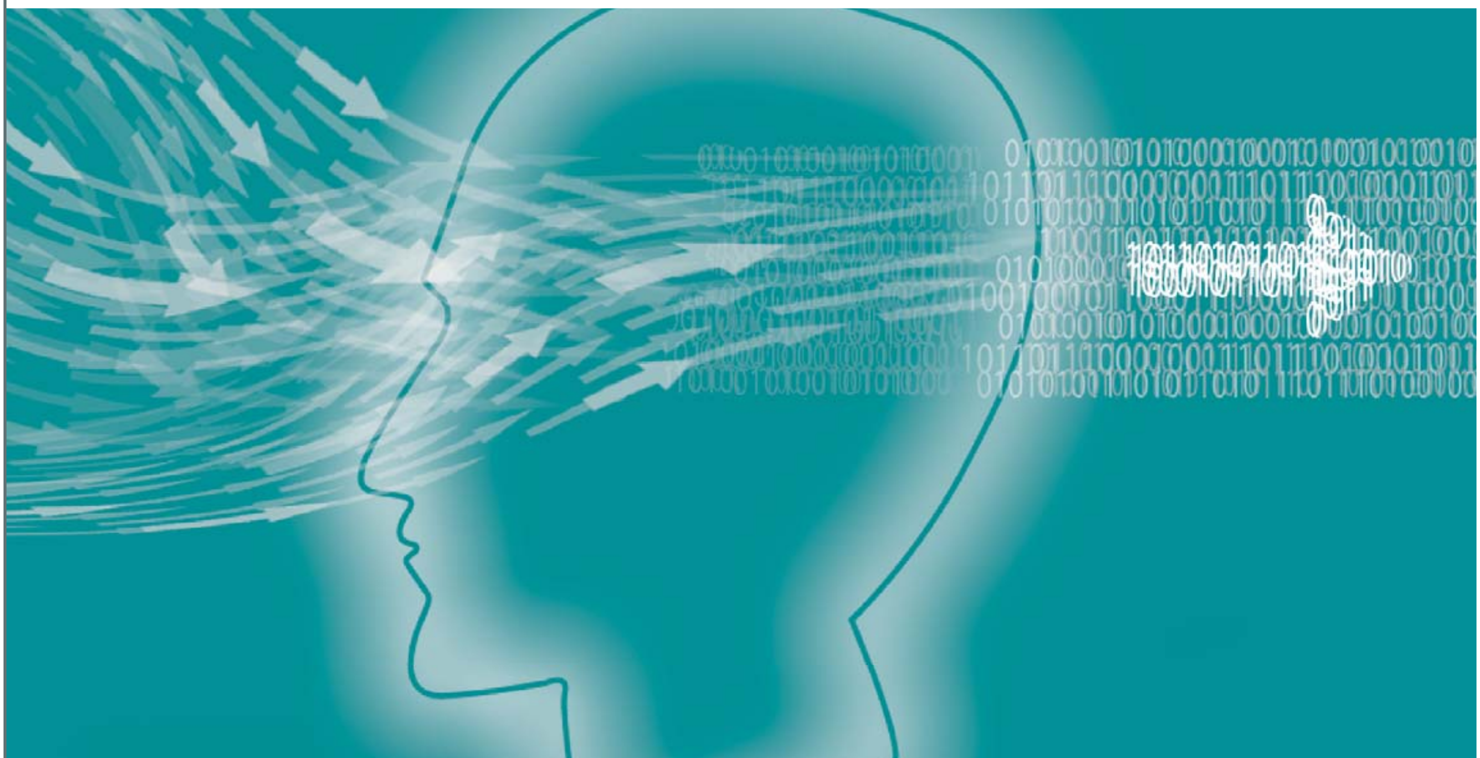
The Influence of Decision Support Systems, Context Effects, and Cognitive Style on

Decision Strategy Selection



Frans Feldberg

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THE INFLUENCE OF DECISION SUPPORT SYSTEMS, CONTEXT EFFECTS, AND COGNITIVE STYLE ON DECISION STRATEGY SELECTION

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geboren te Alkmaar

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To Brigitta, Maartje, and Florian

PREFACE

Ever since I learned the basics of information technology during my study of Business Informatics in the early eighties, I have been interested in how information technology can be employed to improve decision making. The field of decision support systems (DSS) has always been very appealing to me because it brings together three fascinating research areas: cognitive psychology (what is more interesting than being afforded a glance behind the scenes of human behavior?), information technology (the engine of our information society is fascinating anyway), and business administration (thinking about the challenges that face modern businesses makes me feel like a kid in a candy store: nearly everything is appealing to me). My special interest for decision support systems not only drove the decision to enroll in dedicated classes on this topic, but influenced important choices in my professional career as well.

I used to be a business intelligence consultant before I decided to enter academia on a fulltime basis. Although I chose a living as a business consultant after graduating in Business Administration, I had already set my sights on becoming a PhD. In the beginning of my professional career I had the firmly held belief that I could accomplish this in conjunction with being a very busy entrepreneur developing a new business from scratch. (Everyone has to learn sometime...). However much I enjoyed being a business consultant I discovered that I missed the scientific atmosphere I enjoyed so much during my studies at university. That is why I did not need a second thought when the Faculty of Economics and Business Administration of the *Vrije Universiteit* Amsterdam offered me the opportunity to convert my part time teaching position into a fulltime position as assistant professor in Information Systems. As well as a dozen other reasons, this position appealed to me particularly because: 1) it offered me the opportunity to fulfill a long-cherished desire; accomplish a PhD project, and 2) it included the challenge of developing a dedicated course on business intelligence, the area of information technology that has my particular interest.

My choice to enter the *Vrije Universiteit* appears to be a good one: although sometimes hard to combine, to be involved in teaching and research makes me feel completely comfortable. A significant part of this feeling is due to the very positive atmosphere in our faculty in general, and the department of Information Systems and Logistics in particular.

For this I wish to thank the Faculty of Economics and Business Administration of the *Vrije Universiteit* Amsterdam. I appreciate that you stuck out your neck by assigning research time to a business consultant with no scientific track record at all.

Regarding the accomplishment of my PhD project I owe my colleagues a lot of gratitude for their support, feedback and participation in my research. I would like to thank my colleagues Marcel Creemers, Tibert Verhagen and Frank Derksen in particular. Marcel, it all started with you. Thank you for convincing me to join the Information Systems section. Tibert, I appreciate an office mate that shares the same sense of humor. Very important! I really hope we can successfully implement the research plans we discussed. Let’s go for it! Frank you have been very important to me. Not only for creating the ‘launching platform’ needed for the fulfillment of this dissertation, but also because I admire your unselfish attitude towards colleagues. It is rare to meet someone who genuinely enjoys the success of his colleagues as much as you do. A real virtue!

Central to my research was the decision support environment developed by Jurgen van Dongen. Jurgen, your efforts have been invaluable to the accomplishment of my research. Without your aid it would simply have been impossible to execute the DSS experiments reported in this study. As always, the data models developed by you appeared to be shock proof for any analysis required. Not only do I admire your Oracle expertise and data modeling skills, but foremost your unconditional willingness to answer each of my ‘enhancement’ requests, even at times when you were very busy with the development of your business. Thank you very much for your support!

Regarding the scientific aspect of this study I owe gratitude to my supervisors Professor Yao Hua Tan and Professor Hans van der Heijden. I really appreciate the freedom you allowed me in writing this dissertation and the design of my studies. Yao Hua, thank you for being ever enthusiastic about my PhD project, and for teaching me how to survive the disappointments of ‘none significant’ results. Hans, you not only taught me the basics of proper research and to stay focused, but foremost to make the right choices when it comes to selecting external research partners. I admit, selecting research partners is something completely different from business acquisition…..

I wish to thank the following members of the PhD committee, not only for their careful reading and judgment of my manuscript, but also for providing constructive comments and useful suggestions for further improvement: Professor Guszti Eiben, Professor Cees van Halem (Erasmus University Rotterdam), Professor Eric van Heck (Erasmus University Rotterdam), Professor Jos van Hillegersberg (University of Twente), Professor Guus Holtgrefe, and Professor Bob O’Keefe (University of Surrey/United Kingdom).

Due to the nature of my research, proper functioning of IT facilities was an absolute prerequisite. The IT staff of the faculty not only guaranteed smoothly operating IT facilities, but also demonstrated great adaptability in response to my last minute requests for change. Chris Slijkhuis, Coen Wartenhorst, Shaam Manniesing and Andreas Hadjinikolaou thank you for your flexible support!

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I would also like to thank all of the students, friends and acquaintances that voluntarily participated in the pre-tests or final sessions of the experiments.

Finally I wish to express my deep gratitude for the support I received from those closest to me. My parents for their unconditional support in anything I undertook so far. (Alright, almost anything….). ‘Pa’ and ‘Ma’, the things you taught me included more wisdom than anything I learned at elementary, high school, and university together. My wife and kids for never complaining that Papa had to spend so much potential family time in ‘PhD quarantine’. Florian, thank you for understanding that it was not possible for me to print a ‘Pokémon coloring picture’ after finishing each paragraph of my dissertation, and Maartje, I am very glad you understood that not every newly learned word you entered in my texts, while I left my computer unattended, would slip the notice of my supervisors. Brigitta, in my dissertation I refer to some studies that were fundamental for my research, however, your unconditional support was fundamental for me in accomplishing this thing called PhD project. Although you consider supporting me by running our young family so often on your own to be the most natural thing in the world, I know it is *not*! Brigitta, Maartje and Florian you make me realize what really matters in life.

Frans Feldberg
Oudorp, April 2006

"*All we have to decide is what to do with the time that is given to us*."

(J.R.R. Tolkien)

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CHAPTER 1

INTRODUCTION

1.0 Introduction

The business view of the famous car manufacturer Henry Ford (1863-1947), encapsulated in the adage “I can deliver a car in any color you want, as long as it is black”, demonstrates how the world has changed since then: a new Mini Cooper is available in 50,000 different versions. The straitjacket of a single choice no longer fits the business vision of modern organizations claiming to be market oriented. Market oriented businesses listen to their markets and try to develop products and services that satisfy the needs of their customers (Slater & Narver, 2000). Increasing opportunities for choice seems to be the keyword in being market oriented. Product and services assortments are not only getting broader (more products), but deeper as well (more variety). For example, today the number of stock keeping units of an average supermarket outlet easily exceeds 20,000, whereas this number was 500 in the sixties; an average dairy category includes more products than a whole store did in the fifties (Oosterhout, 2005); and a Dutch marketing manger deciding on which market segments to focus can choose among 41 segments (Acxiom, 2005), each defined by 300 distinguishing lifestyle characteristics selected form a database containing 1500 segmentation measures (Cendris, 2005). A Dutch market research company has even reported that modern consumers consider the number of choice opportunities far too large rather than too small, especially in regards to more complex products that require comparisons on several product characteristics (Marketresponse, 2005).

