Decision Strategies
Something Old, Something New, and Something Borrowed

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To life and those who make it enjoyable....

Abstract

In this thesis, some old decision strategies are investigated and a new one that furthers our understanding of how decisions are made is introduced. Three studies are presented. In Study I and II, strategies are investigated in terms of *inferences* and in Study III, strategies are investigated in terms of *preferences*. Inferences refer to decisions regarding facts, e.g., whether a patient has a heart disease or not. Preferences refer to decision makers' personal preference*s* between different choice alternatives, e.g., which flat out of many to choose. In all three studies, both non-compensatory strategies and compensatory strategies were investigated. In compensatory strategies, a high value in one attribute cannot compensate for a low value in another, while in non-compensatory strategies such compensation is possible. Results from Study I showed that both compensatory (logistic regression) and non-compensatory (fast and frugal) strategies make inferences equally well, but logistic regression strategies are more frugal (i.e., use fewer cues) than the fast and frugal strategies. Study II showed that the results were independent of the degree of expertise. The good inferential ability of both non-compensatory and compensatory strategies suggests there might be room for a strategy that can combine the strengths of the two. Study III introduces such a strategy, the Concordant-ranks (CR) strategy. Results from Study III showed that choices and attractiveness evaluations followed this new strategy. This strategy dictates a choice of an alternative with concordant ranks between attribute values and attribute weights when alternatives are about equally attractive. CR also serves as a proxy for finding the alternative with the shortest distance to an ideal. The CR strategy combines the computational simplicity of non-compensatory strategies with the superior information integration ability of compensatory strategies.

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Don't count the days, make the days count.
~Mohammed Ali

It is common conception that writing the final thesis (kappa) is the most difficult and emaciating part of the PhD process. Maybe I am an outlier, but writing this thesis has been the most gratifying part of my time as a PhD student. Mostly, because As Frank Sinatra said "*I did I my way". I* planned it my way, wrote it my way, using my words and my way of telling things and I have never been so satisfied. The second most gratifying part was the discussions, idea exchanges, stimulating talks, and collaborations that I have had the privilege to have with those people who have supported and encouraged me in my pursue as a researcher. I would like to show my gratitude to some of them.

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Neda Karimi
Stockholm, 2011

List of Studies

The present doctorial thesis is based on the following studies:

I. Kerimi, N., Backlund, G. L., Skånér, Y., Strender, L-E., Montgomery, H. (submitted). Judgment Analysis in the Medical Domain: Making a Fair Comparison Between Logistic Regression and Fast & Frugal Models.

II. Kerimi, N., Backlund, G. L., Skånér, Y., Strender, L-E., Montgomery, H. (submitted). Do We Really Need Medical Experts when Modeling in Judgment Analysis? Lack of Difference Between Experts and Non-Experts in Judgment Analysis.

III. Kerimi, N., Montgomery, H., Zakay, D. (2011). Coming Close to The Ideal Alternative: The Concordant-Ranks Strategy. *Judgment and Decision Making*, *6*, 196-210.

Contents

Introduction

> *As soon as questions of will or decision or reason or choice of action arise, human science is at a loss.*
> *~Noam Chomsky*

Making decisions is a part of everyday life that we cannot ignore. For example, a bride, let us call her Jane, about to get married has to make a multitude of decisions. Some of these decisions are based on an old saying *"Something Old, Something New, Something Borrowed…"*[1], where she has to find something in each of these categories to have a happy marriage. This saying is also applicable in research where you can study "old" theories, come up with a "new" theory that can be "borrowed" or built on the "old" theories. In this thesis, I will present some "old" decision strategies (Study I, II, and III). I will afterwards present a "new" strategy (Study III), explain how this "new" strategy relates to and how it might have "borrowed" some of the strengths of the "old" strategies.

Before I get into "Something Old, Something New, and Something Borrowed", I will present different views on *rationality* underlying research in decision making. These different views on human rationality have led to the identification of different *models* and *strategies* in decision making, which I will describe. One thing that differentiates decision strategies from each other is how they utilize *information*. I will focus on how individuals process information in these different decision strategies. Which decision strategies humans use and how they utilize information is also dependent on *degrees of expertise*. Therefore, I will also give a short review of the different views on expertise in decision making.

Finally, before I present results from three studies, I will describe *judgment analysis,* which is a commonly used method in decision making research when decisions concern *inferences* of possible facts, for example, whether a patient has a heart disease or not. Studies I and II use judgment analysis and are, hence, focused on inferential decisions. By contrast, Study III concerns decisions involving *preferences.* Preferences refer to decision makers' personal preferences between different choice alternatives, for example which flat out of many to choose.

Before starting, it is necessary to find a proper definition of what decision making is. In this thesis, I will depart from the following definition of deci-

[1] This is a saying dating back to the Victorian era. It is supposed to bring good luck if the bride ensures that she has something of each category in her wedding outfit.

sion making: "*a choice set of options or courses of action, a background of controllable and uncontrollable events that determine the outcome of the action-event combination that occurs, and subjective satisfaction that is a consequence of the objective outcome.*" (Hastie & Pennington, 1995, p. 1).

It is also necessary to clarify the differences between decision-making and judgment. In connection to a decision, individuals make several judgments, such as judgments of probabilities and values of aspects characterizing the choice alternatives. Judgments may also be holistic and integrate several more specific judgments, but still differ from decisions in that they do not designate the choice of a particular alternative. Thus, decision making and judgment are closely intertwined, but not synonymous. Therefore, the research field in psychology is labeled judgment and decision making (Koehler & Harvey, 2004). In this thesis, I focus mostly on decision making, both in inferential decisions (Study I and II), and in preferential decisions (Study III). In Study III, I will also present data on holistic evaluative judgments of choice alternatives.

It is difficult to talk about judgment and decision making without mentioning and describing rationality. Assumptions of rationality underlie most of the research conducted in decision making (e.g., Gigerenzer, 2007; Hammond, 2007). Next, I will give an account for rationality and how it is defined in psychology.

Rationality

Classical and bounded rationality

Decision making is evaluated as being a more or less rational process depending on how it is defined. The definitions of rationality differ depending on two views: *classical rationality* and *bounded rationality*. According to classical rationality, decision makers such as Jane follow a rational decision process and know exactly which and what information she needs in order to make an optimal decision (Bicchieri, 1993). According to bounded rationality, Jane has limited access to information and limited cognitive capacity that limits her decision making. Simon (1982; 1991) argued bounded rationality is like a pair of scissors in which one blade represents the computational capacities of Jane, and the other blade represents the environment in which Jane uses her capacity. The scissor will only work if the two blades fit and work together. Moreover, Simon (1982; 1991) argued that Jane has adapted to the environment and as a result, based on the information she has, she will try to make satisfying rather than optimal, decisions. Because decision makers, such as Jane, have time constrains and limited cognitive capacity, they use heuristics rather than rigid and utility maximizing computations (Augier, 2000).

Related to bounded rationality is Brunswick's *lens model* (Brunswick, 1952; Wolf, 2000). The lens model describes the difference between the environment (e.g., a disease) and how an individual observes the environment. In addition, this model describes how the individual adapts and reacts to the difference in the two based on cues or information (e.g., symptoms of a disease) in the environment. Brunswick argued that to understand human decision making or cognition in general, the environment in which the decision making is taking place should also be studied.

Coherence and correspondence

Rationality is associated with the notions of *coherence* and *correspondence*. According to coherence theories, Jane is rational when her decisions are coherent with logic or statistical norms. According to correspondence theories, Jane is rational if her decision works well or is fitted to the environment. Hammond (1990, 1996) argued that those who look for coherence will find human beings as irrational while those who look for correspondence will find human beings as adaptive.

The research of Kahneman and Tversky (1973) used the coherence approach as a background for identifying biases in judgment and decision making. They suggested that to overcome the limitations of classical rationality, researchers have to understand the heuristics and biases in people's decision making. It is only when these heuristics and biases are understood that researchers can provide guidelines to improve decision making. Gigerenzer and colleagues (2002), using the correspondence approach to study judgment and decision making, argue that Simon's (1982) bounded rationality is misinterpreted. For instance, they argue that some decision strategies do not explain or consider how and when the information search should stop (Gigerenzer, Todd & The ABC research group, 1999). Gigerenzer suggested an "adaptive toolbox", consisting of simple heuristics that decision makers use and which lead to better decisions than most of the utility-optimization theories (Gigerenzer & Selten, 2002; Gigerenzer et al., 1999). This view came later to be called ecological rationality (Gigerenzer et al., 1999). Hammond argues that the study of human judgment and decision making cannot go forward without the use of both coherence and correspondence approaches (Hammond, 2007).

Similar to most psychological scientists, I do not believe that humans are perfectly rational. Instead, they are boundedly rational because of, among other things, limited cognitive capacity. In this thesis, I will investigate different decision strategies, which either fall into the group of classical rationality (e.g., MAU) or bounded rationality (e.g., elimination by aspects, EBA and fast and frugal heuristics).

Models of decision making

Baron (2008) divides the decision models into three categories: *descriptive, normative, and prescriptive*. The aim of descriptive models is to describe how decision makers, such as Jane, actually make decisions. Heuristics, which are rules of thumbs, can provide such descriptions. Here the description of how Jane makes a decision is usually compared with some ideal way of making decisions. This leads us to normative models.

The aim of normative models is to provide policies or axioms that can aid Jane to make an optimal and rational decision in a certain decision situation. Note that Jane cannot use normative models as such because they are often too computation demanding or time-consuming (Baron, 2008), which leads us to prescriptive models.

The aim of prescriptive models is to model or create prescriptions of how humans should make decisions. Similar to the descriptive models, the prescriptive models can be different heuristics or rules of thumb. Because of the complex nature of decision making, there is not only one prescriptive model for all situations.

Jane's choice of a wedding ring will provide us with an example of the differences between descriptive, normative, and prescriptive models. Most normative models postulate that if Jane prefers sapphire rings (A) to diamond rings (B), and diamond rings (B) to emerald rings (C), then she should also prefer sapphire rings (A) to emerald rings (C). However, in a descriptive model (i.e., how decision makers actually made decisions), decision makers can be intransitive. For instance, Jane might prefer sapphire rings (A) to diamond rings (B), diamond rings (B) to emerald rings (C), but prefer emerald rings (C) to sapphire rings (A). One reason for this intransitivity can be that when Jane compares sapphire rings (A) with diamond rings (B), certain attributes are emphasized, while when sapphire rings (A) are compared to emerald rings (C), other attributes are emphasized. So, from a normative point of view, Jane should be transitive and choose sapphire rings (A) while from a descriptive point of view, she will choose emerald rings (C). A prescriptive point of view could be that Jane should choose the stone ring that gives her highest satisfaction but this can be ring A (from a normative point of view) or ring C (from a descriptive point of view). Therefore, the prescriptive models provide Jane with a guideline of how to find, for example, a balance between normative and descriptive models. For instance, a guideline of how to evaluate different attributes of the rings (for example color) so that eventually the differences between the rings become transitive (i.e., sapphire rings are more beautiful than diamond rings, diamond rings are more beautiful than emerald rings. Therefore, sapphire rings should also be more beautiful than emerald rings).

In this thesis, I will investigate decision strategies in all three types of models: descriptive (e.g., EBA and Lexicographic), prescriptive (e.g., fast and frugal models), and normative (e.g., Maximin and MAU). Some of these decision strategies can be categorized into two of the models (e.g., MAU, which can be both prescriptive and normative), but only one strategy, the CR strategy, which will be introduced and explained in Study III, can be categorized in into all three models.

Decision strategies

Payne, Bettman, and Johnson (1995) defines a decision strategy as ”*a sequence of mental and effector (actions on the environment) operations that transform some initial state of knowledge into a final knowledge state so that the decision maker perceives that the particular decision problem is solved.*” (p. 140).

Usually decision makers have a repertoire of decision strategies, acquired by experience or prior exposure to those strategies (e.g., Larrick, Morgan, & Nisbett, 1990). The majority of the times, decision makers want to use the strategy that requires a minimum effort while at the same time leads to the choice of the best alternative (Beach & Mitchell, 1978; Klayman, 1983; Russo & Dosher, 1983; Shugan, 1980). One important, if not the most important, component in decision strategies is how decision makers process information.

Information processing in decision strategies

Limited cognitive capacity

The way information is processed while making decisions has drawn much attention (e.g., Fischhoff, Slovic, & Lichtenstein, 1978; Griffin, Dunning, & Ross, 1990; Ross, 1987, 1989; Slovic & MacPhillamy, 1974; Yates, Jagacinski, & Faber, 1978). Newell and Simon (1972) coined the term *information processing theory*, which describes how individuals process information when they make decisions. Specifically, the theory describes the cognitive system and the environment in which information is processed. Proponents argue that when researchers study the cognitive limitations of decision makers, they must also study how decision makers search and process information in complex environments (Newell & Simon, 1972). The information processing limitations are compatible with the notion that humans are selective in which information they attend to (Simon, 1978). For example, Russo, Medvec, and Meloy (1996) found that existing preferences could lead to distortion of new information in support of a chosen alternative. This, they explained, is because individuals desire to maintain a consistency in their beliefs and reduce the effort of making a decision by confirming already set-up preferences and rejecting information that goes against the chosen alternative. Using related theoretical perspectives, other researchers have reported similar findings (e.g., Backlund, Skånér, Montgomery, Bring, & Strender, 2003; Dahlstrand & Montgomery, 1984; Holyoak & Simon, 1999; Kuhl, 1984).

Beyond limited cognitive capacity

The sequential sampling process (Busemeyer & Johnson, 2004) gives another view on how a decision maker deals with limited cognitive capacity. In a sequential sampling process, different alternatives and different pieces of information are taken in and processed until one alternative or piece of information exceeds a certain threshold (Newell, 2005). Newell and Bröder (2008) argue that the study of how humans process information should consider not only (i) the limited cognitive capacity, but also (ii) the dual nature of information processing, (iii) the learning ability, and (iv) the regulation capacity or metacognition.

The dual nature of information processing

As for the dual nature of information processing, many theories have been formulated through the years (e.g., Kahneman & Frederick, 2002; Newell & Simon, 1972; Sloman, 1996; Slovic, Finucane, Peter, & McGregor, 2002). The view of the information processing as a dual system has drawn much attention, received many names, and gone through several modifications (for reviews see Baumeister, 2005; Paivio, 2007; Sun, 2002). However, most of these theories share the common view that there are two types of information processes - automatic processes that are unconscious, fast, and associative, and controlled processes that are conscious, slower, and limited by the capacity of the working memory.

Glöckner and Betsch (2008) argued that researchers have focused too much on the controlled processes and that the automatic processes might be more involved in decision making than earlier stated. They presented data confirming that decision makers use associative and integrated information that is stored in the memory and activated as a connected network. This in its turn allows for an additive or multiplicative type of information integration (Glöckner & Betsch, 2008; Juslin, Jones, Olsson, & Winman, 2003). This network connects the information in such a way that one alternative is perceived as superior and finally chosen (Glöckner & Betsch, 2008).

The learning ability

Several studies have shown that learning is important for how we process information and that learning can help to develop and improve decisions (for examples see Barron & Erev, 2003; Erev & Barron, 2005; Newell & Rakow, 2007; Newell, Lagnado & Shanks, 2007). An example of theories adapting this view is categorization theories, which I will describe in more detail later in this thesis.

The regulation capacity

There is a large body of research on how thinking and attentive regulation impacts what information individuals search and utilize to make decisions (Jönsson & Kerimi, 2010; Metcalfe & Finn, 2008). Regulation capacity refers to judgments of how to decide and therefore, how to allocate a piece of the limited capacity to produce the best decision (Newell & Bröder, 2008).

The study of *compensatory* and *non-compensatory* decision strategies can also shed light on how information is processed in decision making situations. Next, I will explain compensatory and non-compensatory strategies in more detail.

Compensatory decision strategies

In compensatory decision strategies, an attractive or high value on one attribute in an alternative can compensate an unattractive or low value on another attribute (Montgomery & Svenson, 1976; Svenson, 1979). Compensatory decision strategies require the decision maker to identify all possible attributes that can influence the decision. For instance, if Jane needs to choose between which catering firms out of different alternatives to hire, then she must identify all the attributes that have an impact on her final decision. She will then calculate an overall value based on the impact each attribute (i.e., how important the food quality is) has on her final decision, and then choose the catering firm with the highest value. Because there is an overall value for each catering firm, attractive attribute values (e.g., high food quality) can compensate unattractive attribute values (e.g., expensive). Compensatory decision strategies are more analytical (Beach & Mitchell, 1978) and applicable in more situations, but may be more difficult to use. These strategies are typically seen as complex and require much information processing, which can be problematic for decision makers (Chater, Oaksford, Nakisa, & Reddington, 2003).

Non-compensatory decision strategies

By contrast, in non-compensatory decision strategies, attractive attribute values cannot compensate unattractive attribute values (Elrod, Johnson & White, 2004). This puts less cognitive load on the decision maker, for instance, in the catering firm example, Jane might prefer the catering firm which offers higher food quality. This firm might be more expensive but she cannot compensate an unattractive attribute value (low food quality) with an attractive attribute value (cheaper). Non-compensatory strategies are less analytic and easier to use (Beach & Mitchell, 1978) because they do not require the decision maker to compare one attribute to a completely different attribute. However, they are not optimal because they can lead to missing important information. One example of a non-compensatory strategy is the L*exicographic* strategy where the alternative that is best on the most important attribute is chosen (Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999) In Study I, II, and III, I study and compare both compensatory and non-compensatory decision strategies.

Compensatory vs. non-compensatory decision strategies

There are studies showing that compensatory strategies are not as difficult or demanding to use as previously stated. In addition, recent research suggests that the experimental design of previous studies, which have presented evidence for non-compensatory strategies, might have forced decision makers to think in a non-compensatory manner (e.g., Bröder, 2000, 2003; Bröder & Schiffer, 2003; Glöckner & Betsch, 2008). Furthermore, compensatory decision strategies might be preferred because decision makers want to have access to all the available information (for a review see Newell & Shanks, 2007). For example, Lindeman and Markman (1996) found that individuals prefer comparable attributes more than non-comparable, which may make it natural to use compensatory rather than non-compensatory decision strategies in situations where attributes are comparable. In their study, they provided students with important non-comparable information and less-important comparable information about different colleges. They found that the students preferred the comparable information even though it was less important. Because of the traditional view that non-compensatory decisions require less effort (Gigerenzer et al., 1999), Bröder and Schiffer (2003) reasoned that more cognitive capacity should result in using more advanced and compensatory strategies. Therefore, they limited participants' cognitive capacity by putting a high cognitive load on them. Their results showed that decision makers use compensatory strategies even under greater cognitive load and the difference was between the choices of a strategy rather than how decision makers executed a strategy. In Study III, I will adapt this view and suggest a decision strategy that, similar to compensatory decision strategies, search more information while at the same time, similar to non-compensatory decision strategies, is easier to use.

Decision strategies in a nutshell

In a nutshell, strategies differ from each other in the way information is utilized. Newell and Bröder (2008) define information processing consisting of four interplaying parts: the cognitive capacity of humans, the dual nature of information processing, the learning ability, and metacognition. Another way of viewing how information is processed in different decision strategies is provided by the compensatory (an attribute compensating a different attribute) and non-compensatory (an attribute cannot compensate for other attributes) view. I believe that many situations require the use of compensatory decision strategies compared to non-compensatory decision strategies. In this thesis, I will show that, similar to recent research (e.g., Glöckner & Betsch, 2008), decision makers can use strategies that require the integration of different pieces of information in a more nuanced way (Study I, II, and III).

Information processing by experts

How individuals search information, and which decision strategies they use can be related to expertise. There is a large body of research on what makes an expert (e.g., Elstein, Shulman & Sprafka, 1978; Ericsson, Charness, Feltovich, & Hoffman, 2006; Ericsson, Roaring, & Nandagopal, 2007; Patel, Arocha, & Kaufman, 1999; Posner, 1988; Shanteau, 1991; 1992; Wineburg, 1998). Meyer and Booker (2001) defined an expert as *"a person who has background in the subject area and is recognized by his or her peers or those conducting the study as qualified to answer questions"* (p. 3). Similarly, Shanteau argues that those in the domain of the expert should be the ones defining expertise (Shanteau, 1987, 1988, 1991).

Experts can have different degrees of expertise and several classification systems of levels of expertise have been proposed (e.g., Brehmer & Brehmer, 1988; Ericsson & Lehman, 1996; Shanteau, 1988). Shanteau (1988) suggests three expertise levels. *Naïve decision makers* are at the lowest level of expertise and have little skill in their field of expertise. For example, in the medical domain, medical students who have acquired knowledge in the field but not practiced or applied the knowledge yet can exemplify naïve decision makers. *Novice decision makers* are at the medium level of expertise. They have more knowledge and experience than the naïve decision makers. In the medical domain, general practitioners can be an example of novice decision makers for certain types of problems, where advanced expert knowledge is valuable. At the top level are *expert decision makers* who have reached the highest point of expertise in their field. In the medical domain, specialized doctors such as cardiologists can be an example of expert decision makers.

Another more general way of grouping experts is by the way they search for and utilize information. According to the Information-Use Hypothesis, experts use more information because they can better utilize it (Jacoby et al., 2001). However, other studies have shown the opposite, experts might search and utilize less information than non-experts because they can ignore irrelevant information (for examples see Einhorn, 1974; Goldberg, 1970). Another view of the difference between experts and non-experts is how they handle information and not how much. It might be that decision makers with different degrees of expertise use equal amounts of information, but they weigh and utilize the information differently (for examples see Ettenson, Shanteau, & Krogstad, 1987; Shanteau, 1991). Non-experts do not have the ability to ignore irrelevant information. Consequently, when both experts and non-experts might search the same amount of information, they utilize or ignore the information differently. This difference arises from context-dependence. For instance, a piece of information might be important in one situation while unimportant in another. Experts, in contrast to non-experts, have acquired experience and domain knowledge and can therefore, determine if a piece of information is relevant for a given decision situation (Shanteau, 1992).

Expertise and different types of decisions

It may seem self-evident that individuals regarded as experts make better decisions compared to non-experts. However, the evidence for this statement is mixed. This depends partially on the type of decision (Ericsson, Krampe, & Tesch-Romer, 1993). In some domains, such as in physics, experts make decisions using static stimuli. Static stimuli refers to stimuli that are constant and do not change. In other domains, such as medical domain, the stimuli are dynamic, mostly because of human behavior. In domains where expert judgments have been based on tasks involving predictions of human behavior, experts do not necessarily perform better compared to non-experts and these experts are less predictable (Shanteau, 1992). In addition, in some domains, experts make estimations in uncertain areas (e.g., how much fuel a certain engine needs; Krupka, Peaslee, & Laquer, 1983). In other domains, experts make predictions of future events (e. g, how much weapons US might need for future use; Meyer, Booker, Cullingford, & Peaslee, 1982). In estimations in uncertain areas, or in predictions, research has shown that experts are not necessarily better decision makers compared to non-experts (Bennell, Bloomfield, Snook, Taylor, & Barnes, 2010; Faust & Ziskin, 1988; Tetlock, 2005). One reason for this can be due to the response-mode. For example, in predictions experts, and non-experts for that matter, usually provide probabilities of an outcome (e.g., the probability of a patient having heart failure or the probability of rain tomorrow). However, people in general, being an expert or not, are often unable to reason in probabilities (Kahneman & Tversky, 1973). In domains in which experts do better decisions compared to non-experts (e.g., in medical decision making), expert judgments are used to improve and aid decisions (e.g., by modeling the way doctors make medical judgments; Gafni & Charles, 1998).

In this thesis, I will investigate how individuals search and utilize information depending on the different decision strategies they use. However, expertise is domain specific and how much and how information is searched is dependent on how the degrees of expertise are identified (Shanteau, 1991). In this thesis, I will use the expertise levels definition by Shanteau (1988) and investigate the predictability of compensatory and non-compensatory decision strategies for doctors' judgments and decisions.

Examples of decision strategies and related theories

In the following, I will describe several decision strategies in which information is searched and utilized in different ways.

Multiattribute utility rule

One of the most commonly mentioned decision strategy in the literature is the *Multiattribute utility (MAU) rule*. MAU is a normative method of how difficult decisions should be made, but it also serves as a prescriptive method or guideline for how decisions can be made. The idea behind MAU is to help decision makers to formalize what is important to them and make a decision based on those attributes that are important (Fischer, 1975; Keeney & Raiffa, 1993a, 1993b). Some researchers argue that using MAU is an effective and objective way of choosing the best alternative (Edwards, Guttentag, & Snapper, 1975). If Jane made decisions in line with MAU, in order to choose the best venue for her wedding, she would first identify all the venue alternatives. Second, she would identify all the important attributes in each venue. Third, she would quantify the attribute values in terms of utility. Fourth, she would give each attribute an importance weight, and then calculate an overall utility by summing the product of attribute values and weights (Edwards & Newman, 1982; Gardiner & Edwards, 1975). Last, Jane would choose the venue with the highest overall utility (Edwards et al., 1975; Keeney & Raiffa, 1993a, 1993b). In Study III, MAU will be included in the repertoire of tested strategies.

Many researchers have criticized MAU by referring to bounded rationality (Kahneman, 2003; Simon, 1991). It has been shown that decision makers do not search information in the manner MAU describes (Russo & Dosher, 1983; Tversky, 1972). Additionally, proponents of MAU presume that decision makers have stable and unchangeable attribute preferences while research show that this is not the case. Instead, preferences are constructive in the sense that they are changed and shaped depending on the decision situation (Hsee, Loewenstein, Blount, & Bazerman, 1999; Lichtenstein & Slovic, 1971; 2006; Miyamoto & Eraker, 1988). Another theory that is similar to MAU is the Subjective Expected Utility (SEU), which claims that decisions can be made by weighing the utility by the probability of its occurrence (Wallsten, 1971). Thus, the difference between MAU and SEU is that SEU is a theory of decisions among uncertain alternatives while MAU is a theory of decisions with more or less certain outcomes (Luce, 1992).

Prospect theory

As stressed in SEU theory, risks, or the uncertain outcome that comes with decisions play an important role in decisions. This is an essential ingredient in *Prospect Theory* (PT). PT, which is a more descriptive variant of SEU, was developed as a critic to the more normative expected utility (EU) model. EU does not consider the limitations in the uncertainty and probability judgments individuals actually make while PT does. PT replaces the utility concept in EU, which refers to absolute values, with relative values defined in terms of their relationship to certain reference values, meaning that the subjective value of a given value will change across situations and individuals. Value in PT refers to gains and losses rather than to absolute levels. According to PT, individuals weigh gains and losses differently and this, in turn, will have a huge impact on decisions (Tversky & Kahneman, 1980). More specifically, the value function of losses is steeper than it is for gains, implying that a loss of an *x* amount of money feels much stronger than the gain of the exact same amount of money. This asymmetry is called loss aversion. Further, according to PT, the same decision outcomes will be different depending on how the decision situation is framed. If a decision situation is framed as a loss, then decision makers will be risk seeking while if the decision situation is framed as a gain, then decision makers will be risk aversive (Kahneman, Knetsch, & Thaler, 1990). Moreover, PT considers probabilities differently than SEU does. PT assumes that small probabilities will be over-weighted while high probabilities will be under-weighted (Tversky & Kahneman, 1981). Finally, PT predicts the so-called certainty effect. According to certainty effect, sure gains are favored to less sure gains even though the less sure gain is better in terms of expected value.

Distances

How decision makers process information is dependent on their memory, which is demonstrated in categorization theories (e.g., Murphy & Medin, 1985). According to these theories, when an individual observes an object, such as a cat, the object's distance to a prototype or exemplars, which are associated with a certain category (e.g., the category of cats) in the individual's memory, is estimated in order to decide whether the object can be put into the category in question. In exemplar models, instances of events or objects are stored and represented as points in an *n*-dimensional psychological space in memory. For example, when Jane observes a new dress (i.e., a new object), she compares the observed dress to all the exemplars of dresses that she has stored in her memory. The newly observed dress is then saved in Jane's memory in the exemplar the dress has shortest distance to, for instance, the exemplar of wedding dresses (Erickson & Kruschke, 1998; Juslin, Olsson & Olsson, 2003; Nosofsky, 1986; Nosofsky & Johansen, 2000; Nosofsky & Palmeri, 1997; Smith, Patalano & Jonides, 1998). Distance estimations are typically assumed to be based on similarity judgments or correlations between stimulus judgments (Yushi, 2006). A Euclidean distance is the length of the straight line between two points (Goldstone & Son, 2005; Tenenbaum, 1999; Tversky, 1977; Yushi, 2006). There are many distance functions; of interest in this thesis is the *Euclidean distance* (ED) and *weighted Euclidean distance* (WED). The difference between ED and WED is that in ED individuals are assumed to share the same psychological weightings and that these weightings are equal to each other while in WED it is assumed that these weightings differ between individuals (Carroll & Chang, 1970; Horan, 1969). Rubinstein and Zhou (2000) derived a mathematical model showing that when the given alternatives are part of a Euclidean space, an individual will choose the alternative with the shortest Euclidean distance to a reference point within this space. This model, however, was not tested psychologically or empirically and therefore, we cannot know if it is psychologically plausible or not.

Theories of distance have, however, been criticized for being too general and hence failing to consider the impact of the environment, for instance, by not considering that preferences can be constructive (Lichtenstein & Slovic, 1971; 2006). Besides, humans need to make sense of their choices, and it has been asserted that using distance functions cannot provide such sense (Tversky, 1977).

Ideal alternative

Closely related to distances and categorization theories is the concept of *ideal alternatives*. For instance, a category, according to categorization models, consists of a centroid (i.e., a prototype) or a group of exemplars Nosofsky, 1986; Nosofsky & Johansen, 2000; Nosofsky & Palmeri, 1997). This centroid or group of exemplars can sometimes be an ideal alternative (e.g., the ideal wedding dress). Similarly, Klein (1993), in his *recognition primed decision making model*, suggested that decision makers do not compare alternatives to one another, rather to a mental simulation, which tests that the alternative fulfills the requirements of an ideal alternative.

The idea of ideal alternatives is not new. Long before Zeleny (1976), Thurstone (1926, referred to in De Soete, Carroll, & DeSarbo, 1986) developed the *ideal point model* (IPM). According to IPM, the closer an alternative is to an ideal point, the higher preference will it receive (Bockenholt, 1998; De Soete, Carroll, & DeSarbo, 1986; MacKay, Easley, & Zinnes, 1995). Similarly, Zeleny (1976) argued that alternatives close to some anchor (ideal) should be preferred. For instance, Jane might find two wedding dresses to both have satisfactory fit and look. However, the dress that is most similar to Jane's ideal wedding dress (e.g., because it reminds Jane of her mother's dress) will be preferred and appeal as more satisfactory. Zakay and Dil (1984) tested Zeleny's notion of ideal alternative and found that participants chose the alternative that was closest to an ideal alternative. In another study, they found that this strategy had a high predictive ability in actual choices (Zakay & Barak, 1984). In both studies, distance was calculated by summing the importance weights across those attributes where the attribute values of an offered alternative and the ideal alternative differed, thus not accounting for how much the attribute values of the offered alternatives differed from the attribute values of the ideal alternative. Also in consumer research, researchers have found that consumers have different ideals that they try to choose in line with (Desarbo, Atalay, Lebaron, & Blanchard, 2008).

In Study III, I will build on the notion of ideal alternatives and test this strategy against other more established strategies mentioned above.

Heuristics

Researchers in cognitive psychology have found vast evidence that decision makers use heuristics to make decisions (e.g. see Gigerenzer, 2006; Gigerenzer & Selten, 2002; Gigerenzer et al., 1999; Gilovich, Griffin, & Kahneman, 2002; Kahneman & Frederick, 2002). Heuristics are simplified strategies or rules of thumb, which help individuals to make decisions. Even though many of the heuristics have been found to violate axioms of rationality (one such violation is *intransitive preferences*; Tversky, 1969), these violations are regarded as acceptable. This is because these heuristics work for the greater good, that is, they help decision makers to make decisions even though they might be somewhat disabled because of their limited processing capacity (Tversky & Kahneman, 1974).

There are at least three reasons why individuals such as Jane would use heuristics: first, because of limited cognitive capacity, she might not have other possibilities, second, she might not have the time or resources, and third, because these heuristics have worked satisfactory earlier, she might find them suitable for future decisions as well (Payne & Bettman, 2004). Heuristics differ from sequential sampling process described earlier in the sense that what and how much information to process is pre-determined.

There are many heuristics, most of them non-compensatory. Some of interest for this thesis is: The *Dominance rule,* often used when people look for justifying their choice, implies the choice of an alternative that is better than all other alternatives on at least one attribute and not worse on other attributes. In his dominance structuring theory, Montgomery (1983) suggested that if Jane cannot find a dominating alternative, she will change the structuring of the alternatives so that one of the alternatives will eventually become dominant. Dahlstrand and Montgomery (1984) found that individuals, in their search for a dominance structure, applied the Lexicographic heuristic explained earlier (Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999) and the *Maximin* heuristic, choice of an alternative that has the best worst outcome (Dahlstrand & Montgomery, 1984). Another heuristic is Tversky's (1972) *Elimination by aspects* (EBA) heuristic. Here Jane assigns each attribute in an alternative an importance weight and a threshold value. Jane starts by investigating the most important attribute and eliminates alternatives that do not meet the threshold value of that attribute. Jane continues to the second most important attribute value and repeats the same procedure. She continues this procedure until there is only one alternative left.

Fast and frugal heuristics

Alongside the mentioned heuristics, there is a full body of research on heuristics called fast and frugal (F&F) heuristics, which are seen as serving ecological rationality (Gigerenzer et al., 1999; Gigerenzer, 2000). Except for being fast and frugal, what differentiates F&F heuristics from the heuristics mentioned in previous paragraph is that the F&F heuristics are inferential while the above-mentioned ones are preferential (Gigerenzer, 2007). According to Gigerenzer (2007), there are no criteria to evaluate how successful for instance the Lexicographic rule is and therefore the usage of this rule only shows if the decision maker has a preference for using it or not. In contrast, for the F&F heuristics, there are criteria that individuals and researchers can use to make inferences about how well these heuristics work.

The core of F&F heuristics is that they do not require search or integration of all the information (i.e. the attributes). Instead, decision makers using F&F heuristics base their decisions on one attribute, hence the name frugal (Dhami & Harries, 2001; Gigerenzer & Goldstein, 1996; Gigerenzer et al., 1999; Gigerenzer, Hoffrage, & Kleinbölting, 1991). Proponents of F&F heuristics argue that it is more plausible to use these heuristics because they cope with the limited cognitive ability by only searching a limited amount of information (Todd & Gigerenzer, 2003).

One of the most well-known F&F heuristics is the *Take the best* heuristic in which attributes are searched in order of their importance until one discriminates, and then the search stops and all other attributes are ignored (Gigerenzer & Goldstein, 1996). Other examples of F&F heuristics are the *Recognition heuristic* and the *Tallying heuristic*. In the Recognition heuristic, the one out of two alternatives that is recognized by the decision maker is chosen (Goldstein & Gigerenzer, 2002). In the Tallying heuristic, the number of favoring attributes is counted and the alternative with the highest number of favored attributes is chosen (Gigerenzer & Goldstein, 1996). Some of the F&F heuristics could be characterized as F&F trees. Here more than one cue can be considered. However, this does not mean that all the cues will de facto be considered, instead if a decision is not reached with only one cue, then the next cue in the tree is considered and so forth (Fischer et al., 2002).

Studies have shown that sometimes F&F heuristics are more valid and accurate than, for example, regression models (e.g., by having better predictive accuracy of human judgment than the more complex and cognitive demanding heuristics; Gigerenzer and Goldstein, 1996). On the other hand, there are arguments and studies showing that these simple heuristics might not be as simple as claimed. For instance, in order to decide which cue or piece of information to attend to, complex computations are needed (Dougherty, Franco-Watkins, & Thomas, 2008; Juslin & Persson, 2002).

Examples of decision strategies and related theories in a nutshell

Decision makers have a repertoire of decision strategies that they can use in different situations (Payne et al., 1995). Different theories and decision strategies focus in different aspects. In MAU, the focus is to choose the alternative with the highest utility (Keeney & Raiffa, 1993a). Prospect theory, stresses the importance of risks and uncertainty in decisions (Tversky & Kahneman, 1980). Decision strategies based on distances focus on how memory and how distance functions play a role in decision making (Murphy & Medin, 1985). Theories of ideal alternatives, closely related to distance theories, focus on how individual's ideals guide the decision making process (Zakay & Dil, 1984). Heuristics focus on how humans have developed simple rules of thumb in order to cope with the limited cognitive capacity (Dahlstrand & Montgomery, 1984; Gigerenzer & Goldstein, 1999). In this thesis, I will investigate and compare several decisions strategies and theories against each other. In particular, I will investigate and compare MAU, distance functions, a strategy based on an ideal alternative, different heuristics and, regression models. I will also introduce a new strategy that can better account for human decision making compared to these strategies.

Judgment Analysis

One method that makes it possible to study decision strategies and how individuals search and utilize information is judgment analysis (Cooksey, 1996). In order to understand judgment analysis, a short description of its origins is needed. Judgment analysis is a method originating from the *social judgment theory* (SJT), which in turn originates from a Brunswickian approach (Brunswick, 1952). SJT is a framework for studying human judgments and the decision environment. Put differently, SJT concerns people's ability to make inferences about facts in the environment. According to SJT, a judgment process is defined by the integration of information (i.e., cues) from multiple sources. As an example, consider Jane, who is a doctor examining a patient in order to diagnose heart failure. According to SJT, the first step for Jane is to define the cues, in this case the symptoms (e.g., age and gender), that might affect the final diagnosis. The second step is to define the relationship and the importance of the identified symptoms (e.g., how age and gender together can increase or decrease the risk of heart failure). Finally, Jane's diagnosis (i.e., the presence of heart failure or not) is studied and explained with the relation between the different symptoms, and how Jane interpreted the symptoms (for a review see Brehmer & Joyce, 1988). SJT focuses on not only the decision maker and the decision environment but also on how the judgment of one decision maker agrees to the judgment of another.

Judgment analysis is a method for fulfilling the goals of SJT. In judgment analysis, decision makers are asked to make a decision or judgment based on a number of cues. The decision maker's decision policy is then inferred from the way s/he made the decision based on the provided cues (for instance, Jane's way of judging based on the symptoms). This policy or model is then used to predict judgments and decisions without the actual help of the original decision maker (i.e., without the help of Jane). Traditionally, SJT theorists have worked on the supposition that judgments are a product of linear and compensatory integration of cues (Brehmer & Brehmer, 1988). Therefore, in judgment analysis, it is a common practice to use different regression models such as logistic regression (LR) or multiple regression to model and predict judgments and decisions (for overviews see Cooksey, 1996; Engel, Wigton, LaDuca, & Blacklow, 1990; Wigton, 1988, 1996).

In judgment analysis, researchers have relied on the notion that experts have adapted to their task environment and are, hence, superior to novices in their decision-making (for reviews see Dhami, Hertwig, & Hoffrage, 2004). Therefore, most of the judgment and decision data for building models on decision strategies has come from experts. However, as demonstrated by Kee et al. (2003), different degrees of expertise, model, and methods might provide different results. In the study by Kee and colleagues (2003), training-grade pediatricians, consultants, and junior and senior doctors decided, based on 60 patient vignettes, whether to admit a patient because of asthma. Kee and colleagues then used two judgment analysis models, a regression and a F&F one, in order to model the different doctors' decisions. Kee and colleagues found that the regression models' ability to predict decisions was lower for consultants than for training-grade pediatricians. The F&F model did not find such difference. It was concluded that models built on logistic regression are better at capturing decision behavior than the matching heuristic (the F&F strategy they used).

Regression models in judgment analysis

Regression models have proven to be good at modeling experts' decision making (Cooksey, 1996; Dawes & Corrigan, 1974; Goldberg, 1970), especially in policy capturing studies (For examples see Backlund, Bring, Skånér, Strender, & Montgomery, 2009; Dhami & Harries, 2001). Policy capturing, or bootstrapping as it is sometimes called, is a special method in judgment analysis for gaining insight of how decision makers weigh and integrate information in order to make a decision (Zedeck, 1977). Regression models are compensatory models that give a statistical description of a decision (Brehmer & Brehmer, 1998; Wigton, 1988). As an example of regression models in judgment analysis, medical doctors are presented with made-up patient cases where the doctor's task is to make a clinical judgment or decision, which is considered as the dependent variable. Each patient case can consist of a number of cues (e.g., age, gender, blood pressure and so forth), which are considered as the independent variables. The doctors' decisions are then regressed on the provided cues that give a judgment policy or model of how the cues are weighted and integrated. The outcome of the regression model is different weightings of the cues (that is, the weights of the information provided in the cases) and the regression model consists of the cues with the highest weightings (Cooksey, 1996). The model or policy can then be compared with the decision maker's own statement of the judgment in order to see how well it predicts the decision of the decision maker. Judgment analysis is not used only in the medical domain but also in other domains such as accounting and education (Heald, 1991; Waller, 1988).

One of the main critics against regression models is that they are not psychologically plausible because the cognitive ability of the human mind is limited and regression models require extensive calculations (e.g., Kahneman, 2003). Several studies have shown that people are not good at reasoning in a statistical manner, and instead reason in line with a heuristic manner (for examples see Kahneman & Tversky, 1972, 1973, 1982; Tversky & Kahneman, 1974). However, there are situations where people might reason in a statistical manner, especially in situations where the decision maker has expertise (Nisbett, Krantz, Jepson, & Kunda, 1983).

Fast and frugal models in judgment analysis

Lately, many studies in judgment analysis have tested simple heuristics such as F&F models in order to investigate their predictive accuracy. An example of F&F trees used in judgment analysis is the *Matching heuristic* (Dhami & Ayton, 2001; Dhami & Harries, 2001). Similar to regression models, in the Matching heuristic the judgments provided by the doctors are the dependent variable, and the cues are the independent variables. In order to determine the number of cues (independent variables) in the model based on the Matching heuristic, first a critical value for each cue is identified. The critical value is identified as the cue value that has the highest frequency of hits (in heart failure this would be patients diagnosed with heart failure). For example, if out of 100 patients, 70 male patients (the cue here being gender) are diagnosed as having a heart failure (hits) while only 30 patients are diagnosed as not having heart failure (non-hits), then the critical value for gender is the value that has the highest number of heart failure diagnoses, in this case male patients. If the number of diagnoses is the same for both males and females, then the critical value is based on the cue value with the lowest number of "non-hits". When these were also the same, the critical value is chosen randomly. Second, cue validity is identified as the proportion of cases with the critical value that is associated with a diagnosis. For example, if the critical value had 70 hits and 30 non-hits, then 70 is divided by 100 (total number of judgments). Third, the cue validities are ordered by their validity as defined in the preceding step, and this order indicates the order the cues are searched by the model. Finally, in order to calculate how many cues should be included in the model, a fit is calculated by adding each of the cues in the model. The number of cues that lead to the highest fit is chosen as the number of cues in the model. This model is then fitted to the data.

Regression vs. Fast and frugal models

The results from studies that have compared regression models against F&F models point to different directions (e.g., Backlund et al., 2009; Czerlinski, Goldstein & Gigerenzer, 1999; Dhami & Harries, 2001, Gigerenzer & Goldstein, 1999; Kee et al., 2003; Martignon, Kastikopoulos, & Woike, 2008; Smith & Gilhooly, 2006). Some studies show that F&F heuristics have better predictive accuracy of human judgments and decisions compared to regression models (Czerlinski et al., 1999; Gigerenzer & Goldstein, 1996) while other studies show that regression models better predict human judgment and decision (Backlund et al., 2009; Kee et al., 2003). There are good reasons to be cautious in drawing conclusions from the results of the previous studies. For instance, in some of the studies (e.g., Backlund et al., 2009, Dhami & Harries, 2001) the validity of the models has not been measured by using cross-validation. This does not automatically indicate the model's predictive ability, applied on other data sets. In fact, fitting and predicting the same data set can lead to over-fitting (Plutowski, Sakata, & White; 1994; Roberts, & Pashler, 2000). Czerlinski et al. (1999) investigated the predictive accuracy and frugality of F&F and LR strategies by applying cross-validation. They found that the data were over-fitted, especially for the regression models. Other studies show the same results (Martignon, 2001; Martignon & Hoffrage, 2002). In studies where cross-validation has been used, the data have concerned factual relations such as cities being a state capital or not depending on having a soccer team (Czerlinski et al., 1999; Gigerenzer & Goldstein, 1996; Martignon, Kastikopoulos, & Woike, 2008). Consequently, the dependent variables in these studies have concerned ecological facts instead of human decisions or judgments hence having high ecological validity but maybe lower psychological validity. Furthermore, the regression models have often included all the information (i.e., cues). This can led to over-fit in the regression models (Pitt, Myung, Shaobo, 2002).

Judgment analysis in a nutshell

Judgment analysis origins from social judgment theory that is a framework for studying how, for example, information is utilized and how well a decision strategy predicts human judgments. Some common models to capture judgment policies are regression models (Brehmer & Brehmer, 1988) and F&F models (e.g., Dhami & Harries, 2001). However, previous studies have shown conflicting results in whether regression models or F&F models are better at capturing human judgments (for different results see e.g., Backlund et al., 2009; Czerlinski et al., 1999; Dhami & Harries, 2001, Kee et al., 2003; Martignon, Kastikopoulos, & Woike, 2008). I have identified three weaknesses from the previous studies, which might explain why the different results are conflicting. In some studies cross-validation has not been used (e.g., Backlund et al., 2009), or only ecological facts has been used as the dependent variable (e.g., Czerlinski et al., 1999), while in other studies the regression models have used all the available information (Gigerenzer & Goldstein, 1996). Because of the above-mentioned shortcomings of the previous studies, the question of which strategy that can better predict and model for human judgment is still unanswered. In Study I and II, I aim to answer this question by overbuilding the found weaknesses. In Study II, I will also add expertise as a dependent variable.

Research objectives

After all, the ultimate goal of all research is not objectivity, but truth.
~Helene Deutsch

Even though the research on decision making has been interdisciplinary with a long history, there are gaps of knowledge that need to be filled. In this thesis, I aim to pay more attention to a few of these gaps. I will start by investigating some "old" decision strategies that individuals might use and that might best describe human decision making. With old, I refer to the strategies that have been subject of research. I will use judgment analysis to compare the inferential ability of these strategies. The data to build models based on the decision strategies will be ecological data in terms of actual diagnoses and human judgments of medical professionals. The investigated strategies in Study I are two "old" strategies, one compensatory (logistic regression), and one non-compensatory (F&F). However, in judgment analysis most of the times, the judgment and decision data come from experts. As discussed earlier decisions made by experts may differ in many ways compared to decisions made by non-experts (for instance, because experts might, depending on the type of decision, produce better decisions). Therefore, in order to be able to generalize the results to non-experts as well, I will test decision strategies where participants with different degrees of expertise (Study II) make the judgments.

Judgment analysis establishes the inferential ability of different strategies, but not which decision strategy individuals actually prefer or use. Besides, there are many more "old" decision strategies than those tested in Study I and II. Therefore, in Study III I will investigate other compensatory and non-compensatory decision strategies. I will use an experimental setting to investigate the choices and preferences of decision makers. As mentioned earlier, both compensatory and non-compensatory decision strategies have advantages and disadvantages. For instance, a disadvantage of most non-compensatory decision strategies is that they are too simple to represent human decision making. I believe, in line with recent research (Glöckner & Betsch, 2008) that humans search and integrate more information than stated in those simple strategies. In Study III, I will present a "new" decision making strategy that goes beyond the compensatory versus non-compensatory perspective by incorporating the strengths of the two (Study III). This "new" strategy, the Concordant-Ranks strategy, integrates and searches more information (similar to compensatory decision strategies) while being simple and therefore not overloading the human brain (similar to non-compensatory decision strategies). The CR strategy manifests itself by choosing the alternative that is closest to an ideal alternative in terms of distance in a multiattribute decision space. This alternative will also present a pattern (concordant ranks between attribute weights and attribute values in the alternative that is at hand for the decision maker when choosing) when the MAU is the same for the different alternatives. In order to test the superiority of this strategy, I will compare the CR strategy with other commonly used strategies, such as MAU, EBA, distance strategies, and “one reason strategies” such as the Lexicographic and Maximin strategy.

Empirical Studies

To finish it, it took me five years, little did I know I had been doing it all my life.
~Anonymous

Study I - Comparison of decision strategies using judgment analysis

Aim

The aim of this study was to compare, and test the inferential ability of different compensatory (logistic regression) and non-compensatory (F&F) strategies. For this aim, judgment analysis was used. One benefit of using judgment analysis is that the policies it produces are not sensitive to memory recall biases, for example, biased because participants cannot correctly recall how they made a decision (Wilson, Laser, & Stone, 1982). In addition, using judgment analysis has shown to produce reliable models (e.g., Brehmer & Brehmer, 1988). However, there are a few methodological weaknesses in previous studies that have used judgment analysis; (i) low generalizability,(ii) lack of cross-validation, and (iii) inappropriate criteria for inclusion of cues in the models. Some studies have adjusted for some, but not all, of these weaknesses. For instance, concerning low generalizability, some studies, to build models, have used ecological facts and not human judgment as dependent variables. Therefore, the predictability of these models cannot be trusted when they are applied on human judgments. Studies that have used human judgments have not used cross-validation, and studies that have used human judgments or/and cross-validation, have not used proper cue inclusion in the regression models. In the present study, all three mentioned weaknesses were avoided in order to more properly compare different decision strategies. In order to increase the generalizability, the data used in order to model the strategies were based on participant judgments on two different medical decisions, one about prescription of medicine (Hyperlipidemia study), and one about diagnose of heart failure (Heart failure). In the heart failure data, also actual diagnoses of the same patient cases based on a thorough investigation at a heart clinic were used. Moreover, cross-validation was carried out when building the different models. Lastly, in order to build models based on logistic regression, different significant levels for including cues in the model were used.

The five investigated models (two F&F models and three logistic regression models) were tested and compared in terms of:

- Predictive accuracy: how well a model built according to the tested strategies can predict judgments on a new set of data.
- Frugality: amount of information (i.e., cues) that a model consists of and amount of information the model actually utilizes for predicting.

Method

Participants

In order to collect judgments of whether to prescribe or not prescribe a cholesterol-lowering drug (Hyperlipidemia[2]), 38 general practitioners from Stockholm, Sweden, were randomly selected. In order to collect human judgments regarding heart failure diagnose, 68 doctors from Stockholm, Sweden were selected.

Patient cases

In both Hyperlipidemia and Heart failure study, each participating doctor judged 40 actual patient cases. In both studies, participants marked, on a scale from 0-100%, their willingness to prescribe medicine (Hyperlipidemia study) or marked the probability that the patient suffered from heart failure (Heart failure study). The patient cases in the Hyperlipidemia study consisted of seven cues (age, sex, cholesterol value, triglyceride value, diabetes, hypertension, and history of coronary heart disease). The patient cases in the Heart failure study consisted of 10 cues (age, sex, history of myocardial infarction, dyspnea, atrial fibrillation, leg edema, rales, systolic blood pressure, cardiac volume, and signs of pulmonary congestion on lung X-ray). In both studies, participant judgments were coded as 1 if the response was equal or greater than 50%, and coded as 0 if it was 50% or below.

Case sampling

In order to decide which cases to include in the fitting set (i.e., which cases to use in order to build a model) and to use in the prediction set, Monte Carlo simulations were used. For each participant the simulations were repeated 100 times and the participant model consisted of the average value of the 100 simulations. In addition, four fitting sample sizes were used in order to build a model; 25% of the total dataset (10 cases), 37.5% of the total dataset (15 cases), 50% of the total dataset (20), and 75% of the total dataset (30 cases).

[2] Hyperlipidemia is the condition of high cholesterol.

Model building

The strategies, which the models were built according to, were two fast and frugal models (F&F 1 and F&F 2) and three logistic regression models (LR 5, LR 10, and LR Enter) where each regression model used different significance levels (5%, 10%, and 100%) of how many cues to include in the regression model. Below, I will describe each model in more detail.

Fast and frugal model 1(F&F 1)

This model was based on the matching heuristic described by Dhami and Harries (2001). This procedure is identical to the one described earlier in the fast and frugal section of judgment analysis. In short, first, a critical value of each cue is determined. Second, a validity of each cue is calculated. Third, the cue validities are rank-ordered and the fit is calculated by adding one cue at a time, starting with the cue with the highest validity, until the fit does not improve anymore. The model is then established as the model with the number of cues that lead to the highest fit value.

Fast and frugal model 2 (F&F 2)

The simulation of F&F 2 was based on the model described by Backlund et al. (2009). This model is identical to F&F 1 except that in this model the critical value is identified differently. While in F&F 1, the critical value is identified by the cue value that has the highest frequency of hits, in F&F 2 the critical value is identified by the cue value that has the highest frequency of hits and true rejections.

Logistic Regression (LR)

For modeling according to logistic regression, the cues (7 in Hyperlipidemia and 10 in Heart failure) were used as the independent variables and the participant responses were used as the dependent variable. Actual diagnoses from the Heart failure study were also used as dependent variable. In logistic regression, different significance levels can be used in order to determine which cues to include in a model. In this study, three different significance levels were used: 5% (LR 5), 10% (LR 10), and 100% (LR Enter).

Results and discussion

Predictive accuracy

Each of the five models were compared with one another in terms of how accurately they predicted new set of data (predictive accuracy).

Hyperlipidemia

Figure 1 shows the different predictive accuracy values for the different models and different samples. The predictive accuracy of the models was compared by using ANOVA followed by post hoc analysis. The analysis showed that LR Enter had significantly lower predictive accuracy than all the other models. LR Enter had the lowest predictive accuracy in all the sample sizes as well. However, this pattern was only significant in the fitting set using 75% of the total data set.

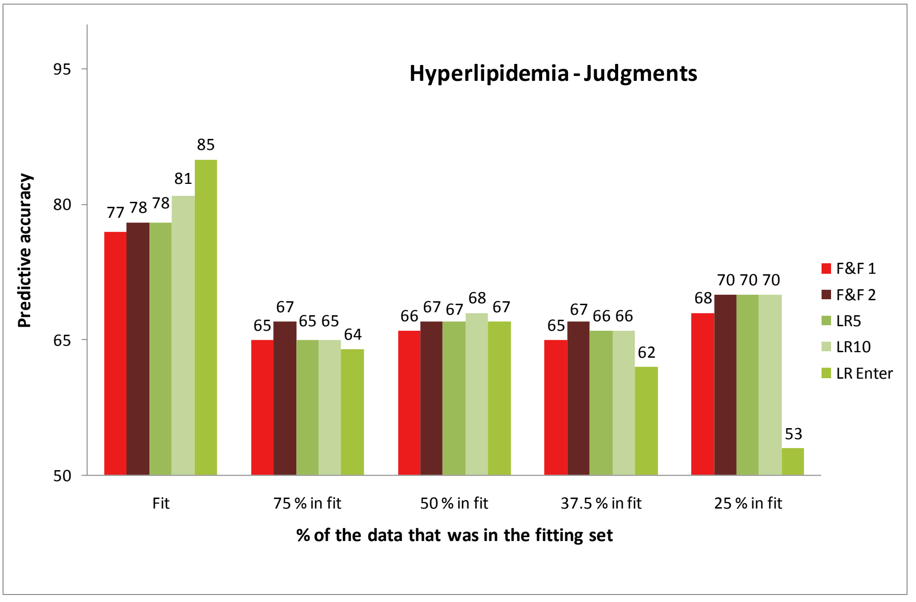

Figure 1. Percentage of fit and predictive accuracy for the different models and different fitting set sizes in the Hyperlipidemia study.

Heart Failure

In the heart failure study, building a model using only 25% of the data (which was equal to 10 cases), meant using the same number of cases as the number of independent variables in the LR Enter model. Therefore, two ANOVA analyses were conducted, one without LR Enter but with fitting set 25% (4 models x 4 samples) and one with LR Enter but without fitting set 25% (5 models x 3 samples). For levels of predictive accuracy for the different models and fitting sample sizes, see Figure 2. The analysis without LR Enter showed no significant main effect of model, meaning that the predictive accuracy for the models did not differ significantly between F&F 1, F&F 2, LR 5, and LR 10. There was also a main effect of sample size, where the greater fitting samples provided higher predictive accuracy. There was a significant interaction effect of model and sample size where LR 5 and LR 10 did slightly better than the other models in all samples except for the fitting set 75%.

In the analysis with LR Enter but without fitting set 25%, there was a main effect of model. There was also a main effect of sample size where further analysis showed that the differences were significant between all sample sizes. Remember that in the analysis where LR Enter was excluded there was no main effect, however when LR Enter was included but fitting set 25% was excluded, there was no main effect. This indicates that LR Enter must have caused the main effect where the predictive accuracy of LR Enter decreased the most compared to the other models, while the predictive accuracy of the other models (F&F 1, F&F 2, LR 5, and LR 10) did not differ significantly.

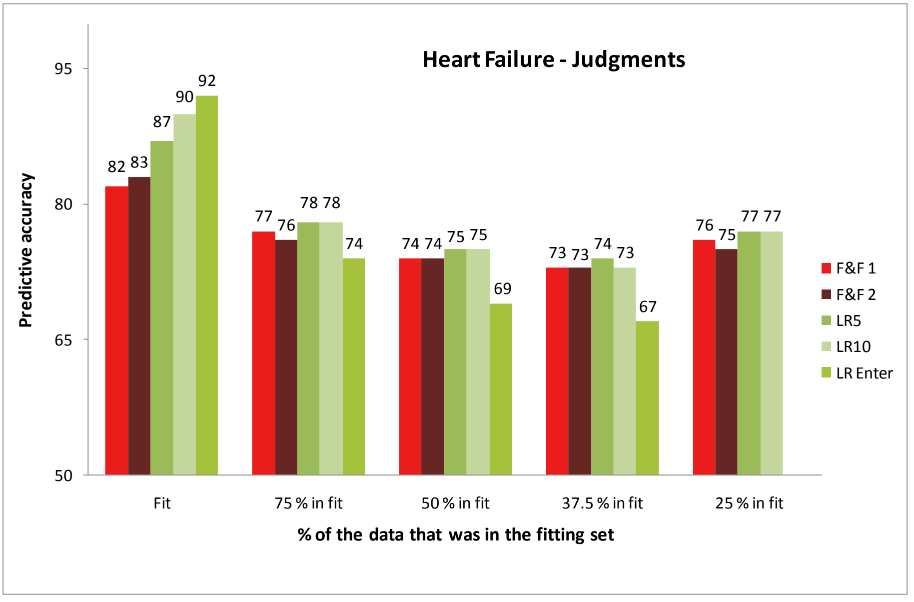

Figure 2. Percentage of fit and predictive accuracy for the different models and different fitting set sizes in the Heart failure study using participant judgments.

The models were also built using actual diagnoses as dependent variables. In contrast to participant judgments, which were given by the participants, actual diagnoses were based on a thorough investigation at a heart clinic. As illustrated in Figure 3, LR Enter provided the highest predictive accuracy when it was not cross-validated but when cross-validated, instead F&F 1 provided the highest predictive accuracy (in all sample sizes except for fitting set 37.5% where it did equally well as F&F 2 and LR 10). However, notice that this difference was very small.

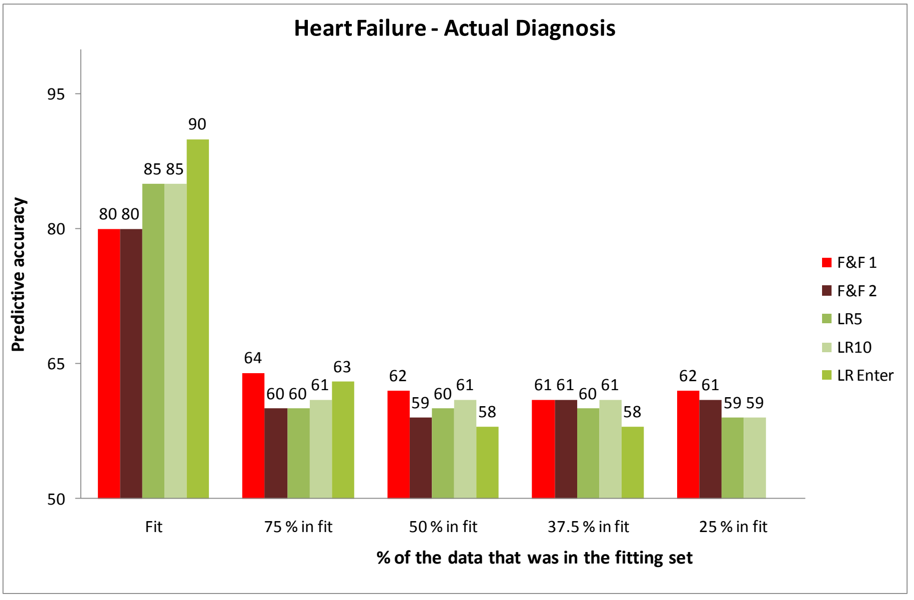

Figure 3. Percentage of fit and predictive accuracy for the different models and the different fitting set sizes in the Heart failure study, using actual diagnoses.

In models based on both participant judgments and actual diagnoses, the trend was the same with regard to the predictive accuracy of LR Enter. However, after cross-validation the predictive accuracy of all the models decreased markedly more when the models were built using actual diagnoses compared to when participant judgments were the dependent variable.

In sum, results show in terms of predictive accuracy fitting set sample size mattered more in the Heart failure study while mattered only in one of the fitting sample sizes (the greatest one) in the Hyperlipidemia study. However, not considering the sample size, it seems that in both studies when cross-validation is used, LR Enter provides the lowest predictive accuracy compared to the other models.

Frugality

As mentioned earlier, in contrast to previous studies, which have measured frugality in terms of the number of cues in the model, in this study frugality was measured on two dimensions. One dimension was the number of cues in the model (cues in model). Another dimension was the number of cues actually utilized for predicting (cues actually utilized).

Hyperlipidemia – Cues in Model

In terms of cues in model, ANOVA showed a significant main effect of model, and an interaction effect between model and fitting sample. In all sample sizes, the LR 5 model consisted of fewer cues than any other model (see Table 1). Post hoc analysis on models showed that the differences were significant between all models, except for the difference between F&F 1 and LR 10.

Turning to the different fitting samples, the smaller the fitting set sample was, the more cues in the model for the F&F models while the opposite was true for LR 5 and LR 10. That is, in the smaller the fitting set sample was, the fewer cues in LR 5 and LR 10. Additionally, for the smallest fitting samples, LR 5 (1.18, 1.45) used fewer cues than F&F 1 (2.53, 2.40) and F&F 2 (3.19, 3.03).

Table 1. *Frugality in Terms of Cues in Models and Cues Actually Utilized for the Different Models and Different Fitting Sets in the Hyperlipidemia Study.*

	Number of Cues in the Model				
	Fit	75% in fit	50% in fit	37.5% in fit	25% in fit
F&F 1	2.37	2.34	2.37	2.40	2.53
F&F 2	2.32	2.39	2.56	3.03	3.19
LR 5	1.74	1.76	1.56	1.45	1.18
LR 10	2.63	2.41	2.19	2.06	1.63
LR Enter	7.00	7.00	7.00	7.00	7.00
	Number of Cues Actually Utilized				
	Fit	75% in fit	50% in fit	37.5% in fit	25% in fit
F&F 1	1.61	1.69	1.27	1.61	1.31
F&F 2	1.68	1.77	1.36	2.05	2.10
LR 5	1.74	1.76	1.56	1.45	1.18
LR 10	2.63	2.41	2.19	2.06	1.63
LR Enter	7.00	7.00	7.00	7.00	7.00

Hyperlipidemia – Cues Utilized by Model

In terms of number of cues actually utilized, ANOVA showed a significant main effect of model, significant main effect of fitting sample, and an interaction effect between model and fitting sample. As seen in Table 1, regarding cues actually utilized by the model, the F&F 1 model utilized the fewest number of cues in the greater fitting samples sizes. The differences were significant between all models except for between F&F 1 versus LR 5 and between F&F 2 versus LR 5 and LR 10 when the fitting set was small (75%). Further, there were significant differences between fitting set sample 25% and both 37.5% and 75%, between 37.5% and 50%, and between 50% and 75%. Results showed also an interaction effect between sample size and model. Number of cues in F&F 1 decreased when the fitting set sample got smaller, while in F&F 2 number of cues increased.

The regression models use the same number of cues in model and cues actually utilized. However, this is different for the F&F models. The F&F models did not use all the cues that the model consisted of in order to predict.

Heart Failure – Cues in Model

In terms of number of cues in model, ANOVA showed a significant main effect of model, a significant main effect of fitting sample, and an interaction effect between model and fitting sample. As seen in Table 2, LR 5 used fewest cues in a majority of the fitting sets samples (except for fitting sample 75%). LR 10 used fewer cues compared to the F&F models in the smaller fitting sample sizes. Number of cues in the LR models decreased due to fitting set sample size while the number of cues in the F&F models increased. The differences were significant between all fitting sets. In addition, in the smallest fitting set sample the mean number of cues in model was lower for LR 5 (1.21, 1.58) than for F&F 1 (2.83, 2.65) and F&F 2 (3.18, 3.23).

Turning to actual diagnoses, as seen in Table 2, LR 5, followed by LR 10, used fewest numbers of cues in model while F&F 2 model had more cues than any other model.

Table 2. *Frugality in Terms of Cues in Models and Cues Actually Utilized for the Different Models and Different Fitting Sets in the Heart failure Study.*

	Number of Cues in the Model				
	Fit	75% in fit	50% in fit	37.5% in fit	25% in fit
Participant Judgments					
F&F 1	2.07	2.39	2.53	2.65	2.83
F&F 2	2.93	2.95	2.99	3.23	3.18
LR 5	2.48	2.43	1.90	1.58	1.21
LR 10	3.33	3.44	2.85	2.34	1.73
LR Enter	10.00	10.00	10.00	10.00	10.00
Actual Diagnosis					
F&F 1	3.00	2.73	2.56	2.59	2.75
F&F 2	4.00	3.19	2.96	3.12	3.15
LR 5	2.00	1.65	1.78	1.41	1.19
LR 10	2.00	2.36	2.48	2.34	1.77
LR Enter	10.00	10.00	10.00	10.00	10.00
	Number of Cues Actually Utilized				
	Fit	75% in fit	50% in fit	37.5% in fit	25% in fit
Participant Judgments					
F&F 1	1.55	1.39	1.78	1.58	1.72
F&F 2	1.99	1.56	1.35	1.78	2.01
LR 5	2.48	2.43	1.90	1.58	1.21
LR 10	3.33	3.44	2.85	2.34	1.73
LR Enter	10.00	10.00	10.00	10.00	10.00
Actual Diagnosis					
F&F 1	2.36	2.10	1.97	2.00	2.05
F&F 2	2.88	2.35	1.49	2.34	2.33
LR 5	2.00	1.65	1.78	1.41	1.19
LR 10	2.00	2.36	2.48	2.34	1.77
LR Enter	10.00	10.00	10.00	10.00	10.00

Heart Failure – Cues Utilized by Model

In terms of number of cues actually utilized, ANOVA showed a significant main effect of model, a significant main effect of fitting sample, and an interaction effect between model and fitting sample. As seen in Table 2, in the bigger fitting samples F&F 1 utilized least number of cues compared to the other models. Furthermore, in the F&F models the number of cues utilized increased in the smaller fitting samples. Post hoc analysis showed that while all the models differed significantly, regarding fitting sample size, differences were significant between fitting set 75% and both 37.5% and 50%, between 37.5.5% and 75%, and 50% and 75%. Regarding actual diagnoses, LR 5 utilized fewest numbers of cues followed by F&F 1.

In sum, it seems that also the LR models are as frugal, if not more, than the F&F models. In addition, there seem to be a linear relation between frugality and fitting set sample size while such linearity was not found in the F&F models. However, this relationship requires that the amount of information in the model can be limited, which has not been the case in previous studies such as those by Gigerenzer and Goldstein (1996).

Conclusion

Overall, our data suggest that also when cross-validation is used, the regression models (or compensatory strategies) predict as efficiently as the so-called F&F heuristics, if only significant cues are included in the model. In fact, because the models built on logistic regression also used very few cues, they also can be considered as frugal. In addition, because the regression models use the same number of cues in model as number of cues actually utilized, they can be considered as more frugal than the F&F models. In sum, it can be noted that the compensatory strategy, in this case logistic regression, had equally high predictive accuracy while being more frugal than the F&F strategies.

Study II - Comparing decision strategies while controlling for expertise

Aim

In Study I, it was found that if the studies are carried out properly then regression models are as good as, if not better, than the F&F models in terms of predictive accuracy and frugality. However, earlier studies have shown that the degree of expertise of participants lead to different decisions, especially in the case where expertise and knowledge matters (e.g., Shanteau, 1991; 1992; Jacoby et al., 2001). Consequently, the results from Study I can only be generalized to those with the same level of expertise as our participants in Study I. Therefore, in order to increase the generalizability of the results from Study I, Study II was conducted.

The main aim of Study II was to investigate whether different decision strategies are differently suitable when the judgments come from individuals with different degrees of expertise. For this aim, different strategies: F&F strategies (F&F 1 and F&F 2) and logistic regression strategies (LR 5, LR 10, and LR Enter) were cross-validated and tested. The judgments came from individual doctors with three different degrees of expertise: students, general practitioners, and cardiologists. These different experts differ both in terms of knowledge (more knowledge in the higher degree of expertise) and in terms of experience (longer practice in the higher degree of expertise).

Method

Participants

The participants in this study were 21 medical students (14 women) from two courses in family medicine, 27 general practitioners (13 women) randomly selected from a list of specialists in family medicine, and 20 cardiologists (5 women) from two cardiology clinics. The medical students were in their last semester (11 semesters) in medical school. The general practitioners had practiced for 9.8 years in average. The cardiologist, which had practiced as general practitioners for some years before becoming cardiologists, had practiced as cardiologists for 11 years in average. The same data set was also used in Study I.

Procedure and model building

The procedure of getting participant judgments, presentation of the patient cases, and model building was identical to the Heart Failure study in Study I. Similar to Study I, the models were two fast and frugal strategies (F&F 1 and F&F 2) and three logistic regression strategies (LR 5, LR 10, and LR Enter). However, because in Study I, sample size was of little importance for the predictive accuracy, only one sample size consisting of 75% in the fitting set (30 cases) and 25% in the prediction set (10 cases) was used.

Results and discussion

Fit and prediction

Table 3 shows the predictive accuracy for each model and expertise level. Even though ANOVA analyses showed a significant main effect of model, there was no significant interaction effect between the predictive accuracy of the five models and participants with different degrees of expertise. Post hoc analysis showed that in fit the differences were significant between all models except for Original and LR10, and Extended and LR10. In prediction, only LR 5 and LR 10 provided significantly higher predictive accuracy as compared to LR Enter.

Table 3. *Mean and (Standard Deviation) of Fit and Prediction (in Percent) of Different Models for Participants with Different Degrees of Expertise.*

Model	% Fit	% Prediction
	Students	
F&F 1	83.18 (6.56)	75.14 (10.03)
F&F 2	84.20 (6.37)	74.19 (9.90)
LR 5%	88.12 (6.07)	76.43 (9.75)
LR 10%	91.09 (5.79)	76.19 (9.22)
LR Enter	95.69 (5.11)	72.43 (6.28)
	General Practitioners	
F&F 1	85.63 (6.03)	77.22 (9.14)
F&F 2	86.33 (5.75)	76.33 (9.00)
LR 5%	89.56 (6.39)	78.93 (10.17)
LR 10%	92.41 (6.09)	79.00 (9.48)
LR Enter	96.78 (4.24)	76.00 (8.31)
	Cardiologists	
F&F 1	84.76 (6.03)	77.82 (8.50)
F&F 2	85.46 (5.70)	77.15 (9.23)
LR 5%	87.35 (4.77)	78.51(6.98)
LR 10%	85.71(20.79)	78.43 (6.35)
LR Enter	89.85 (21.60)	73.60 (7.33)

Number of cues in Strategy

As seen in Table 4, LR 5 used fewer number of cues. ANOVA analyses, however, showed no significant main effect of expertise or interaction effect of expertise and model.

Table 4. *Frugality of the Models in Terms of Number of Cues in Model.*

Model	Students	General Practitioners	Cardiologists
Original	2.60 (0.77)	2.43 (0.70)	2.57 (0.70)
Extended	3.12 (0.55)	2.98 (0.68)	3.11 (0.52)
LR 5%	2.16 (0.82)	2.35 (0.69)	2.24 (0.85)
LR 10%	3.07 (1.05)	3.39 (0.93)	3.19 (1.06)
LR Enter	10.00	10.00	10.00

Conclusion

To sum up, similar differences in the models, which were found in Study I, was also found in Study II. However, even though there were differences between the models dependent on different degrees of expertise in terms prediction and frugality, these differences were not significant. Therefore, it is plausible to conclude that no matter expertise level, compensatory decision strategies are about equally good as the non-compensatory F&F decision strategies in terms of predictive accuracy and frugality.

Study III – The "New" Concordant-ranks Strategy

Aim

In Study I and II, it was found that compensatory strategies provided equally high predictive accuracy than the non-compensatory decision strategies. However, even though the results from Study I and II reveal how adapted decisions are to the environment, they were not focused on how decision makers actually make decisions. Therefore, the aim of this study was to investigate which decision strategies decision makers actually use and whether the differences between the strategies are similar to those in Study I and II. Because both the compensatory and non-compensatory strategies provided high predictive accuracy, the results from Study I and II suggest that maybe a strategy that combines the strengths of both compensatory and non-compensatory decision strategies might better account for human decision making. Therefore, another aim of this study was to test a strategy that combines some of the strengths of both compensatory and non-compensatory decision strategies.

In Study III participants had to, choose the most promising alternative, out of five alternatives. The alternatives in a choice set were equally attractive in terms of having equal MAU but differed in terms of being in line to a specific decision strategy. Therefore, participants' choice would reveal the strategy they used. One of the strategies was a "new" strategy, the Concordant-Ranks strategy (CR), which I describe in more detail in the next section. The other tested strategies were: Lexicographic, Maximin, EBA, MAU, Euclidean distance, or some other arbitrary strategy.

Using the CR strategy means choosing the alternative that is closest to an ideal alternative. As I will later show, such an alternative will also have the same rank-order within its attribute values as the attribute importance weights, given that all alternatives are equally attractive in terms of MAU. However, even if the CR alternative is chosen in a majority of the times, and this alternative is proven to be closer to an ideal alternative than other alternatives, it can be argued that the CR alternative was chosen as a tiebreaker and not because it was closer to the ideal alternative. Therefore, in an additional task participant had to evaluate the attractiveness of the different alternatives one by one. That is, in contrast to the decision task where participants had to choose one alternative out of five, in this task participant only saw one alternative at a time while evaluating it. Because in the other tested strategies attributes are compared with one another among the different alternatives, in the attractiveness evaluation task, these alternatives should not be evaluated as more attractive. CR does not require comparison between other alternatives; instead, the evaluated alternative is compared with an ideal alternative. Therefore, if it is true that CR is used as a proxy for minimizing the distance to an ideal alternative, then the CR alternative should receive higher attractiveness evaluations.

To increase the validity of the results, the alternatives were individually tailored by using attributes that the participants themselves provided. In Experiment 1, two different procedures were used for identifying attributes: inferring attributes from thinking aloud (Thinking-aloud) about an imagined decision or directly stating (Direct-stating) relevant attributes. This precaution is in line with previous research showing that different procedures for getting data on decision processes (e.g., think aloud data or retrospective reports) may influence the decision process (Russo, Johnson, & Stephens, 1989). Similarly, in order to be sure that the procedure for constructing alternatives did not favor any of the tested strategies, in Experiment 2, the constraints for constructing alternatives were relaxed. In Experiment 2, one alternative was in line with the CR strategy while the other alternatives consisted of arbitrary attribute values.

What is “The Concordant-Ranks Strategy”?

In order to explain the rationale behind CR an example is needed. Jane, the bride to be, has an idea of what kind of venue she wants for her wedding. She knows that the attributes location, size, and environment are the most important attributes where the importance weights are 3, 2, 1, respectively). Using the same measuring scale for all the attributes (from 0 to 100), her ideal alternative would have maximally perfect values (i.e., 100) on these attributes. She has already eliminated those venues that are far away from her ideal venue (in Study III, this is achieved by eliminating alternatives with low MAU), and ended up with two venues. Still, the venues that she is looking at are not 100 on all the attributes because such venue would be outside the price budget. Jane assigns the following points to the two venues on each attribute: Venue A: 65 (location), 60 (size), 50 (environment); Venue B: 70 (location), 30 (size), 95 (environment). Because both venues have the same overall attractiveness (if we use MAU as an attractiveness scale then both venues would have the same MAU equal to 365), Jane cannot choose between the two. Therefore, she starts investigating the two venues on each of her important attributes in a non-compensatory manner, starting with the most important attribute location. Looking at location, she realizes that Venue B is superior (70 vs. 65). However, she does not want to base her decision only on location because the other attribute values might be unattractive (if she would have stopped her information search now, her decision strategy would have been similar to F&F or lexicographic heuristics). Thus, she also investigates the value on her second most important attribute, size. She finds that the leading venue, Venue B, is unattractive regarding size (value equal to 30) and Venue A has a better value on size (60). She then continues to the third most important attribute and finds that Venue B (value equal to 95) is superior compared to Venue A (value equal to 50) on environment. However, because different attribute values favor different venues, she cannot choose one. Therefore, she decides to choose the venue that is most similar to her ideal venue (the one with maximal values on each attribute). Jane sees that Venue A has an appealing pattern where the rank order of attribute importance weights and attribute values coincide, whereas this is not true for Venue B and therefore, she finds Venue A as more similar to her ideal venue.

What she might not know is that in Venue A, all the *weighted* distances to her ideal alternative on each attribute (attribute weight x (100 – attribute value)) are relatively short for all attributes. This is shown in a mathematical proof in appendix A in Study III. This is because the rank-order of the attribute values coincides with the rank-order of the attribute importance weights. The choice process of Jane gives a rationale behind the processes of the CR strategy, where weights of the underlying attributes are taken in consideration when trying to find an alternative that is proximate to an ideal alternative.

Method

Participants

In Experiment 1, 61 (42 women) participants and in Experiment 2, 31 (21 women) participants took part in the study. Participants could choose to receive either course credits or a movie ticket as reimbursement for their participation.

Procedure

Both experiments in this study followed the same 5-step procedure:

1. *Presentation of experiment and the think-aloud task.* In Experiment 1, one group of participants were only informed about the purpose of the experiment (Direct-stating group) while the other group were also introduced to the think-aloud method, because they were going to think aloud in some parts of the experiment (Think-aloud group). In Experiment 2, only the Direct-stating procedure was used.

2. *Identification of attributes.* In the Direct-stating group, participants were asked to state their most important attributes when choosing a house/car. In the Think-aloud group, participants were asked to imagine they were going to buy a house/car and think aloud while doing so. Attributes provided by the Think-aloud group were identified by rerunning think-aloud recordings. In both groups and both experiments, some attributes were relabeled. For instance, if the participant had said that it was important for him/her to have a big apartment, this attribute was relabeled as an attribute called size. After re-labeling, the attributes were written in the computer program (see Figure A1 in Appendix A)
3. *Review and ranking of attributes.* Participants were asked to distribute 100 points between the attributes they had provided, in a manner so that the points would reflect how important each attribute was (see Figure A2 in Appendix A). Further, participants were not allowed to give zero or equal points to two different attributes.
4. *Presentation and choice of alternatives.* Participants were instructed to choose the most promising alternative out of five alternatives. This was repeated 10 times, each time with five new alternatives. Each alternative consisted of the attributes the participant had provided earlier. Each of the five alternatives was constructed according to the tested decision strategies: Lexicographic, Maximin, Euclidean, weighted Concordant-ranks, and an alternative consisting of arbitrary values. For an example of how the alternatives were presented see Figure A3 in Appendix A.
5. *Attractiveness evaluations.* Participants were shown one alternative and were asked to rate the alternative according to how attractive it was perceived on a scale from 0 to 100(see Figure A4 in Appendix A). This was done for 10 different alternatives.

Results and discussion – Experiment 1

Choices

As seen in Table 5, the CR alternative was chosen (significantly) more often than the other alternatives. The lexicographic alternative was chosen significantly more often than the arbitrary alternative, and the maximin alternative was chosen significantly more often than the lexicographic and the arbitrary alternative.

Table 5. *Choice Frequency for Each of the Five Types of Alternatives.*

	Think aloud		Direct stating	
	Frequency	%	Frequency	%
Chosen alternative				
Lexicographic	77	17.1	24	15.0
Maximin	80	17.8	36	22.5
CR	187	41.5	65	40.6
Euclidean	59	13.1	18	11.3
Arbitrary	47	10.4	17	10.6

The method for getting attribute weights (step 3 in the procedure) could result in more equal weights than is true for other weight elicitation methods. For instance, this method could lead to two attributes having the importance relationship 55:45 while other methods could lead to for example 70:30 for the same attributes (Wedell & Parducci, 1988). Too equal weights could lead to MAUs that in fact were not equal, which in turn could mean that the choices were not based on CR but maybe MAU calculated . Therefore, a new MAU calculation was tested, where the weights were stretched out. The CR alternative and highest "new" MAU alternative coincided in 52% of the cases. However, choices of the CR-alternative were significantly more common (42% of the choices) than choices with highest new MAU-value (32% of the choices). It can be concluded that the predominance of CR-choices in line with CR, seen in Table 5, does not seem to result from an equal weighting bias.

Attractiveness evaluations

As seen in Table 6, the CR alternatives were evaluated as significantly more attractive compared to all the other alternatives and the maximin alternatives were evaluated as significantly more attractive than the Euclidean and arbitrary alternatives. The CR alternative had the lowest WED followed by the maximin, lexicographic, arbitrary, and Euclidean alternative in that order, meaning that the CR alternative had the shortest WED to an ideal (85.6 % of the times).

Table 6. *Means, Standard Deviations (SD) for the Attractiveness Evaluations, Mean WED[a] Values of Each of the Five Alternative Types and Percent of Alternative Type With the Lowest WED.*

	Think aloud			Direct stating			Both groups
Type of alternative	M	SD	WED[a]	M	SD	WED	% lowest WED
Lexicographic	56.0	17.0	1052	64.9	17.7	1026	8.0
Maximin	59.3	17.1	1024	66.8	18.2	1024	3.3
CR	65.0	12.4	949	72.3	18.2	934	85.6
Euclidean	50.4	18.7	1121	60.9	21.4	1134	0.2
Arbitrary	53.8	14.9	1065	61.6	18.9	1058	3.1

[a] Weighted Euclidean distance

Results and discussion – Experiment 2

Choices

Similar to Experiment 1, the CR alternative was significantly more chosen (29.4%) compared to the arbitrary alternatives (17.7%).

Attractiveness evaluations

The CR alternative was rated as significantly more attractive (70.23) than the arbitrary alternatives (65.15).

Conclusion

The results of Study III show that concordance between the rank order of the attribute values and attribute weights of an alternative seems to play an important role when choosing the most promising alternative. This concordance is important also in attractiveness judgments of the alternatives. The CR strategy was shown to be superior compared to MAU, EBA, Euclidean and other “old” commonly used strategies. Furthermore, the alternative consistent with the CR strategy had also the shortest weighted Euclidean distance to an ideal (for proof, see Appendix A in Study III).

Discussion

A scientist's aim in a discussion with his colleagues is not to persuade, but to clarify.
~Leo Szilard

Below I will first discuss Study I and II combined, and then discuss Study III. Afterwards I will give a general discussion of all three studies.

Main Findings

Something old

Investigation of some existing decision strategies

In Study I and II, the tested strategies were two F&F models, which fall into the category of non-compensatory decision strategies, and logistic regression models, which fall into the category of compensatory decision strategies. Results showed that logistic regression, when the information inclusion level was limited, provided equally high predictive accuracy as the tested F&F models. Additionally, the logistic regression models with limited information used less information in the models and sometimes utilized fewer cues than the F&F models. Because logistic regression models combine and compensate information, one would expect them to use more information than the tested F&F models. However, this was not the case, at least when only significant cues were considered. Important here is also the difference between the numbers of cues a model consists of and number of cues actually utilized by the model. If this difference is small then it implies that the model is better at actually utilizing the information in a saturated way. However, results showed that in the F&F models, the number of cues actually utilized was 26-48% less than the number of cues in the model.

In Study I, the different models (built according to five different strategies) were tested on participant judgments as the dependent variable, but also on actual diagnoses. Both the actual diagnoses and participant judgments gave the same fit in all the models when not cross-validated. However, when the data was cross-validated, the predictive accuracy in actual diagnoses decreased markedly more than the participant judgments.

When modeling using actual diagnoses as the dependent variable, the F&F models used more information than models using participant judgments as the dependent variable. This was also the case in terms of the amount of information actually utilized. However, in the logistic regression models the opposite was the case. Here LR 5 and LR 10 used fewer cues in models using actual diagnoses as the dependent variable compared to models using participant judgments as the dependent variable. Considering that actual diagnoses, as compared to participant judgments, provided lower predictive accuracy, it is plausible to assume that the realism of the judgmental task used for building models is important when comparing different decision strategies.

An interesting finding from Study I and II is that in both studies the compensatory decision strategies used a limited portion of information in the model (even though compensatory) and still were comparable with F&F models in terms of predictive accuracy. This makes the compensatory decision strategies (logistic regression in this study) equally or even more frugal than non-compensatory decision strategies (F&F strategies in this study). Therefore, it makes sense to conclude that compensatory decision strategies can better predict human decision making in the studied tasks.

As mentioned earlier, previous studies have shown conflicting results on whether F&F or regression models are better for predicting judgments. For instance, in one study Dhami and Harries (2001) found that both regression and F&F models were equally good at predicting judgments while in another study (2001), they found that the F&F models were better. One can wonder who is right. In study I and II, the methodological strengths from previous studies were retained, whereas the found methodological weaknesses were avoided. These weaknesses have made the comparison and testing of different decision strategies unfair and biased the results in favor of F&F strategies. Therefore, it is plausible to assume that the results from studies I and II are more accurate than previous studies.

So what were the found weaknesses in earlier research? The first avoided weakness regarded cross-validation. In cross-validation, a subset of the data is used for building a model and the rest is used to test the validity of the built model, by letting the model predict the judgments in the remaining data. When cross-validation is not used, fitting and predicting is based on the same data. When the data is not cross-validated the predictions will be better than they actually are and hence overemphasizing the superiority of the model. In study I and II, it was indeed found that not cross-validating leads to biased results.

The second weakness regarded the dependent variable. Most of the strategy comparisons involving F&F versus logistic regression have used ecological facts rather than judgments as the dependent variable (i.e., Gigerenzer & Goldstein, 1996). This is not necessarily a weakness, but rather restricts the generalizability of the results. In Study I and II both actual diagnoses and participant judgment were used as the dependent variable. The difference between actual diagnoses and participant judgments is that in actual diagnoses, both dependent (the actual judgment) and independent variables (the cues) are ecological facts while in participant judgments, the judgments are more subjective (i.e., weaker related to actual disease in our case). Models built on one of the two sources of dependent variable can give different outcomes and therefore, using both types of data makes the results more generalized. Results from Study I and II showed that indeed the source of the judgments influence the results.

The third weakness regarded the amount of information included in the regression models. Building models on all available cues or information means including also information that does not contribute to the prediction and hence might lead to over-fit, resulting in lower predictive accuracy. For instance, when the logistic regression models consisted of only the significant information or cues, logistic regression provided equally high predictive accuracy of decision behavior. This is something that, for some unknown reason, has been overlooked in previous studies where the compensatory decision strategies have used all the available information (e.g., Gigerenzer & Goldstein, 1996; Martignon et al., 2008). It is therefore, reasonable to assume that indeed, the weaknesses now discussed sometimes have lead to biased results in previous studies in favor of the F&F strategies.

A matter of expertise

It is common belief that experts make better decisions; therefore, usually the judgment data used in judgment analysis in order to model decisions has been judgments from experts. This was the case in Study I. However, because in Study I, the aim was to compare different strategies, independent of expertise, we cannot be sure that the results can actually be generalized to individuals with less expertise. The different decision strategies and the way experts utilize information might not be the same as non-experts. Thus, in Study II, the judgments were from three groups of doctors, each with different degrees of expertise. The groups were formed according to Shanteau's (1988) definition of different degrees or levels of expertise; naïve decision makers, novice decision makers, and expert decision makers.

Some studies have shown that experienced decision makers make better decisions (e.g., Jacoby et al., 2001). If this is also true in judgment analysis, the models built using judgment data from participants with higher degrees of expertise (cardiologists) should provide higher predictive accuracy than models based on novice decision makers (general practitioners) and naïve decision makers (medical students) in that order. When the same decision strategies tested in Study I also were tested in Study II, but now adding expertise as an independent variable, it was again found that the compensatory strategies (logistic regression) provided equally high predictive accuracy of judgments than the non-compensatory heuristics (F&F), however, independent of degrees of expertise. This does not necessarily mean that Jacoby et al. (2001) are wrong but that other factors than expertise can be important when creating models in judgment analysis. Concerning frugality and expertise, Shanteau argues that experts are more frugal than non-experts are (Shanteau, 1991; 1992). If this is also true in judgment analysis, then models based on those with higher degrees of expertise should be more frugal because they can ignore unimportant information. In contrast, Jacoby et al. (2001) argued decision makers with higher degrees of expertise should use more information compared to non-experts because experts have the capacity. If this is also the case in judgment analysis, then models based on those with lower expertise should be more frugal. There was, however, no overall significant difference in frugality for different levels of expertise. Two explanations to the non-differences are possible. One is there is actually no difference, at least not in decisions that are similar to the one in Study II, and the definitions of Jacoby et al. (2001) and Shanteau (1991, 1992) do not apply in the tested setting. Another explanation is that it is possible the differences would have been significant if degrees of expertise had been established differently. For instance, Kee and colleagues (2003) found that there were differences between the models (regression versus F&F) and levels of expertise but they defined expertise differently than how expertise was defined in Study II. Another reason for the difference between their results and the results in Study II can be due to the discussed weaknesses. For example, Kee and colleagues did use neither cross-validation nor different levels of information inclusion in their regression model.

Shanteau and colleagues (Shanteau, Weiss, Thomas, & Pounds, 2002) argued that the nature of the decision task also can affect expert decision making. In Study II, the task of diagnosing heart failure can be seen as a dynamic task (i.e., involving human behavior). As mentioned by Shanteau (1992), in situations involving dynamic decision tasks, experts are not necessarily better or more predictable. This can explain why in Study II the predictive accuracy of the models based on expert judgments did not differ from models based on non-expert judgments. Expertise is very domain specific (Ericsson et al., 1993; Shanteau, 1992) and can vary, not only between domains but also, between different type of decisions in the same domain (i.e., different diagnoses with different task difficulty). For instance, it has been shown that people, being expert or not, have difficulties thinking in terms of probabilities (Kahneman & Tversky, 1974), which was the response-mode used in Study I and II. In addition, the participants with different degrees of expertise could have been differently certain of their judgment. The responses given in probability were coded as either zero or one. However, perhaps more coding categories or using the probabilities themselves could have better differentiated between levels of expertise. For instance, those with higher degrees of expertise can be more confident (Mahajan, 1992) with their response and hence give a probability that is closer to either diagnose or non-diagnose. Those with lower degree of expertise might give probabilities that depending on coding schema lead to different judgments.

In sum, the results of Study II strengthens the results from Study I, suggesting that even though both compensatory and non-compensatory strategies had equally good predictive accuracy, the compensatory strategies are slightly better at predicting human decision behavior, independent of degrees of expertise, because they are more frugal.

Something new

The introduction of a new decision strategy

In Study I and II, while the non-compensatory strategies (i.e., F&F) sometimes used more information compared to the compensatory strategies (i.e., logistic regression), they still predicted rather well. One reason for both strategies doing well could be that each strategy has strengths and weaknesses. Compensatory decision strategies integrate information, for example by compensating one attribute with another, and are hence more nuanced. The judgment of some patient cases might require the decision maker to compensate or integrate different pieces of information while in other patient cases, non-compensatory strategies might do equally well or even better because in these cases, there is no need for integrating and combining the information. In addition, regression models might describe the decision policy of some participants better than F&F and vice versa. Nevertheless, the results from Study I and II speak more about the inferential ability of decision strategies, and less about decision makers' preferences of these strategies. Recent research shows that decision makers integrate the information, use compensatory strategies (e.g., Newell & Bröder, 2008), and are capable of handling computation-demanding decision strategies (Juslin & Persson, 2002). Therefore, it is plausible to hypothesize that the results from Study I and II can also be extended to how decision makers actually make decisions. In Study III, some of the advantages of both compensatory and non-compensatory strategies were combined and a new strategy– The concordant ranks strategy (CR) – was investigated. CR shares the simplicity non-compensatory decision strategies provide (when the attribute value of each attribute is investigated and compared to the importance weight of the same attribute in the ideal alternative) while at the same time integrate the information (when holistic pattern of the alternatives are compared to an ideal). Note that CR does not require that one attribute can be compensated by another attribute, as is in compensatory strategies, but integrates information in order to check whether a certain holistic pattern can be found in the alternative.

Furthermore, compared to the other tested strategies, CR is the only strategy that is descriptive, prescriptive, and normative. Remember that descriptive models describe how decision makers actually make decisions. This is true in CR that empirically gave account for how decision makers go about in order to make a decision. Normative models are theoretical descriptions of how decision makers should make decisions. Because CR implies choosing an alternative with shortest WED to the ideal alternative, it can be seen as a normative model. Prescriptive models are links between the descriptive and normative models. Therefore, CR can also be seen as a prescriptive model where how decision makers actually make decisions is in line with a theoretical rationale. In contrast, the other tested strategies corresponded to only one of the three types of models or at best to two of the models. For example, MAU is a normative model that can also act as a prescriptive model or F&F models are prescriptive models that can also be descriptive.

The concordant-ranks strategy put to the test

Introducing a new strategy is not particularly special; this is why there is a large body of different strategies. However, what validates a new strategy is that, when it is put to the test against other “old” and established strategies, it shows to be superior or equally legitimate to exist in the ecology because in some situations it provides better decision outcome or account for decisions. In Study III, in two experiments, CR competed with a normative linear model (MAU), two simple heuristics (Lexicographic and Maximin), a heuristic that searched more information than the simple heuristics (EBA), and a mathematical descriptive strategy (Euclidean distance). Results showed consistently that the most frequently chosen alternative was the CR alternative, that is, the alternative that had the same rank-order within the attribute values as the importance order within the attributes in the ideal alternative.

The runner-up chosen alternatives in Experiment 1 and 2 was the simple heuristics Lexicographic and Maximin, suggesting that heuristic-based strategies seem to be preferred by some individuals (Dahlstrand & Montgomery, 1984) while majority might prefer, similar to compensatory decision strategies, more information search and integration than the simple heuristics allow. This is coherent with the results from Study I and II where the compensatory and non-compensatory strategies did well, in terms of their predictive accuracy.

Similar to CR, EBA provides the opportunity to use more information than the simple heuristics typically do. EBA is a special case of the more general *Selection by Aspects* (SBA) model (Barthélemy & Mullet, 1992), which includes both the elimination and selection of alternatives depending on whether they pass or do not pass certain threshold values on an attribute or several attributes simultaneously. Using a deterministic version of EBA (see

Gati, 1986; Svenson, 1979), Jane starts by inspecting the most important attribute and then eliminates alternatives falling below a threshold value associated with the most important attribute. Jane continues to the second most important and so forth until one alternative remains and, hence is chosen by Jane. If the rank-order of attribute values within an alternative is in accordance with the rank-order of the threshold values for the corresponding attributes, EBA will coincide more or less closely with the CR strategy. The degree of correspondence depends on the number of attributes used in the elimination procedure and on the distribution of attribute values above the threshold values of each attribute. Turning to the SBA model, it can be noted that agreement between the rank-order of weights and attribute values in a particular alternative may be used as a criterion for *selecting* an alternative as the promising alternative. However, this would require SBA to include ranking patterns as a basis for selection of a promising alternative. In addition, in the attractiveness judgments participants rated the CR alternative as more attractive, something that is not possible if they had used EBA or SBA. This is because if participants used EBA they would need to search the information across the alternatives and that was not possible in the attractiveness ratings. Therefore, it is plausible to assume that choices and attractiveness judgments could not have arisen from EBA or SBA, but rather CR.

It is not only the fact that both choice and judgment data clearly favored the CR strategy that strengthen the support for the CR strategy. Another one is that CR has a clear theoretical rationale, as shown by the mathematical proof (see Appendix A) in Study III. Additionally, the CR alternatives had in a large majority of the choice situations shorter WED to the ideal than was true for the other choice alternatives.

Some might argue that holding MAU constant for all the alternatives is not how alternatives appear in the ecology. However, in experimental settings, there are some trade-offs that must be made in order to control for confounding variables. I believe that these trade-offs are justified because otherwise it would not have been possible to test the different strategies. In addition, MAU was only a tool for eliminating less attractive alternatives, which also happens in the ecology or decision maker’s environment. For instance, Jane would exclude wedding venues that are too expensive for her. She would only consider alternatives that are attractive to her (i.e., being in her budget range) but which cannot be easily differentiated. In our study, less attractive alternatives were excluded by letting the alternatives have high and equal MAU. Jane might (in fact probably do) use other procedures or methods in order to exclude unattractive alternatives, but they lead to the same outcome; the choice set will consist of attractive alternatives that the decision maker cannot easily differentiate. However, one can still argue that CR is used secondary to MAU. That is, participants would have used MAU, but because the alternatives were equal in terms of MAU, they could not apply MAU and hence used CR. However, two different methods of calculating MAU was tested (by changing the ways attribute weights were established) and both methods favored the use of the CR strategy also when the alternative MAU-method predicted the choice of another alternative than the CR alternative.

In summary, when CR was put to the test against some “old” and established strategies, it was shown that CR was superior. CR is not only theoretically (shown in the mathematical proof in Appendix A in Study III, and because CR had the shortest WED compared to the other strategies) superior but also empirically (shown by the strong choice and attractiveness judgments data from Experiment 1 and 2). It was found that in line with CR, participants search for more information (for instance, more than one attribute) than stated in other strategies and that CR combines simplicity that non-compensatory heuristics provide while still considering all the information, something that was believed to take place only in the complex and demanding compensatory strategies.

Something borrowed

The common denominator of the “old” and the “new” decision strategy

The ideas behind CR are not completely new. As discussed earlier, it borrows and combines some of the advantages of both compensatory and non-compensatory strategies. Furthermore, in CR, some of the ideas are “borrowed” from the *prominence effect* (Slovic, 1975; Tversky, Sattah, & Slovic, 1988). According to the prominence effect, Jane would, out of two alternatives, choose the alternative that is better on the more important attribute but worse on less important attribute, although the two alternatives have been matched to be equal in attractiveness. Similarly, Montgomery and colleagues found that the prominence effect takes place not only in choices but also in attractiveness evaluations (Montgomery, Selart, Gärling, & Lindberg, 1994; Selart, Gärling, & Montgomery, 1998; Selart, Montgomery, Romanus, & Gärling, 1994). The prominence effect implies that the more important attributes will loom larger in both choices and attractiveness evaluations compared to matching tasks. The prominence effect might take place in choices in line with choosing the CR alternative; because in both the prominence effect and CR strategy attributes that are more important loom larger in choice and attractiveness evaluations than is expected from MAU estimates. However, what differentiates CR from the prominence effect is that the prominence effect is used as a tiebreaker when alternatives are equal. Moreover, the prominence effect is at hand when the choice is made between alternatives. Because CR was rated as more attractive independent of other alternatives, participants cannot have used it as a tiebreaker or for comparing between alternatives.

In CR, some of the ideas of pattern recognition and categorization theories, where the attributes weights are considered in comparisons (Nosofsky, 1986; Juslin, Jones, Olsson, & Winman, 2003), have also been "borrowed". CR differs from categorization theories in the sense that there is not a prototype or a group of exemplars serving as the ideal alternative. Instead, there is an idea of what is maximally good on all the important attributes (which would correspond to an imagined ideal alternative that may not actually exist) and that decision makers try to choose an alternative that is proximate to this ideal. In fact, prototypes and exemplars can advantage from replacing their definitions with the concept of ideal alternatives. CR offers a simple pattern matching without actually requiring participants to calculate the weighted Euclidean distance to the exemplar. Thus, CR offers Jane a strategy that combines simplicity with the seemingly complex notion of minimizing weighted multidimensional distance (WED) to an ideal alternative.

CR has also "borrowed" some of the assumptions of the dual process theories. Some claim decision-making is a controlled process where rules and strategies are used; others claim that it is an automatic process where exemplars in the memory lead the way to a decision (Murphey & Medin, 1985). In this thesis, I claim that in decision making both controlled and automatic processes interplay and aid each other in the decision-making process. The minimization of WED and pattern matching to an ideal alternative that CR uses is similar to automatic processes. The rank ordering of the attributes is similar to controlled and conscious processes. What strengthens the psychological validity of CR is that it does not go against the view of human beings as a creature with limited capacity. Using the CR strategy means finding a shortcut (by using concordance in ranks) in order to find the alternative with shortest WED, which otherwise would have been a demanding process.

Something to remember

The main focus of this thesis was to investigate the validity of different decision strategies. Several strategies were compared against each other (Study I and II) and it was found that even though compensatory strategies and non-compensatory strategies provided equally high predictive accuracy, they were more frugal. One explanation to why both compensatory and non-compensatory strategies were good as accounting for decision behavior could be that there are intra-individual differences and different situations promote different strategies. Another explanation could be that the underlying processes of both strategies are valid and interplaying. Therefore, in Study III, a new decision strategy – CR –when it is at hand and which better account for human decision making compared to other existing and established decision strategies was suggested.

Finally, to sum up, if there is something to remember from this thesis let it be two things. First, decision makers can use the simplicity of the non-compensatory strategies while also using the superior complexity that compensatory decision strategies offer. Second, there might be more room for ideal alternatives as guide-lines for decision making than has been investigated and choosing according to the ideal alternative (which in our case manifested itself in the CR strategy) can also be explained in terms of weighted Euclidean distance.

Points of caution

A few notes of caution should be made concerning the studies in this thesis. I will give some notes of caution for each study.

The analysis and conclusion drawn from Study I and II are based on means calculated over all the participating doctors, and the models are built using the means. It is possible that some individuals consistently use simple heuristics as seen in Skånér and colleagues (2000). In fact, they might even be using heuristics other than those investigated in this study. However, the aim of Study I and II was neither to re-produce the doctors' decisions nor to re-produce the decision process itself. The aim was to investigate which strategies make better inferences.

When I speak of "no difference in expertise" regarding frugality, I only speak in terms of how the different models searched or utilized data. In fact, there might be differences between degrees of expertise that Study I and II do not account for. Judgment analyses do not fully reflect the cognitive processes that, in fact, might differ depending on degrees of expertise. Therefore, I can only speak of no differences in a judgment analysis study. Related to expertise, there are other ways to group expertise. As Brehmer and Brehmer (1988) pointed out, experience is not the only variable to group expertise. Other variables such as information search, personality, type of education, type of decision task can be used (Ericsson & Lehman, 1996; Shanteau, 1992). In addition, experts might be using other types of information for their decisions than those given in the patient cases. For instance, when a doctor reviews a patient vignette, s/he might see the cue age but ignore it because it not relevant in combination with the other cues. However, when s/he sees the patient in person, the patient's age might become more important.

Turning to Study III, previous studies have shown that the experimental design can promote the use of certain strategies (Glöckner & Betsch, 2008). Therefore presenting the alternatives as pie-diagrams can have promoted the usage of CR. In addition, even though participants chose the alternative according to the CR strategy, they could have used other strategies not tested in Study III.

Future Research

One issue for future research concerns the method for including information in the regression model. For instance, information can be included in the order they are presented to the decision maker, because this might be the order decision makers process the information. One way to see if this is actually the case, the order of the different cues in a patient case can be counterbalanced. Another method for including information in the regression model can be based on theory. For example, if according to guidelines and previous research, age is more determining than gender for the presence of heart failure. Therefore, age should be included in the model first or presented to the decision maker as the first piece of information.

The comparison of different strategies should include other domains than just the medical domain and also other diagnoses than those tested in this thesis. For instance, diagnoses of heart failure are one of the more difficult diagnoses, and doctors differ in their definition and diagnoses based on the cues. Asthma, on the other hand, is more straightforward. As Skånér et al. (2000) pointed out, in heart failure; the difference might be more on individual differences rather on expertise level differences. This point to an important aspect of judgment analysis, that different conditions require different methods and models as well as a deeper investigation on whose judgment and decision data to use in order to model decision making.

Regarding Study III, it would be of interest to design experiments where MAU and WED would predict different choices independently of whether the rank order of attribute values and importance weights agree or not for a given alternative. Furthermore, I suggest investigating whether participants use an alternative based on WED, rank, or both. In Study III, results showed participants chose the alternative that had the same rank-order within its attributes as an ideal alternative and this also implied shortest WED. However, what happens if we present participants with alternatives that have the shortest WED but have not the right rank-order? Alternatively, what happens if an alternative has the right rank-order but does not have the shortest WED? In relation to this, different strategies are differently time-consuming. Because WED is considered as an automatic process, it should require less time than an alternative with concordance in ranks, which is a controlled process. Therefore, response times should shed more light on this issue,

Additionally, the inferential ability of CR should also be tested in a judgment analysis as well as the more general idea that judgments are based on closeness to an ideal. In Study I and II, both compensatory and non-compensatory models were about equally (with logistic regression being more frugal) good at predicting human behavior. As mentioned earlier, both compensatory and non-compensatory strategies have advantages and disadvantages. One and same decision situation can consist of different pieces of information. Some of the information might better be accounted for by compensatory strategies while some other information might better be accounted for by non-compensatory strategies. Because CR is a strategy that combines the strengths of both compensatory and non-compensatory strategies, it ought to be much better at predicting human behavior and maybe better at accounting for the information. Note, however, using the CR strategy requires that there is a CR alternative in the choice set but minimizing the distance to an ideal alternative may always be a possibility. Therefore, the roles of ideal alternatives should be further investigated in future studies.

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Appendix

Appendix A – Experiment procedure in Study III

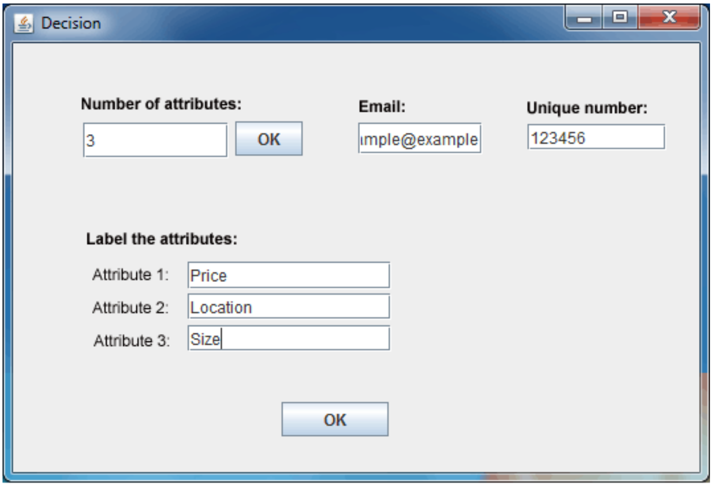

Figure A1. Corresponding to step two in procedure of Study III, where participants had were presented with their identified attributes.

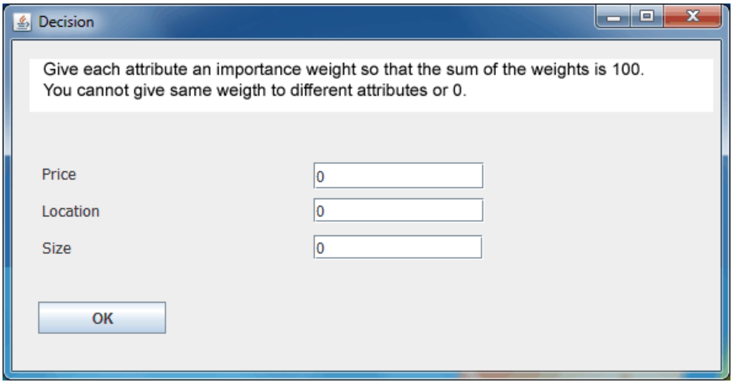

Figure A2. Corresponding to step three in procedure of Study III, where participants were asked to distribute 100 points between the attributes.

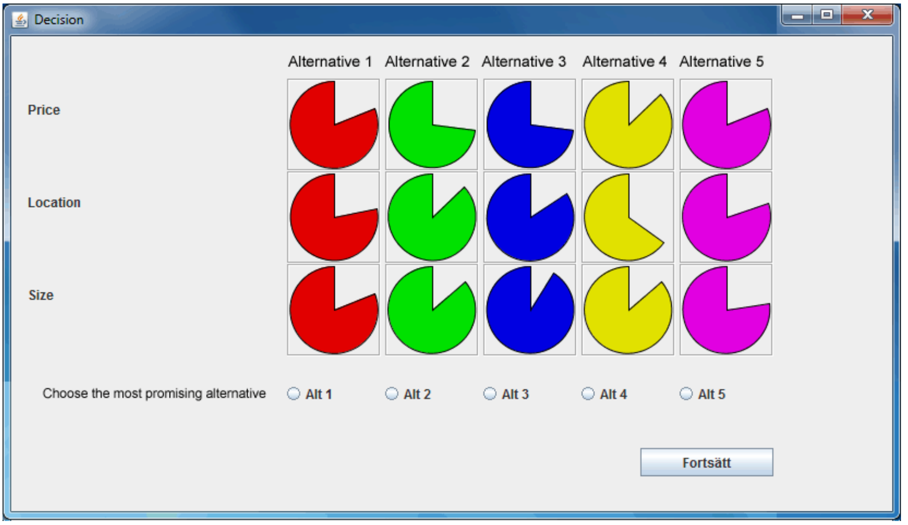

Figure A3. Corresponding to step four in procedure of Study III, where participants had to choose the most promising alternative. Each alternative consisted of the attributes identified earlier. Each alternative was presented in a unique color. This procedure was repeated 10 times, each time with five new alternatives.

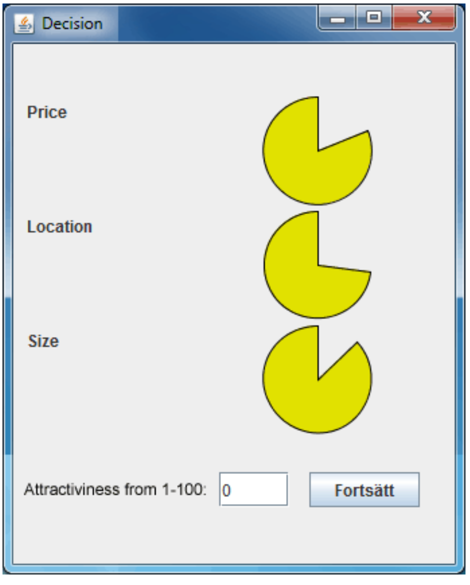

Figure A4. Corresponding to step five in procedure of Study III, where participants were asked to rate each alternative according to how attractive it was perceived on a scale from 0 (not attractive at all) to 100 (most attractive). This was done for 10 different alternatives.