1 (=completely disagree) and 5 (=completely agree). Previous applications of the CSQ have demonstrated high internal consistency and the composite measure has been shown to correspond with strategy use in unaided decision contexts (Shiloh et al., 2001). The complete set of the CSQ items is reproduced in Appendix B (section 4.8.1) for reference.

Eriksen Flanker Task

In order to measure individual differences in inhibitory attentional control, we employed a version of Eriksen and Eriksen's (1974) "flanker task" (EFT). The EFT is a widely used and extensively validated measure in cognitive psychology and is often used as the primary measure for assessing the inhibitory function of selective attention. It has been used in a variety of studies in the psychology of thinking and reasoning and, more recently it has been applied to the study of both micro and macro-economic decision making (Carvalho, Meier, & Wang, 2016; Li, Michael, Balaguer, Castañón, & Summerfield, 2018). The EFT asks subjects to respond to arrays of seven arrows pointing in either the left (<) or right (>) direction. Subjects respond to the direction the central arrow is pointing in, by pressing a corresponding button on their keyboard. Arrows can be "flanked" by others pointing in the same direction (congruent, e.g. >>>>>>>) or in the opposite direction (incongruent, e.g. >>><>>>). A consistent finding from the flanker paradigm is that individuals demonstrate slower response times (RTs) in the incongruent condition and the difference in RTs (i.e. $RT_{incongruent} - RT_{congruent}$) is interpreted as an individual's ability to regulate inhibitory control. For the purposes of the present study, we employ the relative difference in reaction times – averaged across four-hundred twenty experimental trials for each subject – as a between-subjects measure for inhibitory attentional control. Examples of trials in the congruent and incongruent conditions as well as some additional details are provided in Appendix B (section 4.8.2).

Choice Problems

In the main experimental task, participants were presented decision problems in alternative by attribute matrices with differing combinations of alternatives and attributes ($3 \times 5, 3 \times 9, 5 \times 5$ and 5×9). Choices involved the selection of a DVD player from within the choice set by applying a prescribed selection rule. The experimental task was loosely adapted from the adult decision-making competence (A-DMC) subscale for strategy execution (see for example, Bruine de Bruin, Parker, & Fischhoff, 2007). For the compensatory condition, subjects were asked to make their selection based on either an equal weight (EQW) or frequency-based heuristic (FRQ) and in the non-compensatory condition, deterministic eliminations by aspects (DEBA) or satisficing (SAT) (Alba & Marmorstein, 1987; Einhorn & Hogarth, 1975; Simon, 1955; Tversky, 1972). We chose these particular strategies as they have been found to be widely used by decision makers in practice (Payne et al., 1993). Moreover, as a result of their relative simplicity, especially compared to more complex weighted additive difference models, we expected that a naïve subject pool would be able to easily understand and apply these to the choice problems that were presented. While a drawback to this approach is that the idiosyncrasies of the individual rules may be lost as a result of aggregating across the individual strategies – an issue we discuss in the results sections – it also allows us to obtain a more generalisable assessment of the differences between the strategies as a whole.

We made three main adjustments to the A-DMC subscale. First, while the A-DMC consists of ten choice problems with five alternatives and attributes, our choice problems included combinations of $3\times5, 3\times9, 5\times5$ and 5×9 alternatives by attributes. Second, for some choice problems, the A-DMC includes questions which contain an alternative that conflicts with the course of action suggested by the prescribed rule and also dominates all other alternatives on every attribute. In order to remove any possible confounds relating to individuals reliance on dominance rather than the prescribed selection strategy, we ensured that none of the choice problems contained a strictly dominating alternative. Third, of the ten original A-DMC items, seven correspond to non-compensatory selection rules whereas three correspond to compensatory strategies (Bruine de Bruin et al., 2007; for the complete A-DMC along with all subscales see Liang & Zou, 2018). As a result, the original set of problems are skewed towards non-compensatory decision strategies. In contrast, since our primary motivation was to compare the differences between prescribed compensatory and non-compensatory procedures, our experimental task was balanced equally for both sets of strategies with subjects making eight choices in the compensatory condition and eight in the non-compensatory condition, for a total of sixteen choices across the duration of the experiment. Sample choice problems are provided in Appendix B (section 4.8.3).

4.4.4 Procedure

All participants were provided an information sheet explaining that they would be expected to complete a number of unrelated tasks testing their attention and decision making ability. After providing consent for data collection and agreeing to participate in the study, subjects were directed to a standard demographic questionnaire and subsequently completed the CSQ and EFT. Both tasks were randomized across participants so that half of the subjects first completed the EFT while the other half completed the CSQ. This was primarily done to control for any order effects that may have occurred as a result of the sequence of tasks. The CSQ was presented in four blocks with ten items per block in a nearly identical format as used in previous studies (Zakay, 1990). The EFT included two practice blocks consisting of fifty trials in total and six experimental blocks with a total of four-hundred twenty trials (i.e. seventy trials per block). Participants were given the option of taking a break between each block if they desired before moving on to the next section (for details on instructions for the EFT, see Appendix B). On average, this part of the experiment lasted between fifteen and twenty minutes. Next, participants were directed to the section of experiment assessing strategy execution. All subjects were provided additional instructions and were familiarised with the task by completing four practice questions applying each of the prescribed strategies (i.e. EQW, FRQ, DEBA and SAT) to a problem presented in a 3×3 alternative by attribute matrix. We employed an automatic exclusion criteria where subjects that failed to respond accurately to at least three of four questions were directed to the end of the experiment. This was done to avoid including subjects that misunderstood the instructions. Subjects that met the inclusion criteria then completed the sixteen choice problems presented in randomised order. The duration of the entire experiment was between thirty and forty-five minutes.

4.4.5 Dependent Variable

An important consideration in most multiple-criteria decision making experiments is that of identifying a suitable dependent variable. This is one of the trenchant criticisms of previous studies that have investigated preferential choice problems (Bettman et al., 1990; Jacoby et al., 1974). The standard approach in such cases is to infer individuals value functions, preferences and decision strategies through directly examining, fitting and comparing competing models that adequately describe the choice data (Katsikopoulos, 2016). While such approaches provide some insights into the underlying choice process, they do not tell us much about the quality of choices themselves. An alternative approach is to measure choice quality by assessing whether individual choices respect strict dominance (Korhonen et al., 2018). This approach provides a more objective basis to assess the quality of a decision however, it is not particularly amenable to our purposes as strict dominance by its very nature is a highly non-compensatory cue – i.e. once a strictly dominating alternative is identified the choice is already determined and search terminated. Instead, we use a measure referred to here as *constructed dominance* as the dependent variable for the purposes of our analysis. It is difficult to argue for the value of any decision strategy if its application is unable to uncover a dominance relation in environments where strict dominance is not otherwise apparent. Since our primary interest was in evaluating the facility with which individuals can execute prescribed strategies, we employed simple correspondence as our criteria to assess choice quality. More precisely, a choice on the i^{th} decision problem was considered to be dominating, if it corresponded to the solution obtained by applying the prescribed selection rule and dominated, if it did not.

4.4.6 Statistical Model

In order to exploit the mixed factorial design of our experiment – i.e. repeated measures within-subjects along with between subject predictors – we employed a varying intercepts multilevel logistic regression model. This approach is particularly useful for our analyses as it allows us to simultaneously estimate the task level and subject level effects while also accounting for the (unobserved) heterogeneity of choices between subjects (for an overview this method see Gelman & Hill, 2006).

We labelled the selection of dominated responses, y_i as 1 and a dominating choice as 0 and model them as independent, with $Pr\left(y_i = 1\right) = logit^{-1}\left(\mathbf{X_i}\beta\right)$. That is, the model predicts the probability that a choice *does not* correspond to the solution suggested by the prescribed strategy. Our predictors included the number of alternatives (ALT), number of attributes (ATT) and decision strategy (STRAT) at the task level ($n = 768$) and, inhibitory control (IAC) and self-reported decision style (CSQ) at the subject level ($N = 48$). In addition, we included varying intercepts for subjects, $\alpha_{j[i]}$, where the subscript, $j\left[i\right]$ refers to the participant index for the i^{th} choice, made by subject j. Our hypothesised effects propose interactions between variables, however we omit the full vector form representation of the model for aesthetic purposes and to conserve space. We abuse notation slightly (as in Korhonen et al., 2018) and represent our $n \times K$ design matrix, $X = x_1, ..., x_K$ indexed by the set of linear predictors, $p = 1, ..., K$ and label the corresponding beta coefficients as $\beta_1, ...\beta_K$. Our model can then be generalised as:

$$Pr\left(y_i = 1\right) = logit^{-1}\left(\alpha_{j[i]} + \sum_{p=1}^{K} x_{ip}\beta_p\right), \quad \text{for} \quad i = 1, ..., n. \tag{4.1}$$

$$\alpha_{j[i]} \quad \sim \quad N\left(\mu_\alpha, \sigma_j^2\right), \quad \text{for} \quad j = 1, ..., N. \tag{4.2}$$

The error component, $\alpha_{j[i]}$ is assumed to follow a normal distribution and the mean (μ_α) and variance (σ_j^2) for the subject-level intercepts are estimated from the data. Essentially, $\alpha_{j[i]}$ acts as a shrinkage parameter on the estimates, explicitly accounting for the multilevel structure of the data by biasing the beta coefficients towards or away from the pooled population mean, depending on the distribution on $\alpha_{j[i]}$. If $\sigma_\alpha \mapsto \infty$, the model is equivalent to a fully within-subjects specification and if $\sigma_\alpha \mapsto 0$, the model reduces to the ordinary least squares (OLS) approximation.

4.5 Results

The following sections will present the main results from our analyses. We have chosen to primarily focus on the inferential process and report the summary results here. Technical details including model selection procedures and sensitivity analyses have been included in the supplementary material (Appendix A).

4.5.1 Descriptive Statistics

We assessed the consistency of the CSQ by computing Cronbach's reliability metric. Overall, the CSQ demonstrated high item-wise consistency with a Cronbach's $\alpha = .81$. The mean CSQ score across participants ($M = 3.49, SD = .40$) was above the midpoint of the scale suggesting that on average, subjects reported a higher preference for a more compensatory decision style. This is in line with previous applications of this measure (Shiloh et al., 2001; Zakay, 1990). Next, we evaluated subjects relative ability to exercise inhibitory attentional control. We computed response time latencies for each subject between the congruent and incongruent trials on the EFT (i.e. $RT_{incongruent} - RT_{congruent}$). The mean latency between response times in the congruent and incongruent conditions was 75.64 milliseconds ($SD = 29.27ms$) and approximately normally distributed with a slightly fatter tail for slower mean RTs ($skew = .06, kurtosis = -.52$). Finally, we evaluated the number of dominated choices made by subjects on the strategy execution task. Overall, subjects made very few mistakes and on average, exhibited errors on less than five of the sixteen choice problems ($M = 25.78\%, SD = .44$). This suggested that subjects were paying attention to the task and did not find the prescribed decision rules too difficult to execute while, at the same time the errors that were made provided enough variability at the choice level to meaningfully test the hypothesized relationships. Figure 4.3 in Appendix A provides a visualization of the distributions for the variables of interest.

4.5.2 Grouping Structure for Compensatory and Non-Compensatory Strategies

As is to be expected, there was variation between the individual rules with error rates ranging from (highest to lowest): FRQ ($M = 32.81\%, SD = .47$), EQW ($M =$

$28.65\%, SD = .45$), SAT ($M = 24.48\%, SD = .43$) and DEBA ($M = 17.19\%, SD = .39$). Since our hypothesized relationships dealt with compensatory (EQW and FRQ) and non-compensatory (DEBA and SAT) decision strategies rather than the individual rules themselves, we needed to rule out the possibility that the these differences in variation were highly idiosyncratic in nature. In other words, we needed to assess whether the data supported the grouping structure in our experimental design. We fit the model described in the previous section and included individual predictors for each of the four decision rules (with FRQ as the reference category) to assess whether the mean error rates were significantly different across the individual rules. This analysis revealed that while error rates for FRQ and EQW were similar, both DEBA and SAT were significantly lower after controlling for the direct effects of the other independent variables. As an additional weak test for the suitability of grouping the individual strategies, we conducted a likelihood ratio test to assess whether a more complex model with four groups (FRQ, EQW, SAT and DEBA) was a better fit to the data than a sparse model with two groups (Compensatory and Non-compensatory). The more complex model did not improve explanatory power and was a poorer fit to the data ($LRT\chi^2(2) = 4.54, p = .103, ns$). We obtained similar support for models that included interactions between the task level variables. Taken together the results from this analysis supported the grouping of the individual decision strategies to formally test our hypotheses. A more detailed analysis for the effects of the individual rules is provided in Appendix A (section 4.7.2) for reference.

4.5.3 Testing the Hypothesised Relationships

The complete results from our hypothesis tests are summarised in Table 4.2. Additional details regarding model selection procedures along with model evaluation in Appendix A (Cook, 1977; Gelman & Hill, 2006; Hair, Black, Babin, & Anderson, 2018).

As can be seen in Table 4.2, there was a substantial amount of variation in the subject level intercepts ($\sigma_j^2 = 3.29$), thus supporting our use of a varying intercepts model. Interestingly, once we accounted for the fixed effects of the task (number of alternatives, criteria and decision strategy) and individual variables (decision style and inhibitory control), the unobserved subject level heterogeneity exerted very little

TABLE 4.2: Results from multilevel logistic regression predicting the odds of selecting a dominated outcome.

	Estimates		Odds-Ratios	
Level and Variable	B (SE)	z-value	OR	95% CI
(Intercept)	-2.23 (.35)	-7.08***	-	-
Task Level (n = 768)				
STRAT (ref = Compensatory)	.50 (.36)	1.38	1.65	[.81, 3.37]
ALT (ref = 3)	1.23 (.34)	3.63***	**3.42**	**[1.76, 6.63]**
ATT (ref = 5)	.87 (.34)	2.56*	**2.39**	**[1.23, 4.64]**
ALT×ATT	.09 (.38)	.24	1.10	[.52, 2.30]
ALT×STRAT	-.67 (.38)	-1.74†	.51	[.24, 1.09]
ATT×STRAT	-1.52 (.38)	-4.03***	**.22**	**[.10, .46]**
Subject Level (N = 48)				
EFT	-.09 (.14)	-.65	.91	[.70, 1.19]
CSQ	-.89 (.15)	-5.96***	**.41**	**[.30, .55]**
Cross-Level				
EFT x STRAT	.56 (.19)	2.94**	**1.75**	**[1.21, 2.55]**
CSQ x STRAT	.08 (.21)	.38	1.08	[.72, 1.63]
Variance Component				
σ_j^2	3.29			
μ_α	.11			
Fit Statistics				
Log-Likelihood	-383.6			
Marginal R^2 (Conditional R^2)	.29 (.31)			

B = unstandardised regression coefficient, SE = std. error, z-value = test stat., OR = odds-ratio, 95% CI = 95% confidence interval for odds-ratio, σ_j^2 = variance of subject level intercepts, μ_α = mean for subject level intercepts, Marginal R^2 = Variance explained by the fixed effects, Conditional R^2 = Variance explained by full model, R^2 values were computed using procedure outlined in Nakagawa and Schielzeth (2013).

Note. Significant odds-ratios are in **bold-face**.$***p < .001, **p < .01, *p < .05$. $\dagger p < .10, ns$

influence. We can assess this aspect by comparing the difference between the marginal and conditional R^2 values (Nakagawa & Schielzeth, 2013). While the marginal R^2 refers to the variance explained by only the fixed effects in the model, the conditional R^2 also accounts for the additional variation that could be attributed to (unobserved) individual differences. In the present case, unobserved heterogeneity only accounted for an additional 2% of the variance at the data level.

Task Complexity

Hypothesis 1(a) and (b) proposed weak compatibility effects when it came to the role of the number of alternatives and criteria on strategy execution. More precisely, we expected that increasing the number of alternatives and criteria would degrade choice quality for both compensatory and non-compensatory strategies, with this effect being be less pronounced in the latter case.

There was a large positive effect of the number of alternatives on the probability of selecting a dominated outcome. When we increased the number of alternatives from 3 to 5, subjects were 3.42 times more likely to select a dominated choice regardless of which strategy was prescribed ($95\% CI = 1.76 - 6.63, p < .001$). The estimate for the non-compensatory condition was negative ($B = -.67, OR = .51$) and in line with our hypothesis, however the effect was not quite significant ($p = .081$). As a result, Hypothesis 1(b) was rejected.

The role of the number of attributes on strategy execution was more nuanced. Specifically, while in the compensatory condition, subjects were 2.39 times more likely to choose a dominated outcome when the number of criteria were increased from 5 to 9 ($95\% CI = 1.23$–$2.64, p = .010$), in the non-compensatory condition the odds of selecting a dominating choice were increased by nearly the same amount. That is, in the non-compensatory condition increasing the number of criteria actually improved choice quality ($OR = .22, 95\% CI = .10 - .46, p < .001$). Thus, we find partial support for Hypothesis 1(a) and our findings suggest that rather than a weak interpretation of compatibility, as long as the underlying preference structure remains unchanged, non-compensatory procedures are highly robust to the inclusion of additional criteria within the problem context and can improve the correspondence of choices with the recommendations of the prescribed decision strategy.

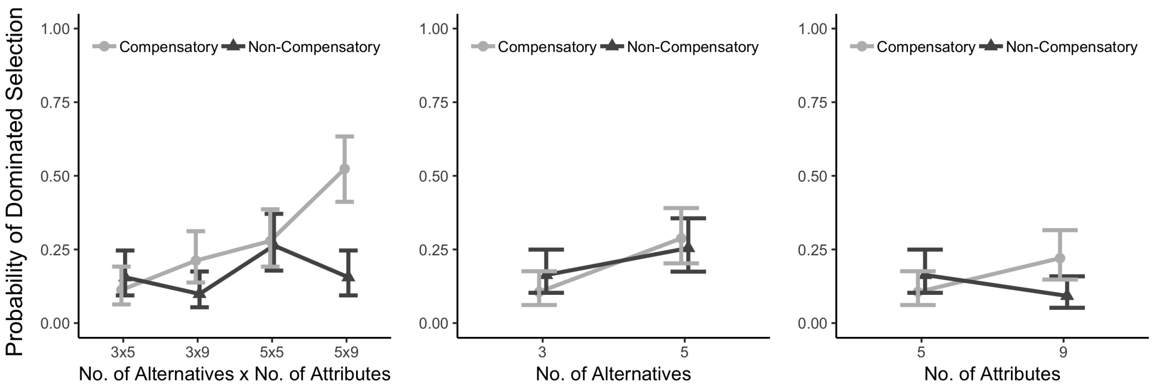


Figure 4.1: The effect of the number of alternatives and attributes on strategy execution in the compensatory (light-grey) and non-compensatory (dark-grey) conditions. The vertical bars represent the 95% confidence interval.

This effect is visualised in Figure 4.1. The left-most panel demonstrates the interaction between the size of the alternatives by attributes matrix and the prescribed decision strategy. It is apparent from the figure that the number of alternatives and criteria exert a distinct influence on strategy execution. This relationship is clearly demonstrated in the middle and right-most panels that highlight the disentangled roles of the number of alternatives and attributes. Note also that the interaction between the number of alternatives and attributes had essentially no effect on task performance.

Decision Style

Based on the rationale from Shiloh et al. (2001) and Zakay (1990), we formulated the expectation that compatibility between subjective decision style and the prescribed decision strategy would improve strategy execution (Hypothesis 2). While our analysis uncovered a significant direct effect of a higher self-reported tendency for more compensatory decision making on overall task performance, the hypothesised interaction between a higher preference for compensatory decision making and compensatory strategy execution was not supported ($95\% CI for OR = .72 - 1.63, p = .704$). As a result, we reject Hypothesis 2. While we cannot completely rule out that the overall effect was the result of a compatibility between a compensatory style and a compensatory task, the fact that we could not establish any discriminatory indication for this – i.e. a more compensatory style was associated with fewer dominated choices for both compensatory and non-compensatory strategies – suggests that an individual preference for compensatory decision making may have more to do with general decision

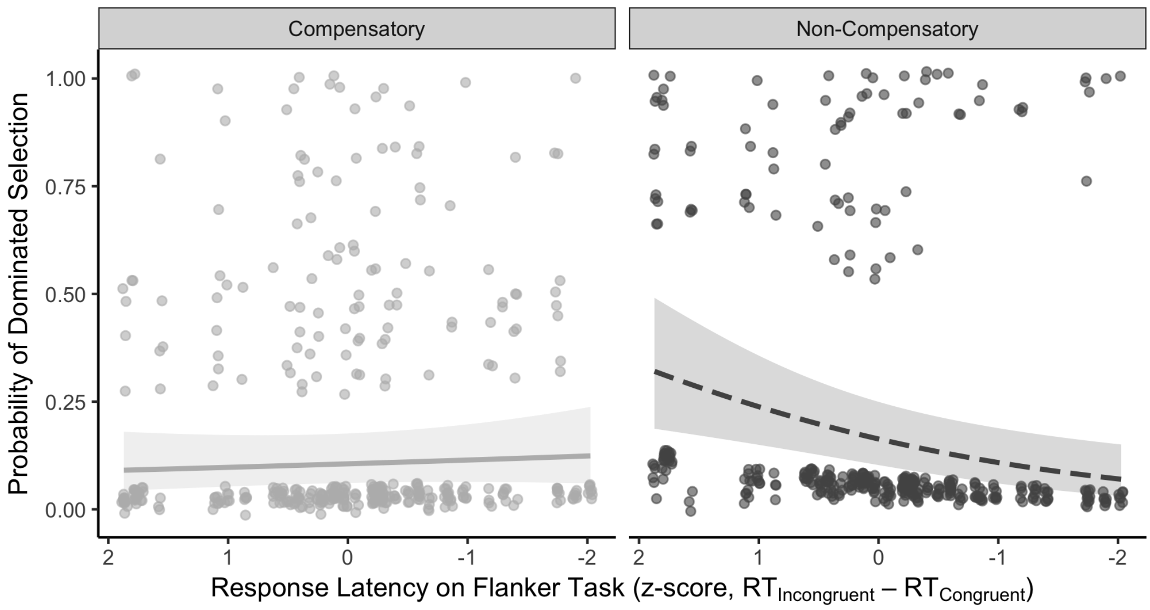


Figure 4.2: The effect of inhibitory control on strategy execution in the compensatory (light-grey) and non-compensatory (dark-grey) conditions. The translucent polygons represent the 95% confidence interval. The point estimates represent residual variance after accounting for the presence of other independent variables in the model. The x-axis is reversed and represents increasing inhibitory control. RTs are represented as z-scores for convenience ($range = 129.85$ to 16.94 ms).

making ability rather than strategy execution per se.

Inhibitory Control

Hypothesis 3 suggested that individual abilities to regulate inhibitory attentional control would be positively related to performance on tasks that called for non-compensatory strategy execution. Our analysis suggested that a standard deviation increase in the mean response latency on the EFT – i.e. lower inhibitory control – increased the odds of selecting a dominated outcome by 1.75 times in the non-compensatory condition ($95\%CI = 1.21 - 2.55, p = .003$). On the other hand, performance on the flanker task did not predict strategy execution in the compensatory condition, with an estimate that was marginally negative, non-significant and extremely close to zero ($B = -.09, p = .510$). Thus, Hypothesis 3 was supported.

As can be seen in Figure 4.2, the relationship between inhibitory control and performance on the strategy execution tasks markedly differs in the compensatory and non-compensatory conditions. Note that increasing response time latencies on the EFT (higher values for $RT_{incongruent} - RT_{congruent}$) are associated with lower inhibitory

TABLE 4.3: Relationships between task and individual variables demonstrating the results from hypothesis tests contrasted between compensatory and non-compensatory decision strategies.

	Decision Strategy		Results	
	Compensatory	Non-Compensatory	Support	Compatibility Effects
Task Level				
No. of Alternatives	− − −	− −	No*	Partial
No. of Attributes	− −	++	Partial	Yes
Individual Level				
Decision Style	+	+	No	No
Inhibitory Control	null	+	Yes	Yes

Note. The negative sign implies a poorer performance and positive sign implies improved performance. The number of operators serve as a schematic representation of the effect size for each variable. *Not supported at 95% level (p = .081). Compatibility effects are partially indicated as the sign of the estimate corresponded to the expected relationship.

control. As a result, the x-axis is reversed so that the figure plots task performance as a function of increasing inhibitory control.

Table 4.3 maps the results from our analysis on the proposed theoretical framework and summarises the relationships between the variables under investigation. The number of operators serve as a schematic representation of the relative effect sizes for each of the independent variables (precise effect sizes are reported in Table 4.2 along with their associated 95% confidence intervals).

4.6 Discussion and Conclusions

In his often repeated metaphor explicating the notion of bounded rationality, Herbert Simon likens human decision making to a scissors whose two blades represent attention scarce agents and the complex environments that they operate in (Simon, 1990). Operational research is perhaps quite naturally placed at the intersection of these extremes, refining models and methods that can help draw the blades together and reasoning about instances in which they might diverge (Franco & Hamalainen, 2015). In this respect, the central insights from the "fast and frugal" paradigm presented by Gigerenzer et al. (1999) may not be all that alien to OR scholars and practitioners. Stark results demonstrating the predictive accuracy of highly intuitive non-compensatory decision strategies suggest that these procedures may be an indispensable addition to the decision analyst's toolbox, provided they are deployed in circumstances that are favourable for their use. In the present study, our primary motivation was to investigate the conditions in which synergies between individual, model and task features can improve strategy execution in aided multiple criteria decision making contexts.

Importantly, our results highlight that once task characteristics are taken into account, there is hardly any discernible difference between the relative accuracy with which individuals can employ prescribed compensatory or non-compensatory selection procedures. Rather than the difficulty associated with executing a particular strategy – at least as far as this can be inferred from the accuracy with which it is employed in practice – the correspondence of choices with a recommended course of action depends to a much larger extent, on the requirements from the task at hand. Our results extend the findings from Fasolo et al. (2007) and provide experimental support to their simulation studies by demonstrating that in cases where the underlying preference relation remains unchanged, the dominance structure implied by a non-compensatory approach can be more easily detected by decision makers when additional criteria are introduced into the problem space. This finding suggests that non-compensatory decision aids may find particularly robust applications in decision contexts characterised by an abundance of attribute information where only a subset of attributes are highly salient. At the same time, we find that such strategies are not totally immune to degraded performance as a function of information load when the number of available alternatives is increased. While we uncovered weak evidence that this effect is partially moderated in the case of non-compensatory strategies, further research is required to assess whether this was a chance artefact or demonstrative of systematic differences between the strategies themselves.

Even in its weak form however, this result suggests the assumption that non-compensatory decision strategies are universally easier to execute, may not necessarily hold in circumstances where they are employed as prescriptive decision aids. Where do these strategy execution costs come from? Our findings highlight that an important determinant of the facility with which individuals can employ non-compensatory strategies relates to their ability to regulate inhibitory control. This makes both intuitive and theoretical sense if we consider that such strategies require decision makers to actively ignore non-instrumental information even if it is accessible in the task environment (Gigerenzer & Goldstein, 1996; Goldstein & Gigerenzer, 2002; Katsikopoulos & Gigerenzer, 2008). Thus, while non-compensatory strategies may be less computationally expensive, they still require individuals to exercise attentional control and their ability to do so may have significant implications for the accuracy with which they can implement the recommendations of a "fast and frugal" decision aid in practice.

Our results partially converge with findings from Del Missier et al. (2010, 2012) – particularly once methodical differences relating to the non-compensatory skew of the A-DMC subscale is taken into account – and suggest that suppressing available information may be an inherently effortful activity. Furthermore, we build on this fundamental insight and demonstrate the boundary conditions for the role of inhibitory control on prescriptive strategy execution, highlighting that individuals' capacity to regulate inhibition is more instrumental for selective (non-compensatory) rather than more integrative (compensatory) modes of information processing. A potential way forward in cases where time or other operational constraints necessitate the use of these principles, is to supplement the application of non-compensatory decision aids with efforts aimed towards training inhibitory control (Allom, Mullan & Hagger, 2016) and automatizing selective information processing (Bröder & Newell, 2008). An important caveat related to this finding however, is the correlational nature of the evidence we have uncovered. While care was taken to minimise the occurrence of confounding factors by incorporating a carefully constructed mixed-factorial experimental design, future research should attempt ruling out the possibility of alternative causal explanations by replicating this result in naturalistic decision making settings.

Finally, on the role of "basic tendencies", our results suggest that a general subjective preference for compensatory decision making may be associated with a greater flexibility with which individuals can apply a variety of decision strategies. This finding is somewhat contradictory to the intuition from previous studies that have proposed that a stable decision style would prioritize a particular mode of strategy execution at the expense of the other (Shiloh et al., 2001; Zakay, 1990). Instead, our results suggest that a more compensatory decision making style may be associated with general decision making ability and provide very little additional qualitative insight into strategy execution. A potentially fruitful line of enquiry for the future may be to investigate the latent factor structure of the CSQ. This could illuminate the role of a personal disposition towards a particular decision style on the strategy execution process at a more granular level and reveal underlying relationships that may have been missed in the present analysis. On this latter point however, there is reason to sceptical. While the search for personality correlates for aided decision making remains elusive (O'Keefe, 2016), the lack of such findings could also suggest that individual decision processes may be more sensitive to situational factors and transient individual states rather than prevailing personal dispositions – this interpretation would in many respects conform to the core insight underpinning the "adaptive toolbox"– reinforcing the ultimate malleability and flexibility of ecologically rational agents.

4.7 APPENDIX A: Supplementary Information on Data Analysis

The sections follow the order of presentation within the paper in section, **4.5 Results**.

4.7.1 Histogram for Experimental Variables

Figure 4.3 plots the distributions on the variable of interest. As can be seen from the plots, the mean self-reported CSQ scores were above the midpoint of the scale and ranged from 2.80 to 4.28 with values approximately uniformly distributed about the mean. The response times on the EFT were approximately normally distributed with a fatter tail for slower response times. On the strategy execution task, most subjects made few errors and the distribution is binomial, supporting the use of logistic regression for our subsequent analyses.

4.7.2 Analysing the Effects of the Individual Decision Rules

Table 4.4 presents the analysis described in sub-section 5.2 Grouping Structure for Compensatory and Non-Compensatory Strategies. The models are identically specified except for the inclusion of 2 (Compensatory and Non-compensatory) or 4 (FRQ, EQW, DEBA and SAT) groups. Along with the description provided in the main paper, the table highlights two additional features. First, it shows that the individual compensatory (FRQ and EQW) and non-compensatory (DEBA and SAT) rules are similarly correlated with task performance. This can be seen both for the models predicting the direct effects and the task-level interactions. The task level interactions further highlight that once dependencies between task characteristics are taken into account, the absolute effect of the decision rules are not significantly different but, when the number of attributes are increased, both non-compensatory rules predict a similar improvement in performance – i.e. they indicate fewer dominated selections. Second, the absolute reduction in the AIC values is small and Likelihood ratio tests (LRT), assessing whether the reduction in deviance is significant, confirm that the more complex model does not improve explanatory power. This would suggest that including the individual predictors for each rule would introduce redundancy into the

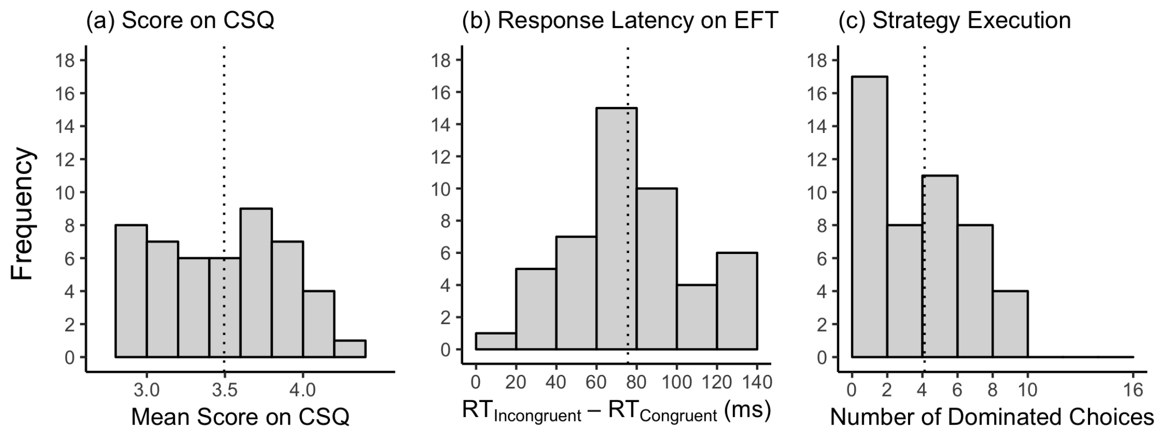


Figure 4.3: Histograms for experimental variables. The dotted line represents the mean.

model and as a result supports a more parsimonious model specification.

4.7.3 Model Selection

Since our conceptual hypotheses proposed interactions between task level variables as well as cross-level interactions (i.e. between individual characteristics and task variables), we needed to assess whether such an empirical model was supported by the observed variation in our experimental data. In other words, similar to the analysis in the preceding section, we needed to assess whether an alternative model specification would significantly alter the inferences drawn from our hypothesised model. In order to do this, we follow the recommendation from Gelman & Hill (2006) and conduct a step-wise analysis, increasing the complexity of our model and assessing whether predictive indices were improved by incorporating higher order effects. The results from this analysis are presented in Table 4.4. In order to inform our model selection process, we rely on three indices. The absolute reduction in AIC values, the absolute reduction in Log-likelihoods and the results from Likehood ratio tests (LRT) for the alternative hypothesis that a higher order model corresponds to a significant reduction in deviance. As can be seen from the table, models (a) through (d) correspond to decreasing AIC and Log-likelihood values while the most complex models (e) and (f) demonstrate increasing values. Model (e) is saturated at the task level and adds the three-way interaction between (STRAT×ALT×ATT), however performs poorer when compared to model (d) on all indices. Similarly, model (f) where an additional

TABLE 4.4: Analysis for the support of the simpler grouping structure for decision strategies.

	Direct Effects		Task Level Interactions	
	(a) 2-Groups	(b) 4-Groups	(c) 2-Groups	(d) 4-Groups
	B	B	B	B
(Intercept)	-1.57***	-1.47***	-2.13***	-2.05***
Task Level ($n = 768$)				
STRAT (ref = Compensatory)	**-.62*** **		**.54**	
EQW (ref =FRQ)		**-.24**		**-.18**
SAT (ref = FRQ)		**-.49***		**.76**
DEBA (ref = FRQ)		**-1.01*** **		**.08**
ALT (ref = 3)	.93***	.94***	1.23***	1.31**
ATT (ref = 5)	.23	.23	.87*	.85*
ALT×STRAT			**-.68**	
ALT×EQW				**-.16**
ALT×SAT				**-.89**
ALT×DEBA				**-.59**
ATT×STRAT			**-1.51*** **	
ATT×EQW				**.05**
ATT×SAT				**-1.49** **
ATT×DEBA				**-1.50** **
ALT×ATT			.09	.09
Subject Level ($N = 48$)				
EFT	.16	.16	.16	.16
CSQ	-.82***	-.82***	-.85***	-.85***
Fit Statistics				
AIC	773.25	772.71	739.31	737.30
Log Likelihood	-379.62	-377.35	-379.6555	-383.15
LRT$\chi^2(df)$	4.54 (2), p = .103ns		5.01 (6), p = .542ns	

Note. The estimates for the grouping variables are in **bold-face**. B = Unstandardized regression estimate. AIC = Akaike Information Criterion, LRT$\chi^2(df)$ = likelihood ratio tests comparing the reduction in deviance from model (b) to (a) and model (d) to (c). df = degrees of freedom. $***p < .001, **p < .01, *p < .05$.

interaction between subject level variables is estimated (EFT×CSQ) is also a poorer fit. Thus, we prefer the more parsimonious model in this case.

Next, comparing models (a) through (d), we can see that AIC values decrease, however model (d) – i.e. our hypothesised model – only corresponds to a small absolute reduction in the AIC ($AIC_{(c)} - AIC_{(d)} = 759.31 - 754.38 = 4.98$) and Log-likelihood values (=4.47). In order to formally test, whether this reduction in deviance was significant, we conducted a likelihood-ratio test and obtain support for the selection of our hypothesised model at the 95% level ($LRT\chi^2(2) = 8.93, p = .011$). Obviously, this not imply that our model is "correct", however it provides support that given our data, the hypothesized model is plausible when compared against alternative empirical specifications.

Additionally, Table 4.4 also reports the model coefficients from our analyses. The primary purpose for this is in order to evaluate whether the estimates display unexpected behaviour that might indicate collinearity or otherwise unstable coefficients. As can be seen from the table, the estimates, p-values and corresponding standard errors are fairly robust to changing the model specifications, providing an early indication that collinearity issues are unlikely.

4.7.4 Model Evaluation

In this section, we evaluate our empirical model and assess collinearity, robustness to outliers and general predictive performance.

Assessing Collinearity

In order to assess multicollinearity, we computed variance inflation factors for all predictors in our model along with an overall condition number. These are reported in Table 4.5. VIFs and other measures were below recommended thresholds and did not indicate any major issues with multicollinearity (Hair et al., 2018)

Robustness to Outliers

In order to evaluate the robustness of our model parameters to the presence of outliers, we employed two approaches. First, we computed Cook's distances in order to assess

TABLE 4.5: Model selection using stepwise multilevel logistic regression

	(a) Intercept Only	(b) Direct Effects	(c) Task-Level Interactions	(d) Cross-Level Interactions	(e) Saturated Task Level	(f) Higher-Order Interactions
Level and Variable	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
(Intercept)	-1.23*** (.16)	1.67*** (.27)	-2.23*** (.35)	-2.23*** (.35)	-2.16*** (.37)	-2.22*** (.35)
Task Level ($N = 768$)						
STRAT (ref = Compensatory)		-.62*** (.18)	.54 (.34)	.50 (.36)	.37 (.42)	.39 (.42)
ALT (ref = 3)		.93*** (.19)	1.23*** (.34)	1.23*** (.34)	1.11** (.39)	1.11*** (.39)
ATT (ref = 5)		.23 (.18)	.87* (.34)	.87* (.34)	.75* (.40)	.75* (.40)
ALT x ATT			.09 (.37)	.09 (.38)	.29 (.51)	.13 (.38)
ALT x STRAT			-.68 (.38)	-.67 (.38)	-.45 (.53)	-.45 (.53)
ATT x STRAT			-1.51*** (.37)	-1.52*** (.38)	-1.27* (.58)	-1.27* (.58)
ATT x ALT x STRAT					-.44 (.76)	-.44 (.76)
Subject Level ($N = 48$)						
EFT		.16 (.10)	.16 (.11)	-.09 (.14)	-.09 (.14)	-.11 (.14)
CSQ		-.82*** (.11)	-.85*** (.12)	-.89*** (.15)	-.90*** (.15)	-.90*** (.15)
EFT x CSQ						-.12 (.12)
Cross-Level						
EFT x STRAT				.56** (.19)	.56** (.19)	.55** (.19)
CSQ x STRAT				.08 (.21)	.08 (.21)	.11 (.21)
Fit Statistics						
AIC	844.09	773.25	759.31	754.38	756.04	757.08
Log-Likelihood	-420.045	-379.625	-369.655	-365.19	-365.02	-364.54
LRT $\chi^2(df)$		80.84 (5), p <.001	19.94 (3), p <.001	8.93 (2), p = .011	.33 (1), p = .563, ns	.97 (1), p = .326, ns

B = Unstandardized regression coefficient, SE = Std. error, AIC = Akaike Information Criterion, LRT $\chi^2(df)$ = likelihood ratio tests comparing the reduction in deviance from model $n-1$ to model n. df = degrees of freedom.
$***p < .001, **p < .01, *p < .05$.

TABLE 4.6: Collinearity statistics.

Level and Variable	VIF	TOL	kappa
(Intercept)	-	-	8.24
Task Level (n = 768)			
STRAT (ref = Compensatory)	3.83	.26	
ALT (ref = 3)	3.24	.31	
ATT (ref = 5)	3.40	.29	
ALT x ATT	3.40	.29	
ALT x STRAT	3.29	.30	
ATT x STRAT	2.64	.38	
Subject Level (N = 48)			
EFT	1.64	.61	
CSQ	1.72	.58	
Cross-Level			
EFT x STRAT	1.66	.60	
CSQ x STRAT	1.86	.54	

VIF = Variance inflation factor, TOL = Tolerance ($1/VIF$), kappa = condition number for full model.

whether any individual observations exerted a large influence on the results. The results from this analysis suggested that based on the recommended thresholds, there was no indication of significant outliers (Cook, 1977; Hair et al., 2018). In order to further investigate this result, we removed any observations with a Cook's distance $\geq$ 2 standard deviations from the mean and re-estimated our model. Additionally, to probe whether the interaction between decision strategy and inhibitory control was the result of the larger number of observations for slower RTs (i.e. there was a marginally higher number of observations for slower reaction times as shown in Figure 4.3). We estimated an additional model suppressing observations for individuals with RTs +/- two standard deviations from the mean. These results are shown in Table 4.7 and contrasted against the results from the model including all observations. As is apparent from the table while dropping influential observations did have an effect on the estimated coefficients, the estimates were fairly robust to the removal of these data points.

TABLE 4.7: Evaluating robustness to outliers.

	Full Model	Removing Large RTs	Cook's Distance
Level and Variable	B	B	B
(Intercept)	-2.23***	-2.10***	-2.09***
Task Level[a]			
STRAT (ref = Compensatory)	.50	.45	.42
ALT (ref = 3)	1.23***	1.22***	1.18***
ATT (ref = 5)	.87*	.86*	.81*
ALT x ATT	.09	.12	.19
ALT x STRAT	-.67†	-.70†	-.59
ATT x STRAT	-1.52***	-1.50***	-1.51***
Subject Level[b]			
EFT	-.09	-.14	-.07
CSQ	-.89***	-.87***	-.90***
Cross-Level			
EFT x STRAT	.56**	.64**	.51**
CSQ x STRAT	.08	.02	.14

B = Unstandardized coefficient, $***p < .001, **p < .01, *p < .05$, $\dagger p < .10$, ns.
[a] $n = 768, n = 720$ and $n = 752$ from left to right for each model.
[b] $N = 48, N = 47, N = 45$ from left to right for each model.

TABLE 4.8: Fit statistics.

Model χ^2 (*df*)	109.71 (10), p <.001
Hosmer-Lemeshow χ^2 (*df*)	25.58 (28), p = .506
Marginal R^2	.29
Conditional R^2	.31

Model χ^2 (*df*) = Likelihood ratio test for null model against the estimated model, Hosmer-Lemeshow χ^2 (*df*) = Hosmer-Lemeshow test for the alternative hypothesis for calibration errors, Marginal R^2 = Variance explained by the fixed effects, Conditional R^2 = Variance explained by full model

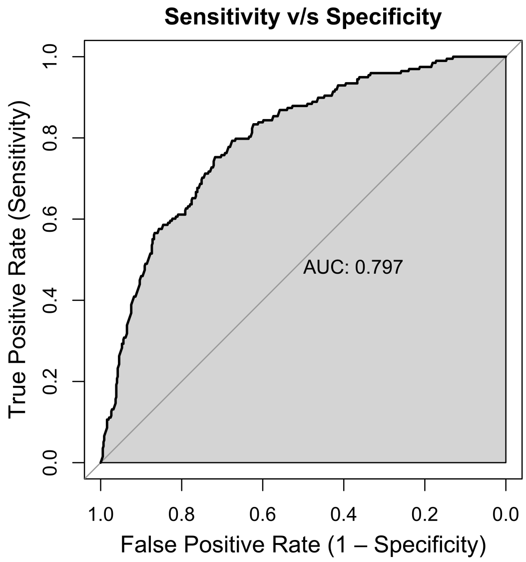


Figure 4.4: Sensitivity v/s specificity plot for the estimated model. AUC value is printed in the shaded area.

Model Performance

Table 4.8 provides likelihood-ratio test for the estimated model against an intercept only (null) model, a Hosmer-Lemeshow test with thirty groups and Marginal and Conditional R^2 values (Nakagawa & Schielzeth, 2013).

Figure 4.4 provides a visualisation of the receiver operating characteristic curve (ROC) plotting the true positive rate against the false positive rate for the logistic model. The area under the curve (AUC) is printed on the figure. The figure demonstrates that the estimated model demonstrates reasonable classification accuracy.

4.8 APPENDIX B: Supplementary Information on Experimental Materials

The sections follow the order of presentation within the paper in sub-section 4.3 Materials and Measures. We distinguish between materials shown to participants and our annotations by using text within % symbols (%%......%%). This text was not presented to participants.

4.8.1 Compensatory Style Questionnaire (reproduced from Zakay, 1990)

%% Items represented with (R) after the period refer to reverse coded items (i.e. the scale is reversed for analysis and not in its presentation to participants). The scale is bi-polar and higher scores represent a greater subjective tendency for compensatory decision making. %%

%% Instructions %%

On the following pages, you will be presented a list of 40 statements related to decision making processes. For each statement you are requested to state to what degree it suits your opinion and feeling regarding decision making. Please mark your answer by indicating your agreement on the following 5-point scale:

1. I do not agree at all with the statement, it does not match my opinion and feeling;

2. I somewhat agree with the statement, it only marginally matches my opinion and feeling;

3. I moderately agree with the statement, it matches to a certain degree my opinion and feeling;

4. I strongly agree with the statement, it matches to a large degree my opinion and feeling;

5. I completely agree with the statement, it totally matches my opinion and feeling.

Please carefully read the instructions for each group, as well as the content of each statement.Please answer each statement as though it stands by itself unrelated to the others. Whenever possible, try to avoid indicating a neutral response unless you are sure that this is the only suitable response reflecting your true feeling or opinion.

%% After this explanation of scale levels, scale markers were labelled (1 = Completely Disagree, 2 = Somewhat Disagree, 3 = Moderately Agree, 4 = Strongly Agree, 5 = Completely Agree) %%

%% Next Page %%

TO WHAT EXTENT DO THE FOLLOWING STATEMENTS REPRESENT BELIEFS ABOUT YOURSELF

1. In the decision-making process, I always take into account all the possible aspects.
2. In the decision-making process, I usually do not compare between cons and pros. (R)
3. In the decision-making process, I evaluate the utility of each alternative before reaching a final decision. (R)
4. I do not believe the advantages of one alternative counterbalance the disadvantages of another. (R)
5. I always try to obtain all possible information regarding all the alternatives before reaching a decision.
6. In my opinion, the alternative that exhibits a strikingly positive quality may be the best one and not the alternative that is better on average than the others. (R)
7. I always decide after much deliberation.

8. I do not believe it is necessary to invest a lot of effort in decision making. (R)
9. It is risky to choose the first thing that comes into mind.
10. I always try to insure the fulfillment of one or two of my goals, even if other goals are left unfulfilled.

%% Next Page %%

TO WHAT EXTENT DO THE FOLLOWING STATEMENTS REPRESENT YOUR BELIEFS ABOUT HOW PEOPLE REACH DECISIONS

1. Good decision makers reach decisions based on one or two key elements while ignoring the others. (R)
2. Good decision makers always take into account all the possible aspects of each alternative before reaching a decision.
3. People usually do not compare between all the cons and pros before reaching a decision. (R)
4. Good decision makers always calculate the utility of each alternative before reaching a final decision. (R)
5. Good decision makers usually choose the alternative that exhibits a strikingly positive quality and not the one that is better on average from the others. (R)
6. Good decision makers always decide after much deliberation.
7. Exerting a lot of effort in reaching a decision does not usually yield better decisions. (R)
8. Good decision makers believe that the advantages of one alternative counterbalance the disadvantages of another.
9. It is very productive and economical to choose the first thing that comes into mind. (R)
10. Bad decision makers do not attempt to acquire all the possible information regarding all the alternatives before reaching a decision.

%% Next Page%%

TO WHAT EXTENT DO THE FOLLOWING STATEMENTS REPRESENT YOUR BELIEFS ABOUT NORMS AND VALUES THAT SHOULD BE IMPLEMENTED FOR REACHING DECISIONS

1. In the decision-making process, it is imperative to attempt and acquire all the possible information regarding all the alternatives before reaching a decision.
2. One must not choose the first thing that comes into mind.
3. The correct manner to reach a decision is to treat the advantages and disadvantages of the different alternatives as counterbalancing each other.
4. One must not exert a lot of effort in reaching a decision, since it is not a prerequisite to making better decisions. (R)
5. It is imperative to always exert a lot of deliberation before reaching a decision.
6. One should choose the alternative that exhibits a strikingly positive quality as the best alternative and not the one that is better on average from the others. (R)
7. It is not always best to compare all the cons and pros before reaching a decision. (R)
8. The correct manner to reach a decision is to take into account one or two key elements while ignoring the others. (R)
9. It is necessary to first calculate the utility of each alternative by itself before comparing it with the other alternatives.
10. It is necessary to reach decisions as spontaneously and quickly as possible.

%% Next Page %%

TO WHAT EXTENT DO THE FOLLOWING STATEMENTS REPRESENT YOUR GOALS AND TARGETS WHILE MAKING DECISIONS.

10. My goal is to ensure that the alternative I choose is better on average than the other alternatives.

2. While making a decision I always strive to take into account all possible aspects.

3. I have no interest in gaining all available information regarding all the alternatives before reaching a decision. (R)

4. I never choose the first thing that comes into mind.

5. I always strive to reach a decision based only on one or two key elements while ignoring the others. (R)

6. I strive to reach decisions only after much deliberation.

7. I strive to examine whether the advantages of one alternative can counterbalance the disadvantages of other alternatives.

8. I strive to reach quick decisions without exerting a lot of effort. (R)

9. I always strive to calculate the utility of each alternative separately before I compare it against other alternatives. (R)

10. I strive to identify the alternative that exhibits a strikingly positive quality in order to choose it as the best one. (R)

4.8.2 The Eriksen Flanker Task (adapted from Eriksen & Eriksen, 1974)

%% The flanker task was conducted presenting white text on a plain black background for contrast. Images are not to scale. %%

%% Instructions for the task were presented as follows. %%

%% After reading these initial set of instructions, participants completed the practice trials. These were presented in 2 separate practice blocks with 25 trials per block. The purpose of the practice blocks was to familiarize subjects with the experiment. In cases where errors were made, along with the color coded feedback on the fixation

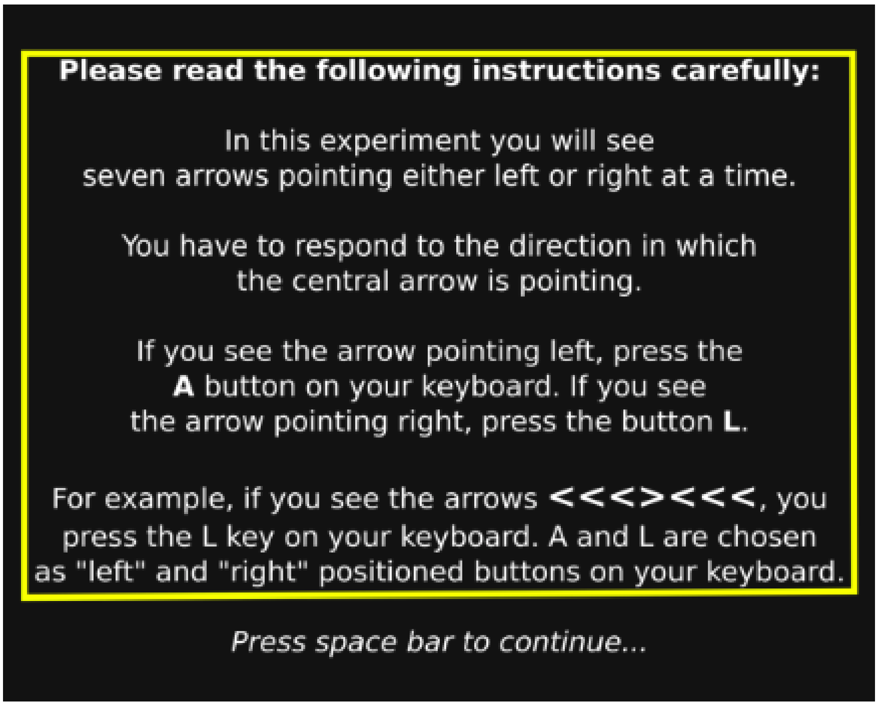


Figure 4.5: Flanker task instructions pg. 1.

cross (+), participants were also presented an additional message reminding them the keys corresponding to "right" and "left" responses. The data from the practice trials was not considered in the main analysis. %%

%% After completing the practice blocks, participants were alerted that the experiment will begin on the subsequent pages. The message shown in Figure 4.8 was presented. %%

%% Figure 4.9 provides an example of the trials in each of the congruent and incongruent conditions. 1) and 2) are examples in the congruent condition and 3) and 4) in the incongruent condition. 3) and 4) also highlight how feedback was provided, correct trials were followed by a blinking green cross and incorrect trials with a blinking red cross. %%

%% The figures are not drawn to scale. In the actual experiment, the fixation cross was presented in the center of the screen and 80 x 80 pixels. The mid-point (i.e. correct response) for the array of arrows was presented 25 pixels directly above the fixation cross and the size of the array was 550 x 180 pixels. %%

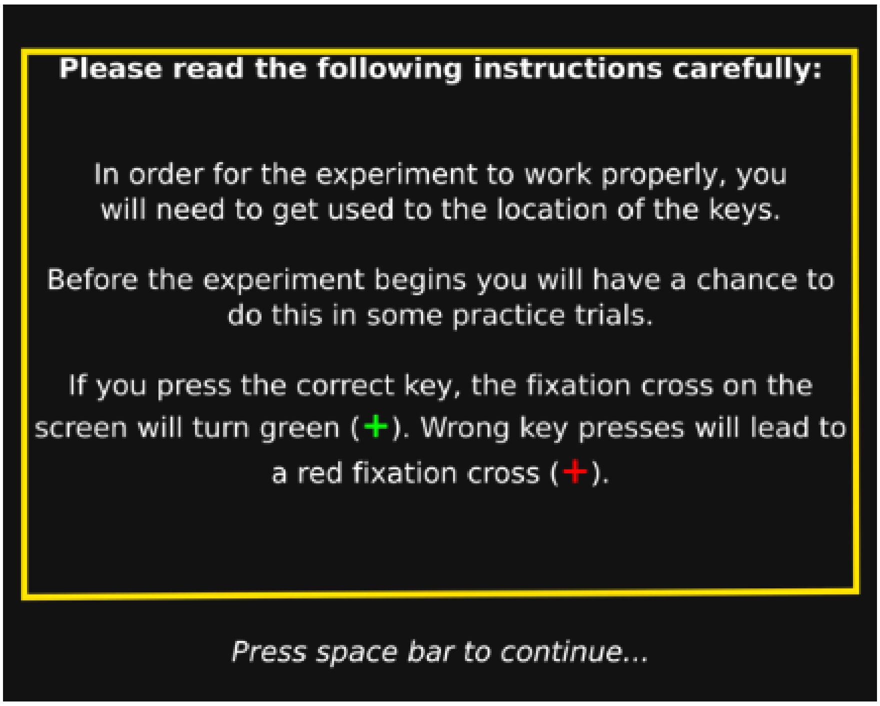


Figure 4.6: Flanker task instructions pg. 2.

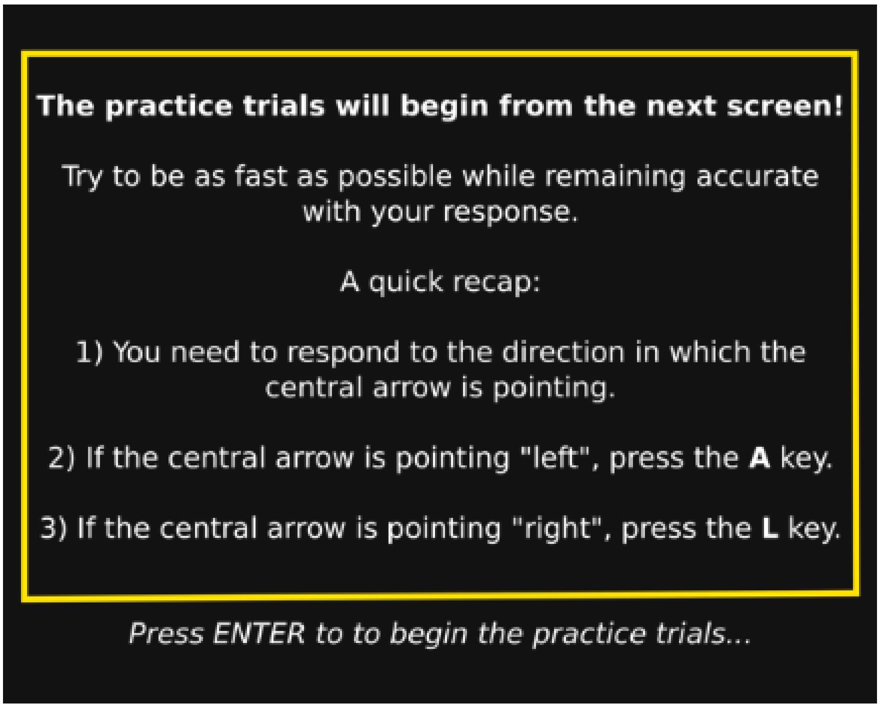


Figure 4.7: Flanker task instructions pg. 3.

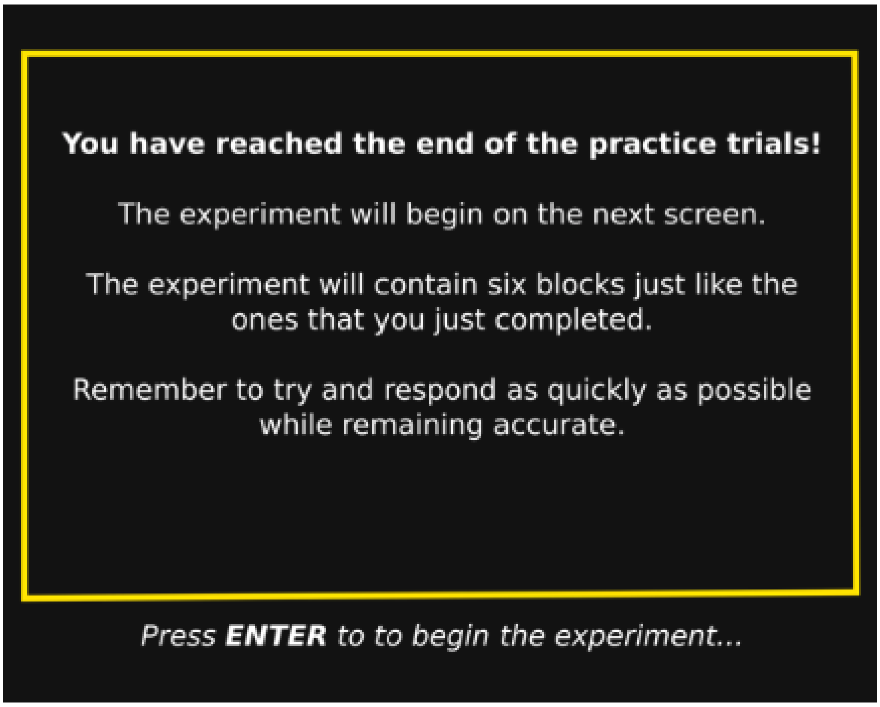


Figure 4.8: Flanker task instructions pg. 4.

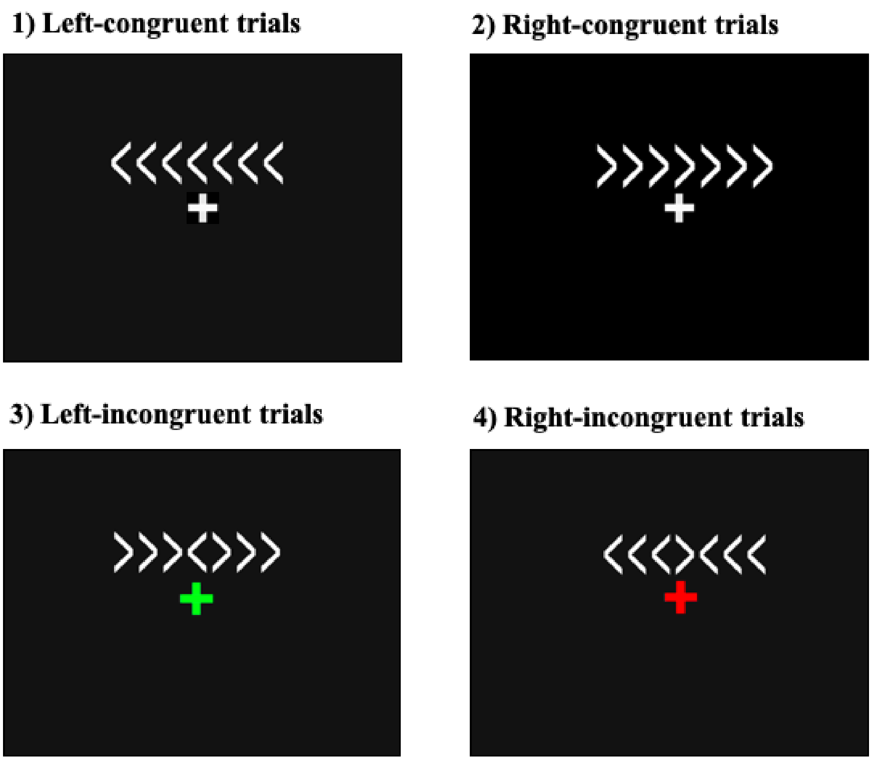


Figure 4.9: Examples of trials in the "congruent" (1, 2) and "incongruent" (3, 4) conditions. 3) and 4) also show how feedback was provided.

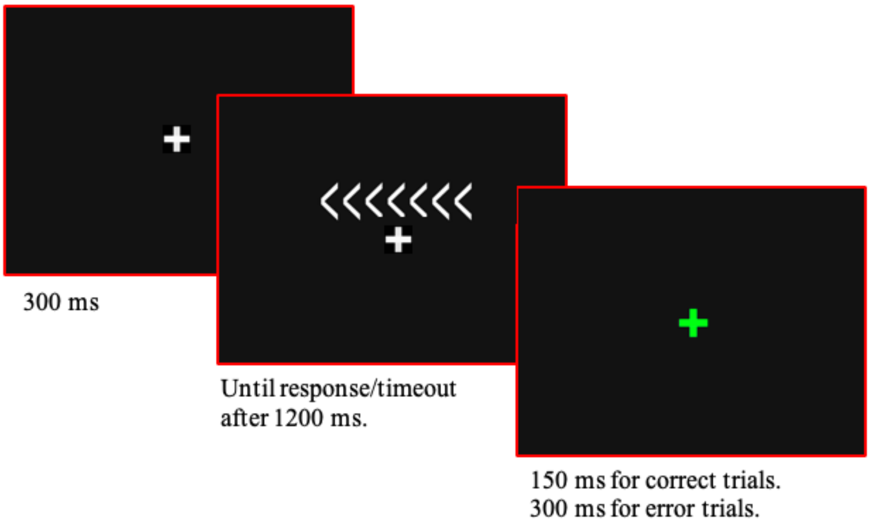


Figure 4.10: Sequence and timing of trials for the flanker task.

%% Only correct trials were used in the response time calculations, error trials were discarded. On average, accurate trials comprised 87.64% of responses ($range = 70.71\%$ to 98.10%). %%

%% Figure 4.10 illustrates the sequence and timing for the experimental trials. For each trial, a white fixation cross was presented on the screen for 300 milliseconds, after which the experimental stimuli were presented until a response was made. If participants took more than 1200 milliseconds to respond, the trial timed-out and was treated the same as error trials with a blinking red fixation cross presented on the screen for 300 milliseconds. For correct trials, a green fixation cross was presented for 150 milliseconds. Note that the red borders are simply for aesthetic purposes and were not visible to participants. %%

%% The experiment included six blocks with 70 trials per block. Between each experimental block, participants were given a break and continued on to the next block at their own pace. %%

%% After completing all experimental blocks, subjects were thanked for participating and directed to the strategy execution section of the experiment. %%

4.8.3 Choice Problems (adapted from Bruine de Bruin et al., 2007)

%% Instructions were presented as follows. %%

Please read the practice problems on this page carefully before going on to the problems on the next page.

Imagine Chris is going to buy a DVD player with the $369 he received for his birthday. He wants to find out how the DVD players that are available for that price compare to each other. A magazine rated various options on the most important features to consider when purchasing a DVD player as follows, where higher is better:

Very Low	Low	Medium	High	Very High
1	2	3	4	5

For example, three DVD players and their ratings on three features are listed in the table below:

		Features		
		Picture Quality	Sound Quality	Programming Options
DVD	A	3	2	5
	B	2	3	3
	C	4	1	4

The following examples use the table above. Please read each carefully and make sure that you are able to clearly understand how the solution provided was obtained by using the table.

Example 1. Chris selects the DVD player with the highest rating in programming options. Which one of the presented DVD players will Chris choose? **Solution: A**

Example 2. Chris only wants a DVD player with picture quality that is rated higher than "Medium". Which of the presented DVD players will Chris choose? **Solution: C**

%% New Page %%

The next set of four practice questions will also use the same table from the examples. This will give you a chance to familiarise yourself with the final task that you will complete. Please read each carefully and try to pay close attention as **the accuracy of your choices will determine your progression to the next section**.

%% The next set of 4 practice questions were presented on separate pages with the table above reproduced on each page. The order of the questions was the same for all participants. %%

%% If participants responded incorrectly to any 1 question, they were alerted that another incorrect response would disqualify them from the study. The following message was presented. %%

Your response was ____, unfortunately this is incorrect, the correct response ____. Please refer to the table and make sure that you understand how this solution was obtained. Please pay close attention, another incorrect response on the remaining practice questions will result in disqualification from the study.

%% Participants that responded incorrectly to more than 1 of 4 questions were automatically directed to the end of the experiment but were still paid for their participation. Correct responses for the practice questions are in bold, not shown to participants. %%

%% DEBA (Non-Compensatory) %%

Chris wants a DVD player with a rating *higher* than "Medium" on picture quality. If there is still more than one option to choose from, he chooses the DVD player with the highest rating on sound quality. Which of the presented DVD players will Chris choose? %% Correct response: **C** %%

%% SAT (Non-Compensatory) %%

Chris doesn't want to spend much time deciding which DVD player to choose. He decides to read the table starting from the top and chooses the first option that has no feature rated *below* "Low". Which of the presented DVD players will Chris choose? %% Correct response: **A** %%

%% FRQ (Compensatory) %%

Chris wants a DVD player with the highest number of ratings *above* "Medium". Which of the presented DVD players will Chris choose? %% Correct response: **C** %%

%% EQW (Compensatory) %%

Chris wants a DVD player with the highest average rating across all features. Which of the presented DVD players will Chris choose? %% Correct response: **A** %%

%% End of instructions and practice questions %%

The questions that will follow are about other people choosing between DVD players, like the ones you just practised. You will need to answer 16 such questions before reaching the end of the survey.

Please read each question carefully, because they ask for different answers. For each question, think about how each person makes their choice, then pick the DVD player they choose. But be careful, because the DVD players and their features will change from question to question.

%% In what follows we provide samples for the each of the strategies in the compensatory and non-compensatory condition presented within a 5x5 matrix. %%

%% In the actual experiment, participants chose from 3x5, 3x9, 5x5 and 5x9 tables and the order in which questions were presented was randomized. The attributes in the 5 attribute condition are as in the tables below, and in the 9 attribute condition also included 'User-Ratings on Amazon', 'Packaging Quality', 'Delivery Speed' and 'Warranty & Service'. These were derived from actual listings for DVD players on Amazon.co.uk. Alternatives were simply labelled A through E. %%

%% No solution obtained by applying a particular selection strategy was dominated on all attributes by any of the other alternatives and vice-versa. %%

%% Correct response is highlighted in bold-face within the table, not shown to participants. %%

%% DEBA (Non-Compensatory) %%

		Features				
		Picture Quality	Sound Quality	Programming Options	Reliability of Brand	Ease of Use
DVD	A	5	4	5	1	5
	B	**5**	**5**	**3**	**3**	**5**
	C	4	5	2	5	2
	D	4	5	3	3	2
	E	5	3	3	3	5

Jimmy first selects the DVD players with the best Ease of Use. From the selected DVD players, he then selects the best on Picture Quality. Then, if there is still more than one left to choose from, he selects the one best on Sound Quality. Which **one** of the presented DVD players will Jimmy choose?

%% SAT (Non-Compensatory) %%

Features

		Picture Quality	Sound Quality	Programming Options	Reliability of Brand	Ease of Use
DVD	A	5	4	2	1	5
	B	5	5	3	3	2
	C	4	5	2	5	2
	D	**4**	**5**	**3**	**3**	**4**
	E	5	3	3	3	5

Gary doesn't want to read the entire table. He decides to read the table row by row starting from the top and select the first DVD player that has no ratings *below* "Medium". Which **one** of the presented DVD players will Gary choose?

%% FRQ (Compensatory)%%

Features

		Picture Quality	Sound Quality	Programming Options	Reliability of Brand	Ease of Use
DVD	A	5	4	2	1	1
	B	5	5	3	3	3
	C	**4**	**5**	**2**	**5**	**2**
	D	4	5	3	3	2
	E	5	3	3	3	5

James selects a DVD player with the highest number of ratings *greater* than "Medium" Which **one** of the presented DVD players will James choose?

%% EQW (Compensatory) %%

		Features				
		Picture Quality	Sound Quality	Programming Options	Reliability of Brand	Ease of Use
DVD	A	5	4	2	1	1
	B	5	5	1	3	3
	C	**4**	**5**	**2**	**5**	**3**
	D	4	5	3	3	2
	E	5	3	3	4	3

Julia wants a DVD player with the highest average rating across all features. Which **one** of the presented DVD players will Julia choose?

5

Conclusions

> *"Human rational behavior is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor."*
>
> – Herbert A. Simon, *Invariants of Human Behaviour*

5.1 Summary of Empirical Findings

The essays comprising this thesis aimed to investigate the role of limited attention in environments characterized by an abundance of information. In the first essay, we addressed the discrepancy between the expectation that the lower material costs associated with online search have not led to a corresponding increase in the extent of search that consumers engage in. Our findings highlighted that this parsimony in consumer search behaviour can be understood through the lens of a fundamental attention allocation problem. Specifically, we demonstrated that across a range of different industry contexts, consumers face a trade-off between the number of alternatives that they actively consider and the time they can spend searching for information on each alternative. Moreover, we showed that this trade-off was sensitive to differing levels of competition for attention in online markets – indicative of the fact that brand salience plays an important role in moderating the intensity of online search.

In the second essay, we evaluated whether individual dispositions towards extending search through an expansion of alternatives affected decision makers' ability to adapt to changing task environments and exercise deliberate analytical judgement.

We uncovered evidence that a tendency to maximise is marginally negatively associated with an analytical information processing style, unrelated to an intuitive style and positively associated with deviations from normatively expected choice behaviour. Moreover, our results highlighted that even in instances where task environments support an alternative course of action and where a biased option is dominated by an objectively superior alternative, maximisers' overreliance on the comparison of easily accessible attributes, arbitrary variety seeking and representativeness predispose them to rudimentary cognitive biases that their satisficing counterparts are better able to resist.

Finally, in the third essay, we investigated the role of selective attentional control, decision style and information load on individuals' ability to execute simplifying decision strategies. Our results highlighted that in cases where decision makers are supported with aids to simplify strategy execution, a compensatory decision style is associated with generally better choices. On the other hand, we uncovered evidence that the facility with which individuals are able to execute non-compensatory decision strategies is extremely sensitive to the structure of task environments as well as individual abilities to exercise inhibitory control.

5.2 Summary of Theoretical Contributions

In most decision making contexts, individuals need to evaluate the information processing demands associated with a particular task at hand and deploy their faculties in resolving the inherent conflict between the amount of information they consider and the effort they can expend on evaluating it (Beach & Mitchell, 1978; Payne, Bettman, & Johnson, 1993). Simon's (1972) notion of bounded-rationality reinforces this idea and suggests that in many circumstances, the integration of all available information within a problem space can become psychologically intractable. In such cases, decision makers must adopt simplifying procedures that allow them to effectively allocate their attention towards relevant parameters within a decision context and their ability to do so – rather than indicating a deviation from rationality – should appropriately be evaluated as an indicator of pragmatic decision making (Gigerenzer, Todd, & ABC Research Group, 1999). Our findings in essence concur with this sentiment. Across the three essays in this thesis, we evaluated the interaction between limited attention and information abundance. Our findings provide fruitful theoretical insights into aspects relating to aggregate consumer behaviour, individual dispositions towards decision making and selective information processing. We elaborate on these aspects in the following sections.

5.2.1 Aggregate Level Behaviour

In Chapter 2, we attempted to explain recent discrepancies between expected and observed search behaviour (Holland, Jacobs, & Klein, 2016; Johnson, Moe, Fader, Bellman, & Lohse, 2000; Zhang, Fang, & Liu Sheng, 2006) and highlighted that individuals are fundamentally constrained in their ability to attend to a limited amount of information while searching online. These findings support previous research suggesting that consumers might use the consideration set as a simplifying heuristic (Hauser, 2014) and search from a pre-determined set of alternatives rather than rely on discovery through direct search (Mitra, 1995). Despite the low material costs of information acquisition, the wealth of information available in online contexts means that decision makers must restrict the extent of search that they undertake in response to the abundance and ease-of-accessibility of online information.

We conceptualize this result as suggestive of the fact that at least at the aggregate level, consumers demonstrate a degree of sophistication in their approach to online search processes. While the traditional information economics based account holds that the lower material costs of searching for information online should result in an expansion of consideration sets (Ratchford, Lee, & Talukdar, 2003), our results highlight the simple accessibility of alternatives in online contexts does not mean that consumers will seek this information out. A clear indication of this fact can be derived from our finding that consumers tend to prefer searching longer for fewer alternatives rather than spread their search over a larger number of alternatives, a basic finding that appeared to be robust across seven market contexts. Moreover, we uncover that the intensity of online search is highly sensitive to the competitive structure of online markets. This latter point underlines that where information on dominant alternatives is highly salient – for instance where a small number of brands control a much larger proportion of the market – consumers respond by reducing the amount of time they spend on direct search. On the other hand in contexts characterized by uncertainty – where a moderate number of equally salient competitors exist – consumers demonstrate a higher degree of sensitivity to the addition of alternatives within their consideration set. This aspect could be indicative of an increasing need to satisfice in order to avoid conflict (Iyengar & Lepper, 2000).

5.2.2 Individual Orientations

Chapters 3 and 4 provide some additional insights on the role of enduring individual dispositions or "basic tendencies", on decision making ability and contribute to the psychometric and trait-based streams of behavioural decision theory (Schwartz et al., 2002; Weber & Milliman, 1997; Zakay, 1990).

In Chapter 4, we considered the role of a subjective decision style favouring compensatory decision making, on strategy execution in aided multiple criteria decision making contexts. We drew on suggestions from Shiloh, Koren, & Zakay, (2001) and Zakay (1990) that a correspondence between a particular decision style and decision strategy would manifest in performance gains where such factors were compatible. On the contrary, our results highlighted that a compensatory decision style is associated with generally improved task performance and does not provide much discriminatory information about strategy execution. This finding echoes previous work that has considered broad personality correlates of strategy execution (Bröder, 2012) as well as investigations of individual differences in aided decision making (O'Keefe, 2016). An important implication of this finding is that an individual disposition towards more compensatory decision making might suggest a greater flexibility with which individuals can adapt to the requirements of changing task environments.

In Chapter 3, we attempted to contend with recently reported findings that maximisers perform poorly on measures of general decision maker competency (Parker, De Bruin, & Fischhoff, 2007). While much of the psychological literature has emphasized the role of negative affect (Roets, Schwartz, & Guan, 2012; Schwartz et al., 2002) and the underlying measurement of the maximising construct (Highhouse, Diab, & Gillespie, 2008), our investigation attempted to address this issue at a conceptual level. Our results reinforce Simon's (1955) original articulation of the psychological intractability of maximising by highlighting that behavioural maximisers are more susceptible to departures from normatively expected outcomes in task environments that exploit their reliance on easily comparable criteria, arbitrary variety seeking and representativeness. Gigerenzer et al. (1999) suggest that simple heuristics can be useful in circumstances where the task at hand supports their use however, our results highlight that maximisers prioritise such heuristics *even* in circumstances where they are objectively inferior to alternative strategies. Thus, we find support for Parker et al.'s (2007) contention that a maximising tendency may be maladaptive and demonstrate that a tendency to behaviourally maximise is systematically related to an overreliance on a small set of choice heuristics that might predispose maximisers to fairly rudimentary cognitive biases that their satisficing counterparts are better able to resist.

5.2.3 Selective Information Processing

Our analysis from Chapter 4 built upon the emerging area of behavioural operational research (Franco & Hamalainen, 2015; Keller & Katsikopoulos, 2016; Morton & Fasolo, 2009) and investigated the circumstances that might facilitate the ease with which individuals can execute prescribed simplifying decision strategies, in contexts where conflicting objectives need to be counterbalanced. We drew on the behavioural decision making (Slovic, Griffin, & Tversky, 1990) and decision support literatures (Keller & Katsikopoulos, 2016) and proposed conditions where compatibility between individual and task characteristics could facilitate the correspondence choices with a recommended course of action. Importantly, our findings highlighted that non-compensatory decision strategies may find particularly robust applications in environments characterized by an abundance of attribute information. This finding provides experimental support to simulation studies conducted by Fasolo, McClelland & Todd (2007) and suggests that in circumstances where decision makers heavily prioritise some attributes over others, strategies based on non-compensatory principles can prove to be valuable decision aids.

A notable contrasting finding from our analysis is that while in Chapter 2, we uncovered that consumers restrict the amount of information they seek out while searching for information online, in Chapter 4, we demonstrated that when information is made available within a problem context, the costs of ignoring it are non-negligible.

Our results in Chapter 4 highlighted that in order to inhibit non-instrumental information, individuals need to exercise attentional control. This finding seemingly argues against the position that non-compensatory strategies are (near) cost-less to execute (Payne et al., 1993). Instead, our findings converge with recent evidence reported in the neuropsychological literature investigating strategy execution (Del Missier, Mäntylä, & Bruine de Bruin, 2010; Del Missier, Mäntylä, & De Bruin, 2012) and suggest that suppressing available information may be an inherently effortful activity – at least in cases where individuals are prescribed a recommended course of action. Moreover, we extend the findings from Del Missier et al. (2010, 2012) and identify the boundary conditions for the role of inhibitory attentional control on strategy execution, highlighting that individuals' capacity to regulate inhibition is more instrumental for selective rather than integrative modes of information processing. This result also speaks to the emerging economic literatures on rational-inattention (Caplin & Dean, 2015; Sims, 2003) and information avoidance (Golman, Hagmann, & Loewenstein, 2017) – both attempting to account for the endogenous costs of ignorance in analytical models of individual decision making. On a tangential and semantic note, our findings suggest that 'ignorance' might not capture this cost as well as does inhibition.

5.3 Directions for Further Research and Extensions

We have outlined a number of important qualifiers to our empirical work in the preceding essays. In this section, we present some general limitations and propose avenues for further inquiry. Broadly, our main caveat, as is fairly common in experimental work, relates to the issue of external validity (Bracht & Glass, 1968; Calder, Phillips, & Tybout, 1982). On this, we fundamentally agree with Payne et al.'s (1993) suggestion that in evaluating decision behaviour, we must attempt to map our observations to the real world decision contexts within which they apply. This is an important goal for future extensions of this work. At the same time, before we can map theoretical constructs on ecological phenomena, we must first identify the instrumental features and variables of importance. Our analysis suggests that the interplay between individual dispositions, cognitive abilities and task contexts is central to informing our understanding about the implications of limited attention on decision making outcomes.

Yet, there is much work still to be done.

Our findings from Chapter 2 would benefit from generalization to other markets outside of the US. Moreover, an important question for the future might be to evaluate the interactions between direct search and the use of comparison websites or meta-search engines (Holland, Jacobs, & Klein, 2016). In Chapter 3, we highlighted that maximisers are susceptible to an overreliance on easily comparable criteria, arbitrary variety seeking and representativeness, which can have negative consequences on the quality of their judgements. Two supplementary lines of inquiry can be forwarded from these findings (Gigerenzer & Goldstein, 1996; Montibeller & Von Winterfeldt, 2015). 1) Are there circumstances where the use of such naïve heuristics might be ecologically beneficial for maximisers? 2) What techniques could be used in order to remove these errors and support maximisers in approaching decisions is a more adaptive manner? In Chapter 4, we highlighted that selective information processing requires attentional control and is therefore, not a cost-less activity. Our analysis was limited in its scope and only considered this aspect in the context of strategy execution. A future line of inquiry might investigate the role of higher order executive functions on issues relating to both prescriptive strategy execution as well as adaptive strategy selection. Understanding the mechanisms that can facilitate decision makers' ability to cope with large amounts of information in their environment is an important goal in decision making research (Simon, 1971), one that is only reinforced by the fact that while information continues to grow at unprecedented rates, our faculty to attend to it is fundamentally limited.

Bibliography

[1] Ackoff, R. L. (1979). The future of operational research is past. *Journal of the Operational Research Society, 30*(2), 93–104.

[2] Agresti, A. (2003). *Categorical data analysis* (Vol. 482). John Wiley and Sons.

[3] Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces. *Journal of Marketing, 61*(3), 38–53.

[4] Alba, J. W., & Marmorstein, H. (1987). The effects of frequency knowledge on consumer decision making. *Journal of Consumer Research, 14*(1), 14–25.

[5] Allenby, G. M., & Rossi, P. E. (1998). Marketing models of consumer heterogeneity. *Journal of Econometrics, 89*(1), 57–78.

[6] Allom, V., Mullan, B., & Hagger, M. (2016). Does inhibitory control training improve health behaviour? A meta-analysis. *Health Psychology Review, 10*(2), 168–186.

[7] Anand, A., Chakraborty, T., & Park, N. (2017). We Used Neural Networks to Detect Clickbaits: You Won't Believe What Happened Next!. In: Jose J. et al. (eds) *Advances in Information Retrieval. ECIR, Lecture Notes in Computer Science, 10193*: 541-47.

[8] Argenton, C., & Prüfer, J. (2012). Search engine competition with network externalities. *Journal of Competition Law and Economics, 8*: 73-105.

[9] Ariely, D. (2008). *Predictably irrational.* New York: Harper Collins.

[10] Ayal, S., Hochman, G., & Zakay, D. (2011). Two sides of the same coin: Information processing style and reverse biases. *Judgment and Decision Making, 6*(4), 295–306.

[11] Ayal, S., Rusou, Z., Zakay, D., & Hochman, G. (2015). Determinants of judgment and decision making quality: the interplay between information processing style and situational factors. *Frontiers in Psychology, 6*, 1088.

[12] Ayal, S., & Zakay, D. (2009). The perceived diversity heuristic: the case of pseudodiversity. *Journal of Personality and Social Psychology, 96*(3), 559–573.

[13] Baltussen, G. , & Post, G. T. (2011). Irrational diversification: An examination of individual portfolio choice. *Journal of Financial and Quantitative Analysis, 46*(5), 1463–1491.

[14] Baucells, A. M., & Carrasco, L. J. A. (2006). Cumulative Dominance and Heuristic Performance in Binary Multiattribute Choice. *Operations Research, 56*(5), 1289–1304.

[15] Baye, M.R., Gatti, J.R.J., Kattuman, P., & Morgan, J. (2009). Clicks, discontinuities, and firm demand online. *Journal of Economics Management Strategy, 18*:935–75.

[16] Baayen, R.H., Davidson, D.J. & Bates, D.M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language, 59*: 390-412.

[17] Beach, L. R., & Mitchell, T. R. (1978). A contingency model for the selection of decision strategies. *Academy of Management Review, 3*(3), 439–449.

[18] Beatty, S. E., & Smith, S. M. (1987). External Search Effort: An Investigation Across Several Product Categories. *Journal of Consumer Research, 14*(1), 83–95.

[19] Bechara, A., Damasio, H., Tranel, D. , & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science, 275*(5304), 1293–1295.

[20] Benartzi, S. , & Thaler, R. (2007). Heuristics and biases in retirement savings behavior. *Journal of Economic Perspectives, 21*(3), 81–104.

[21] Benartzi, S. , & Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. *American Economic Review, 91*(1), 79–98.

[22] Besharat, A., Ladik, D. M. , & Carrillat, F. A. (2014). Are maximizers blind to the future? When today's best does not make for a better tomorrow. *Marketing Letters, 25*(1), 77–91.

[23] Bettman, J. R., Johnson, E. J., Luce, M. F., & Payne, J. W. (1993). Correlation, conflict, and choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19*(4), 931–951.

[24] Bettman, J. R., Johnson, E. J., & Payne, J. W. (1990). A componential analysis of cognitive effort in choice. *Organizational Behavior and Human Decision Processes, 45*(1), 111–139.

[25] Bonner, C. , & Newell, B. R. (2008). How to make a risk seem riskier: The ratio bias versus construal level theory. *Judgment and Decision Making, 3*(5), 411–416.

[26] Borges, B., Goldstein, D. G., Ortmann, A., & Gigerenzer, G. (1999). Can ignorance beat the stock market. In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 59–72). New York: Oxford University Press.

[27] Borges, J.L. (1962) The library of Babel. In *Ficciones*, pp. 92-104, New York: Grove Press.

[28] Bracht, G. H., & Glass, G. V. (1968). The external validity of experiments. *American Educational Research Journal, 5*(4), 437–474.

[29] Bridges, E. & Florsheim, R. (2008). Hedonic and utilitarian shopping goals: The online experience. *Journal of Business Research, 61*: 309-14.

[30] Brighton, H. (2006). Robust Inference with Simple Cognitive Models. *AAAI Spring Symposium: Between a Rock and a Hard Place: Cognitive Science Principles Meet AI-Hard Problems*, 17–22.

[31] Bröder, A. (2000). Assessing the empirical validity of the "Take-the-best" heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26*(5), 1332.

[32] Bröder, A. (2003). Decision making with the "adaptive toolbox": influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29*(4), 611.

[33] Bröder, A. (2012). The Quest for Take-the-Best: Insights and Outlooks From Experimental Research. In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Ecological Rationality: Intelligence in the World* (pp. 216–240). New York: Oxford University Press.

[34] Bröder, A., & Newell, B. (2008). Challenging some common beliefs: Empirical work within the adaptive toolbox metaphor. *Judgment and Decision Making, 3*(3), 205.

[35] Bröder, A., & Schiffer, S. (2006). Stimulus format and working memory in fast and frugal strategy selection. *Journal of Behavioral Decision Making, 19*(4), 361–380.

[36] Bromiley, P. , & Curley, S. P. (1992). Individual differences in risk taking. *In J.F. Yates (Ed.), Wiley series in human performance and cognition. Risk taking behavior.* (pp. 87–132). Oxford, England: John Wiley and Sons.

[37] Bruine de Bruin, W., Parker, A. M. , & Fischhoff, B. (2007). Individual differences in adult decision-making competence. *Journal of Personality and Social Psychology, 92*(5), 938–956.

[38] Bucklin, R.E. & Sismeiro, C. (2009). Click here for Internet insight: advances in clickstream data analysis in marketing. *Journal of Interactive Marketing, 23*:35–48.

[39] Buhrmester, M., Kwang, T. , & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6*(1), 3–5.

[40] Calder, B. J., Phillips, L. W., & Tybout, A. M. (1982). The concept of external validity. *Journal of Consumer Research, 9*(3), 240–244.

[41] Callegaro, M., Villar, A., Krosnick, J. & Yeager, D. (2014). A Critical Review of Studies Investigating the Quality of Data Obtained With Online Panels. In: M. Callegaro, R. Baker, J. Bethlehem, A. Goritz, J. Krosnick & P. Lavrakas (Eds.), *Online Panel Research: A Data Quality Perspective*. UK: John Wiley & Sons.

[42] Caplin, A. , & Dean, M. (2015). Revealed preference, rational inattention, and costly information acquisition. *American Economic Review, 105*(7), 2183–2203.

[43] Carter, T. J. , & Gilovich, T. (2010). The relative relativity of material and experiential purchases. *Journal of Personality and Social Psychology, 98*(1), 146–159.

[44] Carvalho, L. S., Meier, S., & Wang, S. W. (2016). Poverty and economic decision-making: Evidence from changes in financial resources at payday. *American Economic Review, 106*(2), 260–84.

[45] Chapman, C. & Feit, E.M. (2015). *R for Marketing Research and Analytics*. Springer, New York.

[46] Chen, J.V., Lin, C., Yen, D.C. & Linn, K.P. (2011). The interaction effects of familiarity, breadth and media usage on web browsing experience. *Computers in Human Behavior, 27*: 2141-52.

[47] Cook, R. D. (1977). Detection of influential observation in linear regression. *Technometrics, 19*(1), 15–18.

[48] Currim, I.S., Mintz, O. & Siddarth, S. (2015). Information Accessed or Information Available? The Impact on Consumer Preferences Inferred at a Durable Product E-commerce Website. *Journal of Interactive Marketing, 29*: 11-25.

[49] D'Souza, G., & Rao, R.C. (1995). Can repeating an advertisement more frequently than the competition affect brand preference in a mature market? *Journal of Marketing, 59*: 32-42.

[50] Dar-Nimrod, I., Rawn, C. D., Lehman, D. R. , & Schwartz, B. (2009). The maximization paradox: The costs of seeking alternatives. *Personality and Individual Differences, 46*(5–6), 631–635.

[51] Davenport, T. H., & Beck, J. C. (2001). *The attention economy: Understanding the new currency of business*, Boston: Harvard Business School Press.

[52] Dawes, J., Mundt, K. & Sharp B. (2009). Consideration sets for financial services brands. *Journal of Financial Services Marketing 14*:190–202.

[53] Del Missier, F., Mäntylä, T., & Bruine de Bruin, W. (2010). Executive functions in decision making: An individual differences approach. *Thinking & Reasoning, 16*(2), 69–97.

[54] Del Missier, F., Mäntylä, T., & De Bruin, W. B. (2012). Decision-making competence, executive functioning, and general cognitive abilities. *Journal of Behavioral Decision Making, 25*(4), 331–351.

[55] DeMiguel, V., Garlappi, L. , & Uppal, R. (2007). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *The Review of Financial Studies, 22*(5), 1915–1953.

[56] Denes-Raj, V. , & Epstein, S. (1994). Conflict between intuitive and rational processing: When people behave against their better judgment. *Journal of Personality and Social Psychology, 66*(5), 819–829.

[57] Denes-Raj, V., Epstein, S. , & Cole, J. (1995). The generality of the ratio-bias phenomenon. *Personality and Social Psychology Bulletin, 21*(10), 1083–1092.

[58] Desai, S. D. , & Kouchaki, M. (2017). Moral symbols: A necklace of garlic against unethical requests. *Academy of Management Journal, 60*(1), 7–28.

[59] Diab, D. L., Gillespie, M. A. , & Highhouse, S. (2008). Are maximizers really unhappy? The measurement of maximizing tendency. *Judgment and Decision Making, 3*(5), 364–370.

[60] Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*, 135–168.

[61] Dommermuth, W.P. & Cundiff, E.W. (1967). Shopping goods, shopping centers and selling strategies. *Journal of Marketing, 31*: 32–6.

[62] Dodson, I. (2016). *The art of digital marketing : the definitive guide to creating strategic, targeted and measurable online campaigns*. Wiley, New York.

[63] Deloitte (2016). The growing power of consumers. *Deloitte Consumer Report*, Deloitte Touche Tohmatsu USA LLP.

[64] Dreze, X. & Zufryden, F. (2004). Measurement of online visibility and its impact on internet traffic. *Journal of interactive marketing, 18*:20–37.

[65] Driver, M. J. , & Streufert, S. (1969). Integrative complexity: An approach to individuals and groups as information-processing systems. *Administrative Science Quarterly*, 272–285.

[66] Einhorn, H. J., & Hogarth, R. M. (1975). Unit weighting schemes for decision making. *Organizational Behavior and Human Performance, 13*(2), 171–192.

[67] Eliaz, K., Offerman, T. , & Schotter, A. (2008). Creating competition out of thin air: An experimental study of right-to-choose auctions. *Games and Economic Behavior, 62*(2), 383–416.

[68] Ellison, G. & Ellison, S. F. (2009). Search, obfuscation and price elasticities on the internet. *Econometrica, 77*:427–452.

[69] Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *American Psychologist, 49*(8), 709–724.

[70] Epstein, S., Pacini, R., Denes-Raj, V., & Heier, H. (1996). Individual differences in intuitive–experiential and analytical–rational thinking styles. *Journal of Personality and Social Psychology, 71*(2), 390.

[71] Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception & Psychophysics, 16*(1), 143–149.

[72] Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion, 7*(2), 336–353.

[73] Fader, P.S. & McAlister, L. (1990). An elimination by aspects model of consumer response to promotion calibrated on upscscanner data. *Journal of Marketing Research, 27*:322–32.

[74] Falkinger, J. (2007). Attention economies. *Journal of Economic Theory, 133*: 266-94.

[75] Fasolo, B., McClelland, G. H., & Todd, P. M. (2007). Escaping the tyranny of choice: When fewer attributes make choice easier. *Marketing Theory, 7*(1), 13–26.

[76] Fishburn, P. C. (1974). Lexicographic Orders, Utilities and Decision Rules: A Survey. *Management Science, 20*(11), 1442–1471.

[77] Fisk, D. W. , & Maddi, S. R. (1961). *Functions of varied experience.* Homewood. IL: Dorsey.

[78] Flood, A. (2014, October 22). UK publishes more books per capita than any other country, report shows. *The Guardian.* Retrieved from https://www.theguardian.com/books/2014/oct/22/uk-publishes-more-books-per-capita-million-report

[79] Franco, L. A., & Hamalainen, R. P. (2015). Behavioural operational research: Returning to the roots of the OR profession. *European Journal of Operational Research, 249*(3), 791–795.

[80] Franco, L. A., & Montibeller, G. (2010). Facilitated modelling in operational research. *European Journal of Operational Research, 205*(3), 489–500.

[81] French, K. R. , & Poterba, J. M. (1991). Were Japanese stock prices too high? *Journal of Financial Economics, 29*(2), 337–363.

[82] French, S., Maule, J., & Papamichail, N. (2009). *Decision behaviour, analysis and support.* Cambridge University Press.

[83] Gabaix, X., Laibson, D., Moloche, G. , & Weinberg, S. (2006). Costly information acquisition: Experimental analysis of a boundedly rational model. *American Economic Review, 96*(4), 1043–1068.

[84] Galak, J., Kruger, J. , & Loewenstein, G. (2011). Is variety the spice of life? It all depends on the rate of consumption. *Judgment and Decision Making, 6*(3), 230–238.

[85] Gandal, N. (2001). The dynamics of competition in the internet search engine market. *International Journal of Industrial Organization. 19*: 1103-17.

[86] Gelman, A. & Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press.

[87] Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: models of bounded rationality. *Psychological Review, 103*(4), 650.

[88] Gigerenzer, G., Hoffrage, U., & Kleinbölting, H. (1991). Probabilistic mental models: a Brunswikian theory of confidence. *Psychological Review, 98*(4), 506.

[89] Gigerenzer, G., & Selten, R. (2001). Rethinking rationality. In G. Gigerenzer & R. Selten (Eds.), *Bounded rationality: The adaptive toolbox* (pp. 1–12).

[90] Gigerenzer, G., & Todd, P. M. (1999). Fast and frugal heuristics: The adaptive toolbox. In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 3–34). New York: Oxford University Press.

[91] Gigerenzer, G., Todd, P. M., & ABC Research Group. (1999). *Simple heuristics that make us smart.* New York: Oxford University Press.

[92] Gilovich, T., Vallone, R. , & Tversky, A. (1985). The hot hand in basketball: On the misperception of random sequences. *Cognitive Psychology, 17*(3), 295–314.

[93] Glöckner, A., & Herbold, A.K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making, 24*(1), 71–98.

[94] Godfrey, D., & Parkhill, D. (1979). *Guttenberg two.* Toronto: Press Porcepic.

[95] Goldhaber, M. (1997). The attention economy and the Net. *First Monday, 2*(4).

[96] Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: the recognition heuristic. *Psychological Review, 109*(1), 75.

[97] Golman, R., Hagmann, D. , & Loewenstein, G. (2017). Information avoidance. *Journal of Economic Literature, 55*(1), 96–135.

[98] Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E. , & Tatham, R. L. (2006). *Multivariate data analysis* 6th ed. Uppersaddle River: Pearson Prentice Hall.

[99] Hämäläinen, R. P., Luoma, J. , & Saarinen, E. (2013). On the importance of behavioral operational research: The case of understanding and communicating about dynamic systems. *European Journal of Operational Research, 228*(3), 623–634.

[100] Hauser, J. R. (2014). Consideration-set heuristics. *Journal of Business Research, 67*(8), 1688–1699.

[101] Hauser, J. R., & Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research, 16*(4), 393–408.

[102] Hedesström, T. M., Svedsäter, H. , & Gärling, T. (2009). Naïve diversification in the Swedish premium pension scheme: Experimental evidence. *Applied Psychology, 58*(3), 403–417.

[103] Hefti, A. (2011). Attention Competition. University of Zurich. *Working Paper.*

[104] Hefti, A. & Heinke, S. (2015). On the economics of superabundant information and scarce attention. *Economia, 5*:37-76.

[105] Hey, J. D. (1987). Still searching. *Journal of Economic Behavior and Organization, 8*: 137–44.

[106] Highhouse, S. E., Diab, D. L., & Gillespie, M. A. (2008). Are maximizers really unhappy? The measurement of maximizing tendency. *Judgment and Decision Making Journal, 3*(5), 364.

[107] Hilbig, B. E. (2010). Reconsidering "evidence" for fast-and-frugal heuristics. *Psychonomic Bulletin & Review, 17*(6), 923–930.

[108] Hogarth, R. M., & Karelaia, N. (2005). Simple models for multiattribute choice with many alternatives: When it does and does not pay to face trade-offs with binary attributes. *Management Science, 51*(12), 1860–1872.

[109] Hogarth, R. M., & Karelaia, N. (2006). "Take-the-best" and other simple strategies: Why and when they work "well" with binary cues. *Theory and Decision, 61*(3), 205–249.

[110] Holland, C. P., Jacobs, J. A., & Klein, S. (2016). The role and impact of comparison websites on the consumer search process in the US and German airline markets. *Information Technology & Tourism, 16*(1), 127–148.

[111] Howard, J.A. (1963). *Marketing management: analysis and planning.* Richard D. Irwin, Homewood.

[112] Howard, J.A. (1977). *Consumer Behavior: Application of Theory.* McGraw-Hill, New York.

[113] Howard, J.A. & Sheth, J.N. (1969). *The theory of buyer behavior.* Wiley, New York.

[114] Huang, P., Lurie, N.H. & Mitra, S. (2009). Searching for Experience on the Web: An Empirical Examination of Consumer Behavior for Search and Experience Goods. *Journal of Marketing, 73*:55-69.

[115] Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology, 79*(6), 995.

[116] Iyengar, S. S., Wells, R. E., & Schwartz, B. (2006). Doing better but feeling worse: Looking for the "best" job undermines satisfaction.

[117] Jacoby, J. (1984). Perspectives on information overload. *Journal of Consumer Research, 10*(4), 432–435.

[118] Jacoby, J., Speller, D. E. , & Berning, C. K. (1974). Brand choice behavior as a function of information load: Replication and extension. *Journal of Consumer Research, 1*(1), 33–42.

[119] Jacoby, J., Speller, D. E. , & Kohn, C. A. (1974). Brand choice behavior as a function of information load. *Journal of Marketing Research*, 63–69.

[120] Jain, K., Bearden, J. N. , & Filipowicz, A. (2013). Do maximizers predict better than satisficers? *Journal of Behavioral Decision Making, 26*(1), 41–50.

[121] James, W. (1950). *Principles of psychology*, London: Dover.

[122] Jepsen, A.L. (2007). Factors affecting consumer use of the internet for information search. *Journal of Interactive Marketing, 21*:21–34.

[123] Johnson, E.J., Moe, W.W., Fader, P.S., Bellman, S. & Lohse, J. (2004). On the depth and dynamics of World Wide Web shopping behavior. *Management Science, 50*(3), 299–308.

[124] Juslin, P., & Persson, M. (2002). PROBabilities from EXemplars (PROBEX): A "lazy" algorithm for probabilistic inference from generic knowledge. *Cognitive Science, 26*(5), 563–607.

[125] Kahneman, D. (1973). *Attention and effort.* Prentice-Hall Englewood Cliffs, NJ.

[126] Kahneman, D. (2003). A perspective on judgment and choice: mapping bounded rationality. *American Psychologist, 58*(9), 697–720.

[127] Kahneman, D. , & Egan, P. (2011). *Thinking, fast and slow* (Vol. 1). Farrar, Straus and Giroux New York.

[128] Kahneman, D. , & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *In T. Gilovich, D. Griffin, D. Kahneman (Eds.) Heuristics and biases: The psychology of intuitive judgment* (pp. 49–81).

[129] Kahneman, D. , & Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology, 3*(3), 430–454.

[130] Kapstein, M. & Eckles, D. (2012). Heterogeneity in the Effects of Online Persuasion. *Journal of Interactive Marketing, 26*: 176-88.

[131] Karelaia, N. (2006). Thirst for confirmation in multi-attribute choice: Does search for consistency impair decision performance? *Organizational Behavior and Human Decision Processes, 100*(1), 128–143.

[132] Karimi, S., Papamichail, K. N., & Holland, C. P. (2015). The effect of prior knowledge and decision-making style on the online purchase decision-making process: A typology of consumer shopping behaviour. *Decision Support Systems, 77*:137-47.

[133] Katsikopoulos, K. V. (2016). Behavior with models: The role of psychological heuristics in operational research. In M. Kunc, J. Malpass, & L. White (Eds.), *Behavioral Operational Research* (pp. 27–45). London: Palgrave Macmillan.

[134] Katsikopoulos, K. V., Durbach, I. N., & Stewart, T. J. (2018). When should we use simple decision models? A synthesis of various research strands. *Omega, 81*, 17–25.

[135] Katsikopoulos, K. V., & Gigerenzer, G. (2008). One-reason decision-making: Modeling violations of expected utility theory. *Journal of Risk and Uncertainty, 37*(1), 35.

[136] Katsikopoulos, K. V., & Martignon, L. (2006). Naive heuristics for paired comparisons: Some results on their relative accuracy. *Journal of Mathematical Psychology, 50*(5), 488–494.

[137] Keene, O.N. (1995). The log transformation is special. *Statistics in Medicine, 14*: 811-19.

[138] Keeney, R. L., & Raiffa, H. (1993). *Decisions with multiple objectives: preferences and value trade-offs*. Cambridge university press.

[139] Keller, K. L. , & Staelin, R. (1987). Effects of quality and quantity of information on decision effectiveness. *Journal of Consumer Research, 14*(2), 200–213.

[140] Keller, N. , & Katsikopoulos, K. V. (2016). On the role of psychological heuristics in operational research; and a demonstration in military stability operations. *European Journal of Operational Research, 249*(3), 1063–1073.

[141] Khan, U. & Dhar, R. (2010). Price-Framing Effects on the Purchase of Hedonic and Utilitarian Bundles. *Journal of Marketing Research, 47*: 1090-99.

[142] Kirkpatrick, L. A. , & Epstein, S. (1992). Cognitive-experiential self-theory and subjective probability: Further evidence for two conceptual systems. *Journal of Personality and Social Psychology, 63*(4), 534–544.

[143] Korhonen, P. J., Malo, P., Pajala, T., Ravaja, N., Somervuori, O. , & Wallenius, J. (2018). Context matters: The impact of product type, emotional attachment and information overload on choice quality. *European Journal of Operational Research, 264*(1), 270–279.

[144] Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: cognitive basis for stimulus-response compatibility–a model and taxonomy. *Psychological Review, 97*(2), 253.

[145] Kottemann, J. E., & Davis, F. D. (1991). Decisional conflict and user acceptance of multicriteria decision-making aids. *Decision Sciences, 22*(4), 918–926.

[146] Kruglanski, A. W., & Gigerenzer, G. (2011). Intuitive and deliberate judgments are based on common principles. *Psychological Review, 118*(3), 522.

[147] Lai, L. (2010). Maximizing without difficulty: A modified maximizing scale and its correlates. *Judgment and Decision Making, 5*(3), 164–175.

[148] Lambert-Pandraud, R., Mullet, G.L. & Yoon, C. (2017). Impact of age on brand awareness sets: a turning point in counsumers' early 60s. *Marketing Letters, 28*: 205-18.

[149] Lee, M. D., & Cummins, T. D. (2004). Evidence accumulation in decision making: Unifying the "take the best" and the "rational" models. *Psychonomic Bulletin & Review, 11*(2), 343–352.

[150] Li, V., Michael, E., Balaguer, J., Castañón, S. H., & Summerfield, C. (2018). Gain control explains the effect of distraction in human perceptual, cognitive, and economic decision making. *Proceedings of the National Academy of Sciences, 115*(38), E8825–E8834.

[151] Liang, S., & Zou, Y. (2018). Validation of adult decision-making competence in Chinese college students. *Judgment and Decision Making, 13*(4), 393.

[152] Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin, 116*(1), 75–98.

[153] Lütkepohl, H. & Xu, F. (2012). The role of the log transformation in forecasting economic variables. *Empirical Economics, 42*: 619-38.

[154] Lurie, N.H. (2004). Decision Making in Information-Rich Environments: The Role of Information Structure. *Journal of Consumer Research, 30*:473-86.

[155] Lynch, J.G. & Ariely, D. (2000). Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution. *Marketing Science, 19*:83–103.

[156] Malhotra, N. K. (1982). Information load and consumer decision making. *Journal of Consumer Research, 8*(4), 419–430.

[157] Malhotra, N. K. (1984). Reflections on the information overload paradigm in consumer decision making. *Journal of Consumer Research, 10*(4), 436–440.

[158] Marttunen, M., Haag, F., Belton, V., Mustajoki, J., & Lienert, J. (2019). Methods to inform the development of concise objectives hierarchies in multi-criteria decision analysis. *European Journal of Operational Research, 277*(2), 604–620.

[159] McAlister, L. (1982). A dynamic attribute satiation model of variety-seeking behavior. *Journal of Consumer Research, 9*(2), 141–150.

[160] McAlister, L. , & Pessemier, E. (1982). Variety seeking behavior: An interdisciplinary review. *Journal of Consumer Research, 9*(3), 311–322.

[161] McMackin, J., & Slovic, P. (2000). When does explicit justification impair decision making? *Applied Cognitive Psychology, 14*(6), 527–541.

[162] Micu, C.C. & Coulter, R.A. (2012). The Impact of Pretrial Advertising on Post-trial Product Evaluations: Assessing the Effects of Attribute Information for Hedonic and Utilitarian Products. *Journal of Marketing Theory and Practice, 20*: 189-201.

[163] Milosavljevic, M. & Cerf, M. (2008). First attention then intention: Insights from computational neuroscience of vision. *International Journal of Advertising, 27*: 381-98.

[164] Mingers, J. (2011). Soft OR comes of age—but not everywhere! *Omega, 39*(6), 729–741.

[165] Misuraca, R., & Fasolo, B. (2018). Maximizing versus satisficing in the digital age: disjoint scales and the case for “construct consensus”. *Personality and Individual Differences, 121*, 152-160.

[166] Mitra, A. (1995). Advertising and the stability of consideration sets over multiple purchase occasions. *International Journal of Research in Marketing, 12*(1), 81–94.

[167] Montibeller, G., & Von Winterfeldt, D. (2015). Cognitive and motivational biases in decision and risk analysis. *Risk Analysis, 35*(7), 1230–1251.

[168] Morgenstern, O., & Von Neumann, J. (1953). *Theory of games and economic behavior.* Princeton university press.

[169] Morton, A., & Fasolo, B. (2009). Behavioural decision theory for multi-criteria decision analysis: a guided tour. *Journal of the Operational Research Society, 60*(2), 268–275.

[170] Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R^2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution, 4*(2), 133–142.

[171] Nedungadi, P. & Hutchinson, J. (1985). The prototypicality of brands: Relationships with brand awareness, preference and usage. *Advances in Consumer Research, 12*: 498-503.

[172] O’Keefe, R. M. (2016). Experimental behavioural research in operational research: What we know and what we might come to know. *European Journal of Operational Research, 249*(3), 899–907.

[173] Oh, H. (2000). The effect of brand class, brand awareness, and price on customer value and behavioral intentions. *Journal of Hospitality & Tourism Research, 24*:136-62.

[174] Pachur, T., & Forrer, E. A. (2013). Selection of decision strategies after conscious and unconscious thought. *Journal of Behavioral Decision Making, 26*(5), 477–488.

[175] Pacini, R. , & Epstein, S. (1999). The relation of rational and experiential information processing styles to personality, basic beliefs, and the ratio-bias phenomenon. *Journal of Personality and Social Psychology, 76*(6), 972–987.

[176] Pan, B., Hembrooke, H., Joachims, T., Lorigo, L., Gay, G., & Granka, L. (2007). In google we trust: Users decisions on rank, position, and relevance. *Journal of Computer-Mediated Communication, 12*:801–23.

[177] Parker, A. M., De Bruin, W. B., & Fischhoff, B. (2007). Maximizers versus satisficers: Decision-making styles, competence, and outcomes. *Judgment and Decision Making, 2*(6), 342.

[178] Parkin, J.A. (2000). *Essential Cognitive Psychology.* Psychology Press Ltd., Hove, East Sussex.

[179] Patterson, R.A. & Merino, M.C. (2003). Consumer Information Search Behavior and the Internet. *Psychology & Marketing, 20*: 99-121.

[180] Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker.* Cambridge university press.

[181] Payne, E. H., Gebregziabher, M., Hardin, J. W., Ramakrishnan, V. , & Egede, L. E. (2017). An empirical approach to determine a threshold for assessing overdispersion in Poisson and negative binomial models for count data. *Communications in Statistics-Simulation and Computation*, 1–17.

[182] Pinto, Y., van der Leij, A. R., Sligte, I. G., Lamme, V. A., & Scholte, H. S. (2013). Bottom-up and top-down attention are independent. *Journal of Vision, 13*(3), 16.

[183] Potthast M., Köpsel S., Stein B. & Hagen M. (2016). Clickbait Detection. In: Ferro N. et al. (eds) *Advances in Information Retrieval ECIR, Lecture Notes in Computer Science, 9626*: 810-17.

[184] Peterson, R.A., Balasubramanian, S. & Bronnenberg, B.J. (1997). Exploring the Implications of the Internet for Consumer Marketing. *Journal of the Academy of Marketing Science, 25*: 329–46.

[185] Peterson, R. A., & Merino, M. C. (2003). Consumer information search behavior and the Internet. *Psychology & Marketing, 20*(2), 99–121.

[186] Piaget, J. , & Inhelder, B. (1975). *The origin of the idea of chance in children* (Translated by Leake, L., Burrell, P. and Fischbein, H.). Published by Routledge & Kegan Paul Ltd.

[187] Pinheiro, J.C. & Bates, D.M. (2000). *Mixed-Effects Models in S and S-Plus.* Springer, New York.

[188] Polman, E. (2010). Why are maximizers less happy than satisficers? Because they maximize positive and negative outcomes. *Journal of Behavioral Decision Making, 23*(2), 179–190.

[189] Powdthavee, N. , & Riyanto, Y. E. (2015). Would you pay for transparently useless advice? A test of boundaries of beliefs in the folly of predictions. *Review of Economics and Statistics, 97*(2), 257–272.

[190] Purvis, A., Howell, R. T. , & Iyer, R. (2011). Exploring the role of personality in the relationship between maximization and well-being. *Personality and Individual Differences, 50*(3), 370–375.

[191] Queens' Old Library. (n.d.). Retrieved May 4, 2019, from https://www.queensoldlibrary.org

[192] Ratchford, B.T., Lee, M.S. & Talukdar, D. (2003). The Impact of the Internet on Information Search for Automobiles. *Journal of Marketing Research, 40*:193–209.

[193] Rhoades, S.A. (1993). The Herfindahl-Hirschman index. *Federal Reserve Bulletin, March*, 188-89.

[194] Rieskamp, J., & Hoffrage, U. (1999). When do people use simple heuristics, and how can we tell? In G. Gigerenzer, P. M. Todd, & The ABC Research Group (Eds.), *Simple heuristics that make us smart* (pp. 141–167). New York: Oxford University Press.

[195] Roets, A., Schwartz, B., & Guan, Y. (2012). The tyranny of choice: A cross-cultural investigation of maximizing-satisficing effects on well-being. *Judgment and Decision Making, 7*(6), 689.

[196] Rosi, A., Bruine de Bruin, W., Del Missier, F., Cavallini, E., & Russo, R. (2019). Decision-making competence in younger and older adults: which cognitive abilities contribute to the application of decision rules? *Aging, Neuropsychology, and Cognition, 26*(2), 174–189.

[197] Russo, J. E. (1974). More information is better: A reevaluation of Jacoby, Speller and Kohn. *Journal of Consumer Research, 1*(3), 68–72.

[198] Russo, J. E., & Dosher, B. A. (1983). Strategies for multiattribute binary choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*(4), 676.

[199] Saad, G., & Russo, J. E. (1996). Stopping criteria in sequential choice. *Organizational Behavior and Human Decision Processes, 67*: 258–70.

[200] Scheibehenne, B., Greifeneder, R., & Todd, P. M. (2010). Can there ever be too many options? A meta-analytic review of choice overload. *Journal of Consumer Research, 37*(3), 409–425.

[201] Schwartz, B. (2004a). *The paradox of choice: Why more is less* (Vol. 6). HarperCollins New York.

[202] Schwartz, B. (2004b). The tyranny of choice. *Scientific American, 290*(4), 70–75.

[203] Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K. , & Lehman, D. R. (2002). Maximizing versus satisficing: Happiness is a matter of choice. *Journal of Personality and Social Psychology, 83*(5), 1178–1197.

[204] Shannon, C.E. & Weaver, W. (1949). *The Mathematical Theory of Communication*. University of Illinois Press.

[205] Shiloh, S., Koren, S., & Zakay, D. (2001). Individual differences in compensatory decision-making style and need for closure as correlates of subjective decision complexity and difficulty. *Personality and Individual Differences, 30*(4), 699–710.

[206] Shiloh, S., Salton, E. , & Sharabi, D. (2002). Individual differences in rational and intuitive thinking styles as predictors of heuristic responses and framing effects. *Personality and Individual Differences, 32*(3), 415–429.

[207] Siebert, J. , & Kunz, R. (2016). Developing and validating the multidimensional proactive decision-making scale. *European Journal of Operational Research, 249*(3), 864–877.

[208] Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118.

[209] Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review, 63*(2), 129–138.

[210] Simon, H. A. (1971). Designing organizations for an information-rich world. In M. Greenberger (Ed.), *Computers, communications and the public interest.* Baltimore, MD: Johns Hopkins University Press.

[211] Simon, H. A. (1972). Theories of bounded rationality. *Decision and Organization, 1*(1), 161–176.

[212] Simon, H. A. (1983). Search and reasoning in problem solving. *Artificial Intelligence, 21*(1–2), 7–29.

[213] Simon, H. A. (1990). Invariants of human behavior. *Annual Review of Psychology, 41*(1), 1–20.

[214] Simonson, I. (1990). The effect of purchase quantity and timing on variety-seeking behavior. *Journal of Marketing Research*, 150–162.

[215] Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics, 50*(3), 665–690.

[216] Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin, 119*(1), 3–22.

[217] Slovic, P., Finucane, M. L., Peters, E. , & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research, 177*(3), 1333–1352.

[218] Slovic, P., Griffin, D., & Tversky, A. (1990). Compatibility effects in judgment and choice. In R. M. Hogarth (Ed.), *Insights in decision making: A tribute to Hillel J. Einhorn* (pp. 5–27).

[219] Smith, M. D. & Brynjolfsson, E. (2004). Consumer decision-making at an internet shopbot: Brand still matters. *Journal of Industrial Economics, 49*:541–558.

[220] Sonnemans, J. (1998). Strategies of search. *Journal of Economic Behavior & Organization, 35*: 309–32.

[221] Sparks, E. A., Ehrlinger, J. , & Eibach, R. P. (2012). Failing to commit: Maximizers avoid commitment in a way that contributes to reduced satisfaction. *Personality and Individual Differences, 52*(1), 72–77.

[222] Stanovich, K. E. , & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences, 23*(5), 645–665.

[223] Stigler, G. J. (1961). The economics of information. *Journal of Political Economy, 69*(3), 213–225.

[224] Stoet, G. (2010). PsyToolkit: A software package for programming psychological experiments using Linux. *Behavior Research Methods, 42*(4), 1096–1104.

[225] Terech, A., Bucklin, R.E. & Morrison, D.G. (2009). Consideration, choice, and classifying loyalty. *Marketing Letters, 20*:209–25.

[226] Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness.* Penguin.

[227] Todd, P. M. (2007). How much information do we need? *European Journal of Operational Research, 177*(3), 1317–1332.

[228] Trinh, G. (2015). A stochastic model of consideration set sizes. *Journal of Consumer Behaviour, 14*:158-64.

[229] Tversky, A. (1969). Intransitivity of preferences. *Psychological Review, 76*(1), 31.

[230] Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review, 79*(4), 281.

[231] Tversky, A. , & Kahneman, D. (1971). Belief in the law of small numbers. *Psychological Bulletin, 76*(2), 105–110.

[232] Tversky, A., & Kahneman, D. (1974). Heuristics and biases: Judgment under uncertainty. *Science, 185*, 1124–1130.

[233] Vansnick, J.C. (1986). On the problem of weights in multiple criteria decision making (the noncompensatory approach). *European Journal of Operational Research, 24*(2), 288–294.

[234] Van Trijp, H. C., Hoyer, W. D. , & Inman, J. J. (1996). Why switch? Product category: level explanations for true variety-seeking behavior. *Journal of Marketing Research*, 281–292.

[235] Von Winterfeldt, D., & Edwards, W. (1986). *Decision analysis and behavioral research*. Cambridge University Press.

[236] Weathers, D. & Makienko, I. (2006). Assessing the Relationships Between E-Tail Success and Product and Web Site Factors. *Journal of Interactive Marketing, 20*:41–54.

[237] Weaver, K., Daniloski, K., Schwarz, N. , & Cottone, K. (2015). The role of social comparison for maximizers and satisficers: Wanting the best or wanting to be the best? *Journal of Consumer Psychology, 25*(3), 372–388.

[238] Weber, E. U., Blais, A.R. , & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*(4), 263–290.

[239] Weber, E. U., & Milliman, R. A. (1997). Perceived risk attitudes: Relating risk perception to risky choice. *Management Science, 43*(2), 123–144.

[240] Weitzman, M. (1979). Optimal search for the best alternative, *Econometrica, 47*: 641-54.

[241] Wilson, A. (2012). Bounded Memory and Biases in Information Processing. *Econometrica, 82*: 2257-94.

[242] Zakay, D. (1990). The role of personal tendencies in the selection of decision-making strategies. *The Psychological Record, 40*(2), 207–213.

[243] Zettelmeyer, F., Morton, F.S. & Silva-Risso, J. (2006). How the Internet Lowers Prices: Evidence from Matched Survey and Automobile Transaction Data, *Journal of Marketing Research, 43*:168–81.

[244] Zhang, J., Fang, X. & Liu Sheng, O.R. (2006). Online Consumer Search Depth: Theories and New Findings. *Journal of Management Information Systems, 23*:71-95.