Given these examples it is not surprising that a growing number of organizations recognize this trend and endeavor to help decision makers to seeing the proverbial forest from the trees by providing decision support facilities like product-compare and filtering tools. For example, after the implementation of new legislation concerning the financing of the healthcare system, the Dutch government developed a website called ‘www.kiesbeter.nl’ to support their citizens in their choice for a new healthcare insurance. Complex decision making has become a fact of life in economic behavior, not only for individual consumers, but also for organizations.

If we want to support decision making processes it is important to understand decision behavior. How do people decide to decide (Payne *et al.*, 1993)? Decision makers can use a variety of strategies to reach a decision. The selection of a new company car, for example, can be guided by a rule of thumb, whereas the decision to locate a new distribution center may require the use of sophisticated algorithms.

1.1 Decision strategy

Since decision making is a dynamic process in which a decision maker seeks and evaluates information sequentially (Svenson, 1979), information acquisition and processing is principal in any decision process. The method by which people acquire and combine information to make a decision is called a *decision strategy* (Jarvenpaa, 1989). For instance, a consumer looking for a new car can decide to eliminate all cars from consideration that exceed a price of $ 25,000.00. Application of this decision rule requires the consumer to acquire all prices of the cars in the decision set (acquisition) and to compare these prices with the threshold level specified (processing). Another consumer, making the same decision, does not focus on price solely, but chooses to evaluate all available information on all cars prior to making a choice. This consumer prefers a decision strategy that balances price against other attributes for all the alternatives available.

A decision strategy consists of: (1) a set of procedures that the decision maker engages in when selecting among alternative courses of action, and (2) the decision rule that dictates how the results of the procedures will be used to make the actual decision (Beach & Mitchell, 1978). For example, in an expected value strategy, the procedures comprise all calculations needed to compute an expected value per alternative, whereas the decision rule is maximization of expected value.

For any given problem a decision maker must choose which strategy or combination of strategies to use in order to reach a decision (Einhorn & Hogarth, 1981).

Decision strategies play an important role in the decision making process since they influence decision performance (Jarvenpaa, 1989). One can imagine that a decision strategy that takes into consideration all available data as well as the preferences of a decision maker, will result in a better decision than a strategy that excludes data from being reviewed and does not count for preferences at all. Given the role of decision strategies regarding decision performance, it does make sense to focus on factors that influence decision strategy selection. Understanding the relationship between such factors and their influence on decision strategy selection can help to enhance decision performance. Payne, Bettman and Johnson (1993) demonstrated that the selection of a decision strategy is contingent upon three major classes of factors: characteristics of the decision problem, characteristics of the decision maker, and characteristics of the social context. Decision makers also tend to adapt their strategy selection to the type of automated decision support provided (Chu & Spires, 2000; Todd & Benbasat, 1994a, 1994b, 1999, 2000; Wang & Chu, 2004).

Because characteristics of the decision problem, characteristics of the decision maker and the type of automated decision support provided are especially relevant for this dissertation, the next section of this chapter will elaborate on these influential factors of decision behavior. For reasons of tractability we do not deal with characteristics of the social context. This is largely in line with earlier research in this area. For a detailed overview on the influence of characteristics of the social context on decision behavior we refer to Payne *et al.* (1993).

1.2 Characteristics of the decision problem

The characteristics of a decision problem can be divided into two categories: *task* effects and *context* effects (Payne, 1982). Although task effects and context effects have often been used interchangeably in the literature, both effects have different characteristics. Any given decision will include both context and task factors. Task effects "describes those factors associated with the general structural characteristics of the decision problem" (Payne, 1982, p.386). Table 1.1 presents the task effects defined by Payne *et al*. (1993) in their research on decision behavior.

TABLE 1.1: Task Effects

Task effect	*Description*
Number of alternatives	The number of alternatives available in a decision set.
Number of attributes	The number of dimensions or attributes defining the alternatives.
Time pressure	The time available to make a decision.
Response mode	The required response in a particular situation. The two typical response modes used in decision research are: 1) Selection of the most preferred alternative. 2) Assignment of values to individual alternatives, reflecting the psychological worth of the alternatives.
Information display	The way information is displayed to the decision maker.
Agenda effects	The presence of constraints (agendas) to be taken into consideration during the choice process.

Context effects "describes those factors associated with the particular values of the objects of the decision set under consideration" (Payne, 1982, p. 386). The strength of preference of one alternative over another is influenced by the context of the other alternatives available in the choice set (Simonson & Tversky, 1992). Context variables most common in research on decision behavior are shown in table 1.2 (Payne *et al.*, 1993). Choice behavior is context dependent also.

TABLE 1.2: Context Effects

Context effect	*Description*
Similarity of alternatives	The extent to which the objects in a decision set are similar.
Quality of the option set	The quality of an option set is determined by the number of positive versus negative outcomes involved in the choice problem. A choice problem involving only positive outcomes can be considered "high quality".
Reference point effects.	Reference point effects relate to the existence of a neutral reference point that can be used to code outcomes. For example, a consumer deciding which car to buy might include its current car in the decision set as a point of reference.
Framing effects	Framing effects deal with the wording of a decision problem. For example, "people being saved" (gains) versus "people being killed" (losses).

The values of context factors are more dependent on individual perceptions than the values of task factors (Payne, 1982).

According to Payne *et al.* (1993) similarity of alternatives is probably the most studied context variable. Similarity plays a fundamental role in behavioral theories. Tversky (1977), for example, proposes that:

"Similarity plays a fundamental role in theories of knowledge and behavior. It serves as an organizing principle by which individuals classify objects, form concepts, and make generalizations" (p. 327).

Payne (1982) considers the similarity structure among alternatives as an essential component of any theory of contingent decision making:

" ..any theory of decision making that allows for contingent processing will have to incorporate the similarity structure among alternatives as an essential component of the theory" (p. 393).

The importance of alternative similarity in models that explain decision quality can be illustrated by a study from Helgeson and Ursic (1993). They investigated the influence of context effects on decision strategy selection, decision time and accuracy and found a strong inverse relationship between alternative similarity and decision accuracy. In another study, Best and Ursic (1987) found that decision accuracy significantly decreased under the condition of similar alternatives. In their own words, "the similarity of the choices might be an extremely important determinant of decision accuracy" (p. 108). Given these findings, it would seem relevant to study the effects of alternative similarity in a decision support systems (DSS) environment.

1.3 Characteristics of the decision maker

The act of choosing among alternatives does not take place in a vacuum. Decision strategy selection is also contingent upon the characteristics of the decision maker (Beach & Mitchell, 1978; Benbasat & Dexter, 1982; Zmud, 1979). Prior research showed a relationship between *cognitive style* and decision behavior. For example, Levin *et al.*(2000) found that cognitive style influenced depth of information search as well as breadth of information search, Van Bruggen *et al.* (1998) found significant differences in decision performance between high and low-analytical decision makers, their experiment also showed that low-analytical decision makers benefited most from the availability of automated decision support.

To improve decision support systems it would be helpful to enhance our knowledge concerning the relationship between personal traits and decision strategy selection. Do some people prefer one set of decision strategies and other people another set of decision strategies for making a decision?

Although the role of cognitive style is not undisputed in DSS research (Huber, 1983) we concur with Robey (1983) that "some knowledge of the direction and strength of user cognitive characteristics would aid in designing a workable partnership between human being and machine" (p. 581). Exploration of individual decision behavior may well be of common interest for researchers interested in decision processes.

1.4 Automated decision support

Prior research in behavioral decision making proved that the perceived costs associated with the implementation of a decision strategy as well as the perceived decision quality are important considerations in the selection of a decision strategy (Payne *et al.*, 1993). Both factors can be influenced by automated decision aids. For example, a decision strategy delivering high decision quality but requiring a level of information processing that considerably exceeds a decision maker's cognitive capabilities will not easily be chosen by an unaided decision maker, not because the decision maker is not interested in decision quality, assuming rationality, but simply because implementation of this strategy will be recognized as unfeasible. However, when the same strategy is supported by automated decision aids that significantly reduce the cognitive strain associated with its implementation, a rational decision maker will most likely choose for quality and use the system to implement it. DSS research aiming at the investigation of these kinds of effects proved that decision strategy selection is also influenced by automated decision support (e.g. Chu & Spires, 2000; Todd & Benbasat, 1999, 2000; Wang & Chu, 2004).

1.5 Tracing decision behavior

To investigate how decision problem characteristics, personal traits and automated decision aids affect decision behavior it will be necessary to capture the decision processes executed by the decision maker while performing a decision task. For the purpose of capturing decision processes DSS research primarily employs two so called decision process tracing methods: verbal protocol analysis and computerized process tracing (Cook & Swain, 1993; Todd & Benbasat, 1987).

Verbal protocol analysis (VPA) is a methodology that analyses data acquired through the verbalization of think-aloud processes (Ericsson & Simon, 1985). Experimental subjects are asked to think-aloud, reporting every passing thought, while simultaneously working on a decision task. These think-aloud processes are recorded on tape and transcribed into verbal protocols using a coding system. The resulting verbal protocols can be used to investigate what information is examined, which manipulations are conducted on the information acquired, and additionally, "what evaluations or assessments are made by the problem solver" (Todd & Benbasat, 1987, p. 496).

The second method, computerized process tracing (CPT), does not require the decision maker to think-aloud, but employs software to record decision processes. Computerized process tracing tools allow for detailed monitoring of actions performed through a DSS while solving a decision task. The software underlying CPT tools generates computer logs that store interactive decision making activity. These computer logs can be used as input for analyses on decision behavior. CPT is particularly relevant to DSS research for its ability to unobtrusively collect decision process data. Both verbal protocol and computerized process traces can be used to test hypotheses about decision behavior.

Svenson (1979) argued that when process tracing techniques are used to capture cognitive processes, it is necessary to know *what* content or information is acquired and *how* it is processed. Although CPT tools are recognized to be powerful process tracing aids, they primarily focus on *what* information is acquired and offer only limited support for capturing data on *how* information is processed (Biggs *et al.*, 1993). Verbal protocols, on the other hand, are known for their ability to provide rich data on *how* information is processed (Svenson, 1979; Todd & Benbasat, 1987). Given the reach of both process tracing methods, a joint application of concurrent verbal protocol analysis and computerized process tracing will be needed whenever both information *acquisition* and information *processing* behavior must be captured (Biggs *et al.*, 1985; Payne *et al.*, 1978; Todd & Benbasat, 1987). Actually, this will always be the case when cognitive processes need to be captured adequately, since both '*what*' and '*how*' are determinants of decision behavior (Svenson, 1979). Similarly, Payne, Braunstein and Caroll

(1978) even propose: “It is clear, however, that wherever possible, the researcher should adopt a multimethod approach to decision research” (p.41). Further details on both process tracing methods will be explained in chapter 4.

1.6 Research objective and research question

The aim of this research is to study the extent to which the level of decision support provided, problem characteristics (context effects), and the characteristics of the decision maker influence decision behavior.

The attributes of particular interest for the research model employed in this dissertation are *alternative similarity* as a decision problem characteristic, *cognitive style* as a trait of the decision maker, and different *decision aids* defining the level of decision support. This dissertation develops an integrated model combining the constructs: context effects, automated decision support, cognitive style and decision strategy and intends to answer the more narrowly defined *research question*:

“***What is the influence of automated decision support and cognitive style on decision strategy selection, in particular under varying levels of alternative similarity?***”

1.7 Expected contributions

This study aims at synthesis, extension and replication of DSS research. The DSS studies performed by Todd and Benbasat (1991, 1992, 1994a, 1994b, 1999, 2000) and Chu and Spires (2000) can be considered the fundamental studies for this dissertation. An important part of the theories, concepts and methods developed in this study is a synthesis of the DSS research models developed in these fundamental studies. Synthesis will be provided on two different levels: 1) on a theoretical level through the integration of the DSS theories developed in these fundamental studies, and 2) on a methodological level through the ‘merging’ of the decision support systems employed in these studies, as well as through a synthesis of their research variables. Extension will be provided through the development of an enhanced DSS environment and an extended measuring instrument for the purpose of capturing decision behavior, as well as through the introduction of alternative similarity and cognitive style in DSS research on preferential choice decision making. By replicating some of the core elements of the fundamental studies, this study will contribute to the validity of their findings.

The three general contributions addressed above, can be translated into the following four specific contributions:

1) *Development of an enhanced DSS environment*. Concerning the development of an enhanced DSS environment the contributions of this study will focus on: 1) the design and development of a user interface including the appropriate level of detail in decision support needed to improve micro level analyses, and 2) the design and development of a computerized decision process tracing model that will support micro level analyses as well as capture both determinants of decision behavior: information *acquisition* and information *processing* behavior.

The development of these two contributions is primarily driven by two factors. The first factor is a research challenge recognized by Todd and Benbasat (1991): “A second direction for further research leads back to more basic issues, focusing on the impact of individual tools on processing, memory and tracking. Here it would be possible to determine the influence of particular system features, and study in more detail how they impact strategy selection. …… In particular, such studies could allow us to separate the effects of the individual functions and their relative impact on individual cognitive operations. This would take us beyond the current studies to determine exactly how and why the individual functions impact decision making processes. The value of such micro level studies would be in developing a toolkit of techniques which could then be employed by researchers studying comprehensive systems. Such a toolkit would also be of value to system designers in building support tools that were based on known decision behaviors. We believe there is a need for studies at both the macro, or system level, and the micro, or decision aid feature, level. Micro level research will identify the type of features which are beneficial and are candidates for inclusion in DSSs. Macro level research will identify the degree to which these features can be integrated into more realistic DSSs. It is likely that not all decision makers will use the same features to implement a given strategy, and some functions will not be used when others which are perceived to be more powerful or easier to use are present." (Todd & Benbasat, 1991, p. 111).

Todd and Benbasat's appeal for the development of "a toolkit of techniques" that supports "micro level studies" should be considered a frame of reference for the design and development of the DSS employed in this study. This study aims at addressing the need for a more detailed level of analyses recognized as a limitation in prior research (Todd & Benbasat, 1994b).

Another factor driving the need for an enhanced DSS environment is the observation that DSS research so far seems to reconcile to the fact that CPT tools can only be used to capture information acquisition behavior. For example, Chu and Spires (2000), Wang and Chu (2004), and Cook and Swain (1993) evaluate the use of CPT tools for capturing information acquisition behavior, but do not explicitly develop theories in support of the use of CPT tools beyond their current application. This implies that whenever data on information processing behavior is needed researchers must employ VPA. Although VPA provides rich data on information processing behavior, its implementation requires a detailed level of process tracing analysis, which in turn 1) precludes the use of large numbers of subjects, and 2) induces significant financial consequences[1] (Ford *et al.*, 1989). We believe that modern database technology can give input to the development of CPT tools that allow for an extended application scope. This study aims at developing a CPT model that supports the capturing of both information acquisition *and* information processing behavior. As such this contribution can be considered an answer to Svenson's (1979) appeal for the construction of process tracing theories and models, or in his own words: "Process tracing techniques can be fruitfully applied in studies of decision making. However, the use of verbal protocols or information search patterns does not release the researcher from the burden of constructing theories or models." (p.109).

2) *Development of an extended measuring instrument to capture decision behavior*. This study aims at the development and employment of an enhanced set of decision process measures. This contribution is closely related to the development of an extended DSS environment. Each of the aforementioned process tracing methods supports a specific set of measures to operationalize decision behavior. The development of a CPT model that also allows for capturing information processing behavior makes it possible to develop additional information processing measures as well as to integrate traditional 'VPA-measures' in a CPT environment. The joint employment of

[1] A detailed overview of the pros and cons of VPA and CPT will be presented in chapter 4.

VPA and CPT measures, supplemented with newly develop measures for capturing decision processes may contribute to enhanced insights on decision behavior, increase the possibilities to infer on decision behavior, as well as “make information-gathering measures more powerful as process tracing tools” (Klayman, 1983, p.414).

3) *Introduction of context effects (alternative similarity) in DSS research*. Unfortunately, the impact of context effects in general, and alternative similarity in particular, is less developed in the DSS literature. Most if not all DSS research concerning the influence of computerized decision aids on decision accuracy takes only task effects into consideration. To illustrate, context effects are held constant in the pioneering DSS studies by Todd and Benbasat (1991, 1992, 1994a, 1994b, 1999, 2000).

4) *Introduction of cognitive style in DSS research on preferential choice decision making*. To the best of our knowledge, research on the influence of cognitive style on preferential choice decision making under conditions of automated decision support is sparse, if not lacking. For example, none of the fundamental studies for this dissertation integrates cognitive style constructs in their research models. This study contributes to DSS research through the inclusion of personal traits in the research design.

In terms of social relevance, the findings resulting from this study will provide recommendations to enhance the design and development of automated decision aids supporting preferential choice decision making.

1.8 Scope

The primary focus of this research will be on how *decision strategy selection* is influenced by *decision support systems*, *decision problem characteristics* and *characteristics of the decision maker*. Although many social factors can influence decision making (Payne *et al.*, 1993) the social context of decision processes will be beyond the scope of this dissertation.

The classification scheme for MSS (Managerial Support Systems) research, developed by Benbasat and Nault (1990), will be used to define the scope of this dissertation. Since this scheme primarily focuses on research concerning managerial support systems, only those categories of the scheme that offer sufficient methods of handling the behavioral aspects and the decision problem characteristics to be addressed in this study, will be used. Concerning automated decision support this research will focus on the *effects of use* of a decision support system. The consequences of DSS use and the value derived from utilizing a DSS will be examined.

Prior research on the effectiveness of decision support systems employed a variety of decision environments. Dickson *et al.* (1977) describe how simulators can be used to create a particular decision making environment. Benbasat and Schroeder (1977), for example, used an inventory/production simulator to create a decision making setting that was used to determine the relationship between six independent variables (among other things: decision making aids and decision making style) and information system performance. Lerch and Harter (2001) developed a simulation environment that reproduced a mail-sorting factory of the United States Postal Services (UPS) to examine the effects of cognitive support on real-time dynamic decision making, and O'Keefe and Pitt (1991) conducted an experiment in which visual interactive simulation was used to solve a service capacity and allocation problem.

The decision making environment of this research will be a *multi-alternative, multi-attribute preferential choice problem*. In a preferential choice problem a decision maker chooses the preferred alternative from a decision set containing a finite number of alternatives, each defined by a set of attribute values. Many decision activities for which DSS are developed are structured as multi-attribute, multi-alternative choice tasks (Zachary, 1986).

Alternatives in a decision set are usually multidimensional (Tversky, 1969). They vary along several attributes or dimensions relevant to choice. Product reviews in consumer reports, for example, are often presented in a multi-alternative, multi-attribute matrix. An example of a multi-alternative, multi-attribute decision set concerning an apartment selection task is shown in figure 1.1.

FIGURE 1.1: Multi-Alternative, Multi-Attribute Decision Set

	Rent	***Size***	***Brightness***	***Distance***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord***
Apartment A	7	6	9	4	5	6	6	3
Apartment B	8	6	4	6	8	8	9	4
Apartment C	5	7	8	7	8	2	6	4
Apartment E	4	4	6	8	10	7	6	7
Apartment E	1	9	10	8	7	5	5	9
Apartment F	7	3	4	9	9	4	4	5
Apartment G	9	5	7	10	4	8	5	7
Apartment H	9	6	6	8	7	8	6	6
Apartment I	8	3	9	2	6	7	7	5
Apartment J	9	2	5	5	4	9	6	8

The DSS research presented in this dissertation will primarily focus on automated decision aids that support multi-alternative, multi-attribute preferential choice decision processes. Except where otherwise specified, anytime a reference is made to a DSS we explicitly refer to this kind of automated decision aids.

The focus will also be on *individual* decision behavior of people performing a decision task independently of others and under conditions of *certainty*.

The emphasis of this research project will be on the decision *processes* that link information to decision outcomes (Jarvenpaa, 1989), and less on the end products of decision making, such as decision quality and satisfaction. Decision *process* data will be collected to investigate the influence of automated decision support, decision problem characteristics and cognitive style on decision strategy selection. Two methodologically distinct approaches have been developed to study the cognitive processes underlying decision behavior: structural (or statistical) modeling and process modeling. Whereas the focus of structural models is on describing the relation between observable input (information stimuli) and outcomes (decision responses), process models focus on the dynamic aspects of decision making and consider the intervening steps between inputs and decision outcomes. Process models refer to the heuristics and algorithms that people use in dealing with a decision problem. "Structural models focus on the *what* of decision behavior, but process models focus on the *how*" (Abelson & Levi, 1985, p.254). Although process models have often been regarded as somehow superior to structural models (Abelson & Levi, 1985), it has also been suggested that structural models and process-tracing models can provide complementary analyses of judgment and choice behavior (Einhorn *et al.*, 1979). On examining the effectiveness of decision aids, Mackay *et al.*(1992) even highlights the need for researchers to consider problem-solving processes rather than relying solely on outcome measures. In line with prior DSS research considering the influence of automated decision aids on decision behavior (Chu & Spires, 2000; Todd & Benbasat, 1991, 1992, 1994a, 1994b, 1999, 2000; Wang & Chu, 2004) this study will primarily focus on process models.

Although this study aims primarily at theory development, parts of it can be characterized as applied business research. This study does not aim at one single group of decision makers. The findings of this research will be applicable for any decision maker executing a multi-attribute, multi-alternative preferential choice task. In the context of this dissertation a decision maker can just as easily refer to a manager, selecting a reference store for the purpose of a benchmark analysis, as a consumer deciding which new digital camera to buy. Examples related to managerial decision making will whenever possible be alternated with examples related to consumer decision behavior.

1.9 Research strategy

This research can be qualified as explanatory and will be guided by a deductive, hypothesis-driven research strategy. According to the positivist research tradition the hypotheses and propositions will be based on a review of theories. The research model, presented in chapter 6, finds its theoretical foundation in the literature on behavioral decision research, cognitive psychology and research on decision support systems.

The causal relationships between cognitive style, alternative similarity and decision strategy selection under conditions of automated decision support will be tested empirically in two laboratory experiments.

1.10 Dissertation outline

This dissertation consists of four sections. Section 1, encompassing chapters 2 and 3, introduces the concepts, theories, methods and studies considered fundamental for this dissertation. This section will elaborate on behavioral decision making research (chapter 2) as well as on DSS research (chapter 3). Since the research cited in this dissertation focuses primarily on the factors that influence decision behavior, the following questions will be answered in both the context of behavioral decision making research, as well as DSS research: 1) How can decision behavior be modeled? 2) How can decision behavior be influenced? 3) How can decision behavior be captured? And, 4) how can decision behavior be measured?

Section 2, encompassing chapters 4 through 6, includes an investigation into the opportunities for improvement of DSS research concepts and methods (chapters 4 and 5), and develops the research model for this study (chapter 6).The investigation into DSS improvements is structured according to the central questions addressed in the first section of this dissertation, therefore focusing on enhanced methods to influence, capture and measure decision behavior.

Section 3 primarily focuses on the first experiment executed in the context of this research project. This section describes how this experiment was conducted (chapter 7), presents the results of this experiment (chapter 8) as well as examining its findings and recommendations (chapter 9). The findings of this first experiment are used as input for the development of enhanced DSS research concepts and methods. These enhancements are also introduced in this section (chapters 10 and 11).

Finally, section 4 introduces the second experiment executed in the context of this research project (chapters 12 and 13), and discusses this study's general findings and conclusions (chapter 14).

An overview of the general issues addressed in each chapter of this dissertation is presented in table 1.3. Please note that the first experiment introduced in this dissertation will be referred to as 'Experiment 1', whereas the second experiment introduced will be referred to as 'Experiment 2'.

TABLE 1.3: Dissertation Outline

Chapter	***Title***	***Purpose***
1	Introduction	▪ Introducing the problem under study (research objective and research question) and the research strategy. ▪ Describing the purpose of and the rationale for the research project. ▪ Describing the expected research contributions. ▪ Framing of the research project.
2	Behavioral Decision Making	▪ Development of theoretical background concerning behavioral decision making. ▪ Reviewing literature on contingent decision behavior. ▪ Introducing the 'effort-accuracy framework' of choice. ▪ Introducing the behavioral decision making research toolkit.
3	Decision Support Systems (DSS) Research	▪ Development of theoretical background concerning DSSs. ▪ Reviewing the DSS studies considered fundamental for this research project. ▪ Reviewing literature concerning the influence of DSSs on decision strategy selection. ▪ Introducing the DSS research toolkit.
4	Functional Requirements Enhanced DSS Environment	▪ Investigation of limitations recognized in prior DSS literature. ▪ Comparison of process tracing methods. ▪ Development of functional requirements for an enhanced DSS environment.
5	The Experimental Decision Support System	▪ Introducing the DSS environment developed in support of Experiment 1.

TABLE 1.3: Dissertation Outline

Chapter	*Title*	*Purpose*
6	Research Model and Hypotheses	▪ Development of research model. ▪ Positioning of the research model. ▪ Present research model assumptions. ▪ Reviewing literature on alternative similarity. ▪ Reviewing literature on cognitive style related DSS research. ▪ Positioning of hypotheses with regard to the influence of DSS, alternative similarity and cognitive style on decision strategy selection.
7	Method Experiment 1	▪ Presentation of experimental design, task, subjects, apparatus used and procedures. ▪ Description of the experimental treatments and measures.
8	Results Experiment 1	▪ Presentation of a summary of the data collected and the statistical treatments used. ▪ Reporting of analyses of data gathered during the experiment. ▪ Addressing the extent to which hypotheses are supported. ▪ Reporting of relevant post-hoc analyses. ▪ Positioning of results in context of research model.
9	Discussion Experiment 1	▪ Examination, evaluation and interpretation of research findings Experiment 1. ▪ Validation of research findings. ▪ Presenting limitations Experiment 1. ▪ Development of directions for further research.
10	Enhanced Conceptual Framework	▪ Introducing enhanced conceptual framework. ▪ Development of functional requirements DSS environment Experiment 2. ▪ Introducing additional cognitive style dimension. ▪ Introducing research model and hypotheses Experiment 2.
11	Enhanced DSS Environment	▪ Introducing the DSS environment developed in support of Experiment 2.
12	Method Experiment 2	▪ Presentation of experimental design, task, subjects, apparatus used and procedures. ▪ Description of the experimental treatments and measures employed in Experiment 2.
13	Results Experiment 2	▪ Presentation of a summary of the data collected and the statistical treatments used.

TABLE 1.3: Dissertation Outline

Chapter	*Title*	*Purpose*
		▪ Reporting of analyses of data gathered during the experiment. ▪ Addressing the extent to which hypotheses are supported. ▪ Reporting of relevant post-hoc analyses. ▪ Positioning of results in context of research model.
14	Conclusion and Discussion	▪ Summarization, qualification and discussion of final conclusions. ▪ Presentation of implications for theory and practices. ▪ Discussion on implications of research findings for DSS design. ▪ Discussion of study limitations. ▪ Presentation of suggestions for future research.

1.11 Summary

In addition to the fundamental concepts, research question, and expected contributions, this chapter provided the context of the research presented in this dissertation. This research aims at answering the following research question: "*What is the influence of automated decision support and cognitive style on decision strategy selection, in particular under varying levels of alternative similarity*?" On answering this question this research aims at addressing the following expected contributions: *development of an enhanced DSS environment*, *development of an extended measuring instrument to capture decision behavior*, *introduction of context effects in DSS research*, and *introduction of cognitive style in DSS research on preferential choice decision making*. The decision environment of this research will be a *multi-alternative*, *multi-attribute preferential choice problem*, whereas the primary focus of this research will be on *individual decision processes*. The hypotheses to be developed in this study will be tested empirically in two *laboratory experiments*.

CHAPTER 2

BEHAVIORAL DECISION MAKING

2.0 Introduction

Research on the effectiveness of computerized decision aids is rooted in behavioral decision research in psychology. The aim of this chapter is to introduce and explain relevant concepts from behavioral decision making theory. The concepts dealt with in this chapter are not only common in DSS research but also essential for understanding the theories developed in the subsequent chapters of this dissertation. We will first elaborate on decision strategies. Decision strategies are essential in explaining decision behavior and will be the 'recurring motif' of this research. How people *decide* to *decide* will be explained in context of the so called effort-accuracy framework of decision making. Since this dissertation focuses on the factors influencing decision behavior, a basic understanding of the methods used to capture and measure decision behavior will not only be necessary to support the understanding, positioning and valuation of prior research findings, but also because it creates a frame of reference needed for exploring the possibilities to improve these methods. Therefore this chapter will also elaborate on three important elements of the behavioral decision making "research toolkit". In context of this toolkit: 1) the notion of elementary information processes, 2) a set of common operators for measuring decision strategies, and 3) the relevant methods for capturing decision behavior will be explained. Finally, some findings of behavioral decision making research on preferential choice problem solving will be presented.

2.1 Decision strategies

Many of the studies in behavioral decision making research are grounded in frameworks developed by Payne, Bettman and Johnson (1993) on the ways individuals acquire and process information in order to make their decisions. People can choose among different approaches to deal with a decision problem. The method by which people acquire and combine information to make a decision is called a *decision strategy* (Jarvenpaa, 1989). The concept of decision strategy, also called decision rule[2], is central to decision processes.

Svenson (1979) denominates thirteen decision rules applicable to multi-attribute preferential choice problems and classified decision rules "according to their requirements on the metric level of aspect attractiveness, lexicographic order of attributes, and commensurability across attributes" (p. 88). The metric level of aspect attractiveness refers to the scale on which the attractiveness of alternatives or attribute values can be expressed. The following metric levels can be distinguished: ordinal, interval, and ratio terms. Attributes are said to be in lexicographic order when they are rank ordered in importance. Commensurability refers to the extent in which attribute values are comparable across different attributes. For example, if all attribute values are expressed on a five-point scale they are commensurable, whereas the attribute values 'moderate' and 'blue' are not. Commensurable rules are also called compensatory (Svenson, 1979, p.91).

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[2] Similar to academic literature on behavioral decision making (e.g. (Payne *et al.*, 1990, p130) (Payne *et al.*, 1993, p31)) , the terms decision strategies and decision rules are used interchangeably in this dissertation.

Based on the logical combinations of these three requirements, the seven general types of decision strategies that can be distinguished are represented in table 2.1.

TABLE 2.1: Types of Decision Strategies

Type	***Attractiveness***	***Lexicographic order***	***Commensurability***
Type I	Ordinal	No	No
Type II	Ordinal	Yes	No
Type III	Ordinal Attractiveness Differences	Yes	No
Type IV	Ordinal	No	Yes
Type V	Ordinal Attractiveness Differences	No	Yes
Type VI	Interval	No	Yes
Type VII	Ratio	No	Yes

2.1.1 Decision strategies according to Svenson.

Below the thirteen decision strategies as distinguished by Svenson (1979) will be presented. Although Svenson described most strategies with reference to a decision between two alternatives, it should be noticed that a generalization to more alternatives will be straightforward.

Ordinal Attractiveness and No Commensurability (Type I)

1) *The dominance rule:*

This strategy states that an alternative should be chosen over another alternative if it is better on at least one attribute and not worse on all other attributes.

2) *The conjunctive decision rule:*

The conjunctive decision rule requires the decision maker to define a set of threshold values on the attributes which a chosen alternative must equal or exceed. The attribute values of an alternative are compared to the predefined threshold level for each attribute. If any attribute value is below the threshold defined, then that alternative is dropped from the list of remaining possible alternatives. This elimination process proceeds until only one alternative remains. To be chosen by this strategy, an alternative must exceed the cutoff value on all attributes.

3) *The disjunctive decision rule:*

Although this decision strategy also requires a set of threshold values for the attributes involved, it is the mirror image of the conjunctive decision rule. An alternative is chosen if it exceeds the specified threshold value on one or more attributes. For an alternative to be chosen it must have at least one attribute exceeding the specified threshold value, while all the attribute values of any other attribute of the other alternatives fall below or be equal to the cutoff values specified.

Ordinal Attractiveness, Lexicographic Order, and No Commensurability (Type II)

4) *The lexicographic decision rule:*

The first step in the lexicographic strategy is determination of the most important attribute. Subsequently the values of all alternatives on that attribute are examined. The alternative with the most attractive score on the most important attribute is chosen. If two alternatives on this attribute are equally attractive, the attribute next in order of importance is selected and examined for the most attractive score. This procedure will be repeated until one alternative is found to be most attractive on the attributes examined. In the lexicographic decision strategy not all attributes will necessarily be evaluated.

5) *The elimination by aspects rule:*

Where the conjunctive rule examines the information by alternative, EBA evaluates one aspect, or attribute[3], across all alternatives. The elimination by aspects (EBA) strategy also compares attributes against a specified threshold, or cutoff level. The most important attribute is identified and all alternatives that do not meet the threshold level for this attribute are rejected. If there is more than one alternative remaining, the values of the next most important attribute are compared against the cutoff level defined for that attribute. This procedure will be repeated with new attributes successively lower in the lexicographic order until only one alternative remains. The EBA rule can be interpreted as a combination of the lexicographic rule and the conjunctive rule. The EBA strategy does not examine all relevant information in the decision process, however, it is considered "partial" rational (Payne *et al.*, 1993) because it reflects rationality in the ordered use of the attributes. The elimination by aspects strategy was introduced by Tversky (1972).

Ordinal Attractiveness Differences, Lexicographic Order, and No Commensurability

(Type III)

6) *The minimum difference lexicographic rule:*

Basically the minimum difference lexicographic rule works in the same way as the lexicographic rule. The additional assumption is that the difference between two values on the same attribute (Δ_i) must exceed a threshold level in order to determine a decision. This strategy will start by calculating the difference on the most important attribute. If the difference on the most important attribute is less than Δ_i, the attribute next in the lexicographic order will be examined. Consider the following two choice alternatives: $A_1(4,4,9,4)$ and $A_2(3,4,5,3)$. Suppose $\Delta_i = 2$ for all i's, and the attributes are given in the lexicographic order. There is no difference on the first attribute (4-3), and the second attribute (4-4) does not exceed Δ_i either. The difference on the third attribute is large enough for a choice of A_1 .

Ordinal Attractiveness and Commensurability (Type IV)

7) *The maximizing number of attributes with greater attractiveness rule:*

This strategy requires all attributes of a decision alternative to be qualified better, equal, or worse than the attractiveness of the other alternative on the same attributes. The alternative

[3] In literature on behavioral decision making the terms ‘attribute’ and ‘aspect’ are used interchangeably (see for example Zachary (1986, p.26)).

with the greater number of favorable attributes will be chosen. This strategy will not reach a decision in case of equal numbers of positive classifications for both alternatives. Because comparing the number of positive classifications, performed in the final stage of the comparison process, implies commensurability, this strategy is classified as such. However, this strategy does not require commensurability when deciding which alternative is best on each attribute.

8) *The elimination by least attractive aspect rule:*

The alternative with the overall worst attribute will be deleted by the decision maker.

9) *The choice by most attractive aspect rule:*

The alternative with the most attractive aspect should be chosen by the decision maker.

Ordinal attractiveness Differences and Commensurability (Type V)

10) *The choice by greatest attractiveness difference rule:*

This strategy begins with the determination of the attribute showing the greatest attractiveness difference. The decision maker will choose the alternative which is more attractive on this attribute, regardless the other attributes. According to Svenson (1979) this rule can be seen as "analog to the minimax regret principle in game theory" (p. 91).

Interval Attractiveness (Utility) and Commensurability (Type VI)

Svenson replaces the concept of attractiveness by the term *utility* at this higher level of presentation (Type VI). This implies that the value of an attribute equals the utility perceived by the decision maker for that specific attribute.

11) *The addition of utilities rule:*

This rule begins with a summation of all utilities for each alternative. The decision maker should choose for the alternative with the greater sum of utility.

12) *The addition of utility differences rule:*

In this strategy the decision will be based on a summation of the differences between the utilities of different alternatives on the same attribute. Consider two alternatives: A_1(4,4,9,3) and A_2(3,4,5,6). The utility differences can be calculated as follows: (4-3)=1; (4-4)=0; (9-5)=4; (3-6)=-3. The sum of the utility differences will be +2. Because the sum of the utilities has a positive sign, alternative 1 will be the preferred alternative.

Ratio Attractiveness and Commensurability (Type VII)

13) *The subjective expected utility model:*

In this strategy each attribute's utility will be weighted by the subjective probability of its occurrence when summing the utilities for an alternative. The alternative with the greater total expected utility will be preferred. This model requires a ratio representation of at least the attribute of subjective probability or belief.

2.1.2 Decision strategies according to Payne, Bettman and Johnson

Whereas Svenson provides an extensive overview of decision strategies, Payne *et al.* (1993) describe seven of the more common decision strategies used. Although the classification developed by Svenson is more elaborate and the strategies mentioned by Payne *et al.* show a lot of overlap with the decision rules defined by Svenson, we will also present the classification developed by Payne and colleagues for two reasons: 1) most DSS research concerning preferential choice problems refer to this classification (e.g. (Chu & Spires, 2000; Häubl & Trifts, 2000; Levin *et al.*, 2000; Todd & Benbasat, 1994b, 1999, 2000)), and employs the same nomenclature, and 2) the classification developed by Payne *et al.* presents new strategies that either can be considered archetypes from which the strategies mentioned by Svenson are derived, or form prototypical combinations of the strategies mentioned by Svenson. Below we will elaborate on the seven most common decision strategies as distinguished by Payne and colleagues (1993).

The weighted additive (WADD) rule

The WADD strategy is a special case of the expected utility model (Payne *et al.*, 1990). This strategy evaluates one alternative at a time and takes into consideration all the attributes of this alternative. This strategy also considers the relative importance or weights of the attributes to the decision maker. A total score, also called weighted additive score, for each alternative in the decision set will be calculated by summing the product of each attribute's value and its weight. For example, a decision maker evaluating a decision set containing three alternatives, $A_1(4,4,9,4)$, $A_2(3,6,5,3)$ and $A_3(2,6,8,4)$, can assign weights of 0.2, 0.3, 0.4 and 0.1 to the attributes respectively. The WADD-score for alternative one can be calculated as follows: $4*0.2 + 4*0.3 + 9*0.4 + 4*0.1 = 6$. The WADD-scores for the alternatives two and three, 4.7 and 5.8 respectively can be calculated analogously. The preferred alternative will be the one with the highest final score, being alternative one in this case.

An important characteristic of the WADD-rule is its ability to deal with conflict among attribute values. Conflict of values can occur when no one option best meets all of the objectives of the decision maker. A decision maker facing conflicting attribute values can resolve such a "conflict" by considering the extent to which it is willing to tradeoff a good value on one attribute against bad values on other attributes. For example, a manager deciding on the new location of a warehouse can be forced to trade off a high rent against low distance to a highway and the presence of state of the art loading docks. Using the WADD-rule the conflict among values is resolved by using subjective weights, reflecting the extent to which a decision maker is willing to trade off attribute values. Svenson's subjective expected utility rule is related to the WADD rule and can be used in making decisions under risk (Payne *et al.*, 1993). The WADD rule involves substantial computational information processing.

The equal weight (EQW) heuristic

Basically the equal weight strategy is similar to the WADD rule, except that the information about the relative importance or probability of each attribute is ignored. An overall score for each alternative is obtained by summing the values for each attribute for that alternative. This assumes commensurability of the attribute values. The EQW scores for the following alternatives: $A_1(4,4,9,4)$, $A_2(3,6,5,3)$ and $A_3(2,6,8,4)$ are 21, 17 and 20 respectively. The alternative with the highest score will be chosen. In fact the equal weight heuristic is a simplified case of the weighted additive rule.

The satisficing (SAT) heuristic

This strategy compares all the attribute values of an alternative to a predefined threshold (cutoff) level. If any attribute meets the requirements of the threshold it will be accepted. If no alternative can be chosen, the cutoffs can be relaxed and the process repeated.

So far, the SAT heuristic is comparable to the conjunctive decision rule described by Svenson (1979). However, whereas the conjunctive decision rule continues until only one alternative remains, the SAT heuristic processes alternatives in order of appearance, and the first alternative meeting the predefined threshold requirements on all attributes will be chosen. Application of the conjunctive decision rule in accordance with the steps described by Svenson, might result in more alternatives remaining after a single pass through the decision set. This can be solved by stressing the cutoff levels and repeating the procedure until only one alternative remains. The SAT heuristic however, does not necessarily examine all alternatives in a decision set, because the alternatives presented down the list the alternative meeting the threshold requirements will be ignored. Potential ignorance of valuable alternatives can be seen as a major shortcoming of the SAT heuristic. For example, consider three alternatives: $A_1(4,4,9,4)$, $A_2(3,6,5,6)$ and $A_3(4,6,8,9)$ examined against the following cutoff values: 3, 5, 5 and 6. If the alternatives are presented in the order shown, a decision maker implementing the SAT heuristic will choose for the second alternative, ignoring the best choice, alternative three.

The conjunctive strategy and the satisficing strategy are sometimes confused (e.g (Chu & Spires, 2000)), however, the conjunctive strategy is a variation of the SAT heuristic (Payne *et al.*, 1993).

The lexicographic (LEX) heuristic

The LEX heuristic as described by Payne *et al.* does not deviate from the description given by Svenson.

The elimination-by-aspects (EBA) heuristic

The description of the EBA heuristic of Payne *et al.* is equivalent to the description employed by Svenson.

The majority of confirming dimensions (MCD) heuristic

This strategy involves processing pairs of alternatives by comparing attribute values on each attribute. The alternative showing the greater number of better attribute values is retained and then compared to the next alternative. This process of pair wise comparison of alternatives is repeated until one alternative remains. All alternatives will be evaluated. Russo and Dosher (1983) introduced this heuristic and presented empirical evidence supporting its application.

The MCD heuristic is a simplified version of Tversky's (1969) general model of choice called the additive difference model. The MCD ignores the magnitudes of the differences between related attribute values. Each difference is only counted as positive (winning) or negative (losing). The additive-difference (ADDIF) strategy is also based on comparisons of attribute differences between the alternatives. Again, two alternatives are considered at a time. However, the magnitude of the difference for each attribute-pair is determined. These differences are weighted, using weights, and the results are summed over all attributes to calculate a weighted difference score. This score represents the attractiveness of one alternative over another. The inferior alternative will be eliminated from consideration, whereas the preferred alternative will be used for a comparison with the next alternative. This procedure will be repeated until one alternative remains.

Consider the following two alternatives: $A_1(4,4,9,4)$ and $A_2(3,6,5,6)$, and a decision maker assigning the following weights 0.2, 0.3, 0.3 and 0.2 to the attributes involved. The AD score for the two alternatives under consideration will be: $(4-3)*.2+(4-6)*.3+(5-9)*.3 + (4-6)*.2 = -2.0$, meaning that the second alternative is preferred. Although the weighted additive rule and the additive difference rule differ in the way information is processed, under some conditions both rules will produce identical preference orderings (Payne *et al.*, 1993; Tversky, 1969).

The frequency of good and bad features (FRQ) heuristic

The procedure for choosing an alternative in this heuristic is based upon counts of the good or bad features the alternatives posses. Good and bad features will be determined using cutoff values chosen by the decision maker. After the cutoff values are determined the decision maker simply counts the number of good features. The alternative possessing the greater number of good features will be the preferred one. Different variations of this strategy exist, e.g. a decision maker focusing on bad features will choose to reject the alternatives possessing the greater number of such features.

It should be noticed that the list of decision strategies presented above is not exhaustive. It will be possible to develop new strategies by combining these prototypical strategies as well as by combining the constituent sub procedures of existing strategies. The aim of the classifications given is to present and explain the prototypical strategies most common in research regarding multi-attribute preferential choice problems and create a frame of reference for thinking about decision behavior in the context of automated decision support.

2.2 Classification scheme decision strategies

For the purpose of comparing and contrasting decision strategies a classification scheme, based on common characteristics describing each strategy, will be developed. As mentioned in the introduction of this section the classification used by Svenson (1979) is based on three characteristics: 1) requirements on the metric level of aspect attractiveness, 2) lexicographic order of attributes, and 3) commensurability across attributes. Stevenson *et al.* (1990) organize preferential choice strategies by crossing three factors: 1) compensatory versus noncompensatory, 2) dimensional versus holistic, and 3) deterministic versus probabilistic. The classification scheme for decision heuristics developed by Payne *et al.* (1993) is most elaborate. It encompasses the common denominator of the characteristics employed by the aforementioned authors. The classification scheme developed by Payne and colleagues will be adapted in this research, adding the factor deterministic/probabilistic.

2.2.1 Compensatory versus noncompensatory

Decision strategies can be grouped in two basic types: compensatory and noncompensatory (Payne, 1976). Central to the distinction between compensatory and noncompensatory is the extent to which tradeoffs can be made among the attributes of a choice alternative, or in other words, whether a good value on one attribute can compensate for bad values on other attributes. In the case of selecting a used car, for example, a bad value on the attribute 'engine power' can be compensated by a good value on the attribute 'price'. Noncompensatory strategies compare alternatives directly within a specified dimension (attribute). For example, a decision maker eliminating all cars that exceed the threshold of '$ 10.000' for the dimension price applies a noncompensatory decision rule. Such an attribute based decision rule will only compare the cars on the dimension price and does not permit to tradeoff price against the other available dimensions.

Compensatory strategies are alternative based strategies (Payne *et al.*, 1993) using decision rules that allow for a tradeoff among the relevant attributes within a single alternative. These tradeoff processes can be facilitated by the use attribute weights, expressing the personal preference of a decision maker. In the used car case for example, a decision maker can express that it attaches more meaning to color than price by assigning attribute weights of .60 and .40 to color and price respectively. For this decision maker any one (1) point increase in price can be traded off against a one-and-a-half (1½) point decrease in color[4].

2.2.2 Consistent versus selective processing

Decision strategies differ in the degree to which the amount of information processed is consistent or selective across alternatives or attributes. For example, a decision maker implementing a WADD strategy has to evaluate a constant number of attributes across all alternatives available in the choice set. It will not be possible for this decision maker to use different numbers of attributes across alternatives. Information processing across alternatives will be consistent because the same amount of information is examined for each alternative. Consistent processing sometimes involves the evaluation of all the data available in a choice set. Selective processing occurs when different numbers of attributes are examined across alternatives. Application of an EBA strategy, for example, can eliminate alternatives based on the examination of values of a single attribute. Examination of additional attributes of alternatives not being deleted in the early stages of the decision process can take place in subsequent stages. Any additional attribute tested against a cutoff level will increase the amount of information used on the remaining alternatives, resulting in different amounts of information processed per alternative. It has been assumed that more consistent processing is indicative for more compensatory strategies, whereas more selective processing is indicative for more noncompensatory choice strategies (Payne, 1976).

[4] Assuming that attribute values for both price and color are expressed on the same scale and that higher scores represent more attractive values.

2.2.3 Amount of processing

The total amount of processing can vary across strategies. Whereas some strategies (e.g. WADD and ADDIF) attempt to process all relevant information, other strategies (e.g. EBA, LEX and CONJ) explicitly ignore potentially relevant information in solving a decision problem. As information is ignored the amount of processing will be reduced also. The total amount of information examined is independent of whether processing is consistent or selective. After all, a decision maker can choose to examine two of the ten available attributes across all attributes, and thus show consistent processing behavior while only 20% of the available information is evaluated.

2.2.4 Alternative-based versus attribute-based processing

The distinction between alternative-based and attribute-based processing is driven by the order in which the values in a choice set are processed. Alternative-based processing occurs when all of the attributes are evaluated for one alternative before the next alternative is considered. Because dimensions are examined within an alternative this type of processing is also called *inter*dimensional or holistic processing. Attribute-based rules evaluate all alternatives along one attribute before a next attribute is examined. Attribute-based processing is also called *intra*dimensional processing. Compensatory decision strategies are primarily *inter*dimensional strategies whereas noncompensatory are primarily *intra*dimensional decision rules (Payne, 1976).

2.2.5 Formation of evaluations

Strategies such as EQW and WADD explicitly calculate a score per alternative representing its overall evaluation. Whether or not these overall evaluations are explicitly determined can be used as another criterion to distinguish between decision strategies.

2.2.6 Quantitative versus qualitative reasoning

Another distinction between strategies can be made by using the degree of quantitative versus qualitative reasoning involved. This distinction is primarily driven by the extent a strategy makes use of quantitative operations or qualitative comparisons. The reasoning contained in strategies such as EBA and CONJ involves simple comparisons of values and is more qualitative in nature. The EQW and WADD rules include quantitative operations, such as multiplying and summing of attribute values, and thus are more quantitative in nature.

2.2.7 Deterministic versus probabilistic rules

A decision rule is deterministic if it always produces the same choice when an individual is confronted with the same situation. Probabilistic strategies allow for choice variability across repetitions (Stevenson *et al.*, 1990). For example, a decision maker implementing a WADD strategy will always choose for the alternative with the greater overall evaluation, making the

WADD deterministic. The choice of a decision maker that applies a SAT strategy will be dependent on the order in which the alternatives are presented in the choice set.

The prototypical decision strategies described represent different combinations of these general properties. A characterization of the strategies distinguished by Payne *et al.* (1993) is presented in Table 2.2.

TABLE 2.2: General properties of decision strategies most common in DSS research (adapted from Payne *et al.* (1993) p. 32)

	Compensatory (C) versus noncompensatory (N)	*Information ignored? (Yes or No)*	*Consistent (C) versus selective (S)*	*Attribute-based (AT) versus alternative-based (AL)*	*Overall evaluation? (Yes or No)*	*Quantitative (QN) versus qualitative (QL)*	*Probabilistic (P) versus deterministic (D)*
WADD	C	N	C	AL	Y	QN	D
ADDIF	C	N	C	AT	Y	QN	D
EQW	C	Y*	C	AL	Y	QN	D
EBA	N	Y	S	AT	N	QL	P
SAT	N	Y	S	AL	N	QL	P
LEX	N	Y	S	AT	N	QL	D
MCD	C	Y	C	AT	Y	QN	D
FRQ	C	Y	C	AL	Y	QN	D

WADD= weighted additive rule, ADDIF= additive difference rule, EQX= equal weight, EBA= elimination by aspects, SAT= satisficing, LEX= lexicographic, MCD= majority of confirming dimensions, FRQ= frequency of good and bad features.

*) Although all attributes on all alternatives are considered, it ignores information about the relative importance of each attribute.

2.3 How people decide to decide: effort and accuracy in choice

When decision strategies are central to decision making it will be important to investigate the factors that influence the choice of decision strategies. The question: *How do people evaluate and choose among a set of multi-attribute alternatives?* is central to behavioral decision research (Payne *et al.*, 1990). A large body of research has been executed to answer this question. Several factors were found to affect strategy selection. Biggs *et al.* (1985), for example, found that task complexity influences the selection of decision strategies. The overall level of attractiveness of the available alternatives in a choice set is also found to influence the decision process (Bockenholt *et al.*, 1991), and decision makers performing under time pressure are found to apply different decision rules than decision makers not faced by time pressure (Zur & Breznitz, 1981). The need to justify a decision to others (Simonson, 1989) has also been found to influence decision-making behavior.

Payne, Bettman and Johnson (1993) present an extensive overview of research executed in the field of behavioral decision making and empirically proved that the strategies that people use to evaluate and choose among a set of multi-attribute alternatives are highly sensitive to the decision environment.

The most frequently advocated approach to explaining contingent decision behavior (Payne *et al.*, 1990) is the contingency model for the selection of decision strategies developed by Beach and Mitchell (1978). Beach and Mitchell assume that decision strategies have different advantages and disadvantages and hypothesize that an individual selects the strategy that is best fit for the decision task to be performed, or more specific "..,the choice of strategy should depend upon the type of problem, the surrounding environment, and the personal characteristics of the decision maker" (1978, p.439). Whereas Christensen-Szalanski (1978) more fully developed the mechanisms for strategy selection proposed by Beach and Mitchell's model, Payne, Bettman and Johnson (1993) developed a research framework that more specifically addressed what Beach and Mitchell generally called the advantages and disadvantages of decision strategies. According to this framework, called the *effort-accuracy framework*, any decision strategy has certain benefits (accuracy) and costs (effort) associated with its use. Costs refer to the cognitive effort a strategy requires in making a decision. Information acquisition and computational effort involved in using a decision strategy can be considered costs. Accuracy refers to decision quality. The selection of a specific decision strategy is driven by *effort* and *accuracy* considerations of the decision maker (Payne, 1982). These are the key considerations that underlie strategy selection.

2.3.1 Effort in choice

Decision strategies vary in the level of mental operations, or cognitive effort, required to fulfill each strategy. Different strategies are also characterized by different levels of accuracy. For example, a consumer, not supported by automated decision aids, looking for a new DVD-player can, amongst others, choose between two strategies: strategy A and strategy B. The computation of an overall evaluation score for each DVD-player to be considered is the core of strategy A. Strategy B is driven by an elimination process, deleting all DVD-players that do not meet predefined threshold values for product characteristics specified. Application of strategy A implies that the decision maker must assign subjective weights to the different product features, for example 0.5, 0.1 and 0.4 to the attributes price, color and sound quality respectively. To select the most preferred DVD-player requires this consumer to execute mental operations such as: multiply attribute value by weight, sum all weighted attributed values per alternative, determine the alternative with the highest evaluation score. Whereas strategy A takes into consideration the information of all relevant DVD-players, this will not be the case when strategy B is applied. In strategy B all alternatives that do not meet threshold values for specific product attributes will be eliminated. Assuming the following order of ranking for product attributes: 1) price, 2) sound quality, and 3) color, the aforementioned consumer can begin with the definition of a threshold for the most important attribute: price. All DVD-players that exceed $ 250 for price will be eliminated. Then it can choose to delete all DVD-players with a "moderate" score on the product feature sound quality. These elimination steps can be repeated until only one alternative remains. Whereas strategy A requires a lot of arithmetical work, or cognitive effort, to be performed, strategy B only requires comparisons of attribute values and no calculations.

2.3.2 Decision accuracy

If we consider the decision strategies presented on a continuum ranging from ‘rule-of-thumb’ to ‘rational’ one can imagine that the decision quality can vary accordingly. Rational decision rules obey three normative properties: conflict resolution, dominance, and transitivity (Stevenson *et al.*, 1990). Conflict resolution refers to the ability of a decision strategy to uniquely identify one alternative for selection. A decision maker searching for one alternative will remain in a state of conflict when a strategy does not deliver a unique alternative to choose. According to Stevenson (1990), strategies like WADD, ADDIF, LEX, and EBA satisfy this property, whereas the conjunctive strategy does not. The conjunctive rule only marks alternatives in a choice set as ‘accept’ or ‘reject’. If more than one alternative is marked as ‘accepted’ some follow up rule must be applied in order to solve the remaining conflict among the acceptable alternatives. However, in context of this dissertation we would like to challenge the conclusion of Stevenson and propose that the WADD strategy and the ADDIF strategy both might deliver more than one single alternative also. Consider the following two alternatives: $A_1(6,4,5,4)$, $A_2(6,5,4,4)$, and a decision maker assigning the following weights: 0.2, 0.3, 0.3 and 0.2 to the related attributes. Application of the WADD strategy will result in equal overall evaluation scores (4.7) for both A_1 and A_2 . In this case, even after application of the WADD rule or the ADDIF rule, a follow-up strategy must be applied.

An alternative is dominated if at least one of the other alternatives in the choice set is superior on at least one attribute while not being inferior on any of the other attributes. Selection of a non-dominated alternative should always be the result of any rational choice rule (Stevenson *et al.*, 1990).

Transitivity stands for a relation among three alternatives, such that if the relation holds between the first and second alternative (e.g. A > B), and it also holds between the second and third (e.g. B > C), it must necessarily hold between the first and third alternative (A > C). Consider a human resources manager evaluating three job applicants. When she prefers applicant A over B, and B over C, the rule of transitivity implies that she also prefers A over C. Transitivity is guaranteed by both the lexicographic and weighted additive strategy (Stevenson *et al.*, 1990).

Compensatory strategies are believed to lead to better judgments and choices (Payne *et al.*, 1993). These strategies are thought to lead to more accurate decisions because they integrate all available information into the decision process in “a comprehensive fashion and take individual preferences into account in a more detailed and sophisticated way by weighting attributes” (Todd & Benbasat, 1992, p. 376). Compensatory strategies provide a more thorough evaluation of the available information and allow for tradeoffs between different attributes. For example, the use of noncompensatory decision strategies (e.g. Elimination by Aspects) in multi-attribute preferential choice situations can lead to the elimination of potentially good alternatives in the early stages of the decision process. Because the WADD strategy takes into consideration all of the relevant problem information, and explicitly deals with subjective priorities of the decision maker, hereby resolving the issue of conflicting values, this rule, or some variant of it, is often viewed as a normative procedure for solving preferential choice problems (Keeney & Raiffa, 1976; Payne *et al.*, 1990; Todd & Benbasat, 1994b).

2.3.3. Effort versus accuracy

A large body of research, encompassing literature reviews as well as empirical and simulation work, performed by Payne, Bettman and Johnson demonstrated that strategy selection is a tradeoff process resulting in a compromise between the desire to minimize effort and the desire to make a 'good' decision (Johnson & Payne, 1985; Payne, 1982; Payne *et al.*, 1993). Although the selection of a decision strategy is a process in which maximizing accuracy is balanced against saving effort (Payne *et al.*, 1993), both empirical (e.g. (Christensen-Szalanski, 1978, 1980; Russo & Dosher, 1983)) and conceptual (e.g. (Beach & Mitchell, 1978; Shugan, 1980)) studies showed that effort plays an important role in decision behavior.

2.4 The behavioral decision making research toolkit

Given the importance of the concepts of *decision strategy* and *effort* for behavioral decision making research, three questions become relevant: 1) How can effort be measured? 2) How can decision strategies be measured? And, 3) how can decision behavior be captured? To deal with these questions behavioral decision making research developed a kind of toolkit including methods that operationalize the concepts of effort and decision strategy, as well as methods for capturing decision behavior. These methods and techniques will be explained in the subsequent paragraphs of this section.

2.4.1 Elementary information processes: a language to measure cognitive effort

Elementary information processes (EIPs) are the key elements of a method that can be used to estimate the effort associated with the implementation of decision strategies. A measure for cognitive effort is the number of EIPs needed by a decision strategy to complete a specific decision task (Huber, 1980). Huber adapted the idea of EIPs from Newell and Simon (1972) who propose that the behavior of a decision maker (or Information Processing System) can be expressed in sequences of EIPs. An EIP is a basic cognitive operation producing a specific output based on a specific input (Huber, 1980). For example, the set of EIPs for decision making employed by Bettman and colleagues (1990) is shown in table 2.3.

TABLE 2.3: EIPs Used in Decision Strategies (Bettman *et al.*, 1990, p.115)

EIP	Description
READ	Read an alternative's value on an attribute
COMPARE	Compare two alternatives on an attribute
DIFFERENCE	Calculate the size of the difference of two alternatives for an attribute
ADD	Add the values of an attribute
PRODUCT	Weight one value by another (Multiply)
ELIMINATE	Remove an alternative or attribute form consideration
MOVE	Go to the next element of external environment
CHOOSE	Announce preferred alternative and stop process

EIPs can be seen as a common language from which decision strategies can be formulated. The use of EIPs allows for a more detailed analysis of the structure of decision strategies (Huber, 1980). The flowchart presented in figure 2.1 shows which EIPs the WADD decision strategy is composed of.

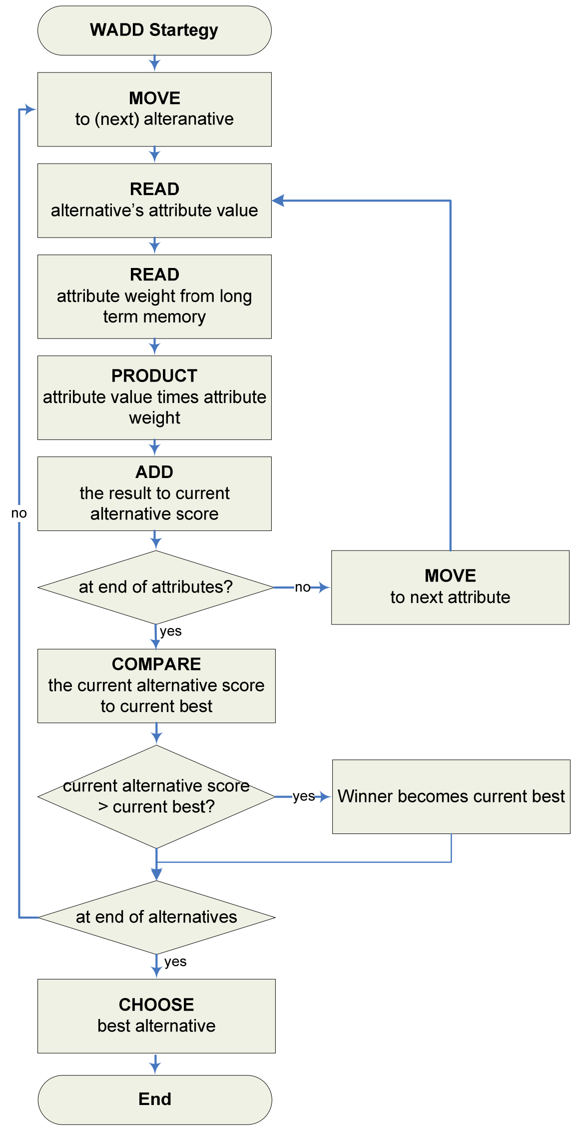

FIGURE 2.1: Componential Analysis of WADD strategy

The two feedback loops in the flowchart show that the total number of EIPs needed for implementation of the WADD-strategy is dependent on both the number of alternatives available in the choice set and the number of attributes used to characterize the choice options. Suppose a decision maker can choose between two alternatives $A_1(5,5,4)$ and $A_2(3,5,7)$. For each attribute five EIPs are needed for calculating a weighted attribute value, regarding the example, the number of EIPs needed to calculate all weighted attribute values for an alternative will be 15 (3 attributes x 5 EIPs). For each alternative, additional EIPs are needed to select the alternative

(MOVE) and to COMPARE each weighted alternative score with the current highest score. The final choice of an alternative requires one additional EIP (CHOOSE). Given our example, this calculation method will result in a ‘cognitive load’ of 35 EIPs needed to choose an alternative using the WADD-strategy.

Structural analyses of decision strategies enable one to determine the cognitive load associated with their implementation and provides the basis for meaningful comparisons among strategies in terms of effort. Bettman *et al.* (1990) found strong support for the EIP approach to conceptualizing and measuring the effort of executing a choice strategy. The use of EIPs to estimate effort expenditure is also common in DSS research (e.g. (Chu & Spires, 2000; Todd & Benbasat, 1994b, 2000).

2.4.2 Capturing decision behavior: process tracing methods

To understand and evaluate human judgment and decision making behavior it will be necessary to open the black box (Todd & Benbasat, 1987) that is in between the trigger starting a decision process (the decision problem), and the output of a decision process (the eventual response or choice). Examination of the issues regarding the cognitive processes that underlay individual decision making has been the focus of a large body of research (Ford *et al.*, 1989).

For the purpose of studying decision behavior a set of techniques, called process tracing techniques, has been developed. The use of process tracing techniques to capture decision behavior is well established in research on behavioral decision making (Abelson & Levi, 1985; Biggs *et al.*, 1985; Cook, 1993; Ford *et al.*, 1989; Lohse & Johnson, 1996; Payne *et al.*, 1993; Russo & Rosen, 1975; Svenson, 1979). Process tracing can be defined as the use of “techniques to trace the decision process by collecting data during the performance of decision tasks” (Cook & Swain, 1993, p. 931). Analysis of this process data offers a researcher the opportunity to (1) determine what information the decision maker used prior to reaching a decision (trace information acquisition behavior), (2) determine how information acquired is structured to form a cognitive representation of the decision problem, and (3) how information is processed prior to making a choice (Abelson & Levi, 1985). According to Svenson (1979) “The aim of a process tracing study is to reveal a train of thought, called a cognitive process, leading to a final decision or solution. When mapping this process it is necessary to know *what* content or information is processed and *how* it is processed” (p.98).

Four categories of process tracing tools can be distinguished (Cook & Swain, 1993):

1) Verbal protocol analysis (VPA). VPA is a methodology that analyses data acquired through the verbalization of think-aloud processes (Ericsson & Simon, 1985). Experimental participants are asked to think aloud while simultaneously performing a decision task. These thought processes are tape-recorded and transcribed into verbal protocols using a coding system. The verbal protocols are used for data analysis. VPA aims at tracing the cognitive processes underlying the decision process. Table 2.4 shows an adjusted and reduced (the full scheme contains 70 codes) version of the protocol coding scheme used by Bettman and Park (1980) for analyzing consumer decision processes.

TABLE 2.4: A Protocol Coding Scheme for Elements of Choice Processes

Code	*Description*
A1	Single attribute, compare difference between two alternatives.
A2	Single attribute, compare two alternatives without taking actual difference.
A3	Single attribute, compare more than two alternatives without taking actual difference.
A4	Single attribute, more than two alternatives, find best alternative.
A5	Single attribute, more than two alternatives, find worst alternative.
B1	One alternative, one attribute, statement of level of attribute.
B2	One alternative, one attribute, evaluation of level of attribute.
B3	One alternative, one attribute, compare to standard for that attribute.
B4	One alternative, more than one attribute, search for worst feature.
G1	Statement of selection of an attribute for processing.
G2	Statement of acceptance of an alternative.
G3	Statement of elimination of an alternative.

Table 2.5 shows a subset of statements made by a decision maker and the coding of these statements using the scheme presented in table 2.4.

TABLE 2.5: Coding Example Verbal Protocol

Statement	*Code*
…well, I consider rent as most important…..	G1
…let's examine all alternatives on the dimension rent….	A3
…well, alternative 5 has the most attractive score on the dimension rent..	A4
…and alternative 3 has worst score on this dimension…..	A5
…so let's eliminate alternative 3….	G3

2) Information display boards. This method requires the decision maker to search explicitly for information about the available alternatives. Information is typically arranged in a matrix and presented on a display board. Each cell of the alternatives x attributes matrix is covered by a card, hiding the value of each alternative on each attribute. In order to reveal the value of an alternative-attribute combination, the decision maker must specifically request to remove the card hiding the value (or open an envelope containing a card with the attribute value). By recording the requests made by the decision maker it will be possible to collect data concerning the information search behavior of the decision maker (Abelson & Levi, 1985). The two measures that characterize information acquisition (percentage of information used, and the sequence in which the data was obtained) can both be derived from this data. Inferences about a subject's decision processes are based on these measures (Billings & Marcus, 1983).

3) Computerized process tracing (CPT) tools. CPT tools are basically an automated sophistication of information display boards (Andersson, 2001). Instead of a physical representation, the decision matrix is presented on a computer display, and all relevant data is stored in a database. CPT tools include (1) a user interface that allows the decision maker to manipulate the decision matrix, (2) a database in which all attribute values of the decision matrix are stored, and (3) process tracing software which can be used to record all decision process data as well as to investigate information search behavior (Biggs *et al.*, 1993). CPT tools offer a richer research setting than automated information display boards (Cook & Swain, 1993).

To fully understand the pros, cons, and potential of computerized process tracing a prototypical CPT application, called Mouselab, will be explained below. Mouselab is not only well established in behavioral decision making research (e.g. (Lohse & Johnson, 1996; Luce *et al.*, 1997; Payne *et al.*, 1993; Schkade & Johnson, 1989; Stone & Schkade, 1991)), but is also a frame of reference for CPT tools developed in support for decision making studies in many other research disciplines such as Economics (e.g (Gabaix *et al.*, Forthcoming)) Consumer Research (e.g. (Lurie, 2004)), and DSS research (e.g. (Chu & Spires, 2000; Wang & Chu, 2004)).

Mouselab thanks its name to the fact that a mouse is used as a pointing device, supporting the acquisition of information from a computer display. Mouselab focuses on monitoring information acquisition behavior by automatically recording what information was acquired, the duration of the acquisition, search order, and the final choice (CEBIZ, 1996). The Mouselab system includes a control language that can be used by researchers to develop user interfaces that best fit the experimental decision task to be performed. The program can be used to present a decision problem in a desired format (e.g. decision matrix or a gamble) and to present the

FIGURE 2.2: Display example decision matrix (Mouselab 6.0)

instructions for an experiment. Amongst other functions, dedicated functionality to support multi-attribute preferential choice tasks is included in Mouselab. A decision set can be presented as a M rows x N columns matrix of boxes (See figure 2.2).

In the initial status all boxes are closed. A decision maker can open a box, and obtain information, by means of a mouse click on a box or just by moving the cursor across a box (dependent on the settings of the program). Figure 2.2, for example, shows that by pointing on the box representing the rent for apartment B the attribute value 225 will be revealed. A box will stay opened as long as the pointer is positioned on the relevant box.

In order to obtain all information necessary to reach a decision, a decision maker must choose which boxes to open. All actions of a decision maker will be stored in an output file. For any box that will be opened during the decision process, two entries will be stored in the output file. The first entry contains the box number and a timestamp representing the moment it was opened, the second entry contains the box number and a timestamp representing the moment it was closed. Table 2.6 presents the format of a sample Mouselab output file.

TABLE 2.6: A Sample Mouselab Output File

Box number	*Time*	*Response*	*Remarks*
100	0.000		
100	2.578	(text reading time)	Time needed to read instruction screen.
Matrix Screen -> Alts: 4	Atts: 4		Comment line showing screen schema.
100	0.000		Start decision task.
1	2.031		Open box: Apartment A/Rent
1	4.961		Close box Apartment A/Rent
2	6.172		Open box: Apartment A/Size
2	9.723		Close box Apartment A/Size
3	10.320		Open box: Apartment A/Kitchen
3	11.871		Close box Apartment A/Kitchen
4	12.422		Open box: Apartment A/Noise
4	13.863		Close box Apartment A/Noise
5	14.492		Open box: Apartment B/Rent
5	16.871		Close box Apartment B/Rent
9	17.133		Open box: Apartment C/Rent
9	17.523		Close box Apartment C/Rent
13	18.340		Open box: Apartment D/Rent
13	20.730		Close box Apartment D/Rent
17	23.031		Move to choice option 1: Apartment A
17	26.090	1	Choose option 1: Apartment A
100	29.902	1	Time units used to fulfill decision task.

The output presented in table 2.6 can be used to produce valuable information about the decision process. Suppose the output file is related to the decision matrix presented in figure 2.3.

Figure 2.3 presents how the decision maker searched through the matrix. The search pattern presented indicates that only 44% of the available information was used (7 of the 16 available boxes), that the decision maker disclosed 100% of the available information on apartment A, while only disclosing 25% of the information available on all other alternatives. The data also shows that the decision maker started with opening all boxes of the first alternative (apartment A) indicating an interdimensional, or alternative-based, search pattern. The movements from box 5 to box 9, and from box 9 to box 13 are all actions within the same dimension (attribute) and are exemplary for an intradimensional, or attribute-based, search pattern.

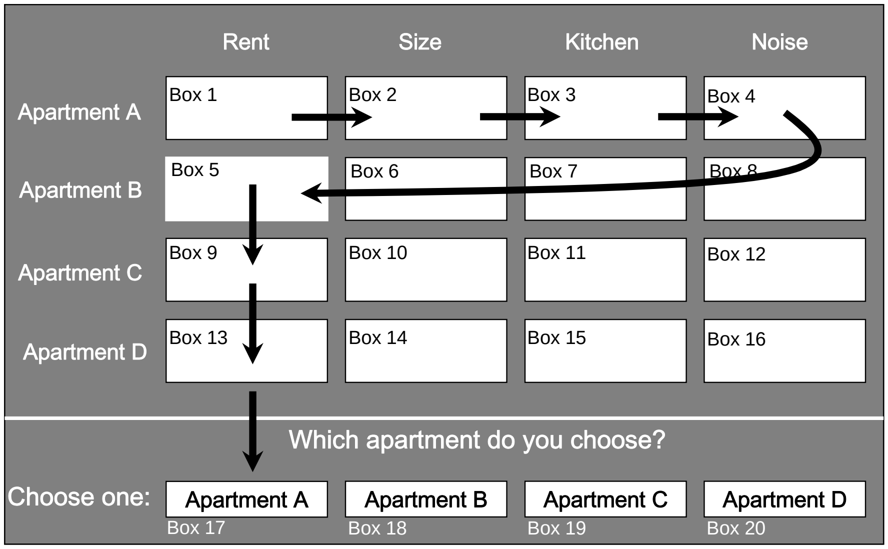

FIGURE 2.3: Reproduction of Search Behavior

Payne and colleagues employed Mouselab for several decision making experiments and used the output to infer about the decision strategies applied by the participants.

4) Eye movement recordings. This method uses photoelectric sensing devices to record data concerning the eye movements of decision makers. Eye movements can be measured on various characteristics (e.g. sequences of eye fixations, duration of fixations) that can be used to infer about a decision maker's information acquisition and processing behavior (Lohse & Johnson, 1996).

Information display boards and eye movement recordings will not be considered in detail in this study. Display boards have become superseded due to the emergence of contemporary information technology. The use of information display boards in DSS research would imply a step back in time. We do not consider eye movement recordings either, not only because of the related methodological limitations (for a review we refer to (Lohse & Johnson, 1996) and (Cook & Swain, 1993)) but also because this technique is considered irrelevant in context of this study.

2.4.3 Measuring decision strategies

A decision maker's pattern of information search provides a method for discriminating among alternative models of decision making "in terms of the information processing behavior assumed to underlie the various models" (Payne, 1976, p. 369). Different information search patterns are related to different models of decision making. To characterize decision behavior Payne *et al.*(1988) distinguished the following aspects of information search behavior:

1) The total amount of processing.
2) Selectivity in information acquisition and processing.
3) Sequence of information acquisitions.

The total amount of processing. A decision maker processing more information will be able to make a better-informed decision. This aspect is considered a key distinction among decision models. Noncompensatory decision strategies, for example, ignore potentially relevant information, and thus reduce the amount of information used to reach a decision. Compensatory strategies attempt to process all relevant information (Payne *et al.*, 1993).

Selectivity in information acquisition and processing provides insight in whether a decision maker searched a constant or variable amount of information across the alternatives. An equal number of attributes evaluated across all alternatives can be considered indicative for the fact that the same attributes are used to evaluate the alternatives. The nature of noncompensatory information processing is such that the number of attributes evaluated per alternative will differ more than in case of compensatory information processing. The alternatives eliminated in the first step of an EBA strategy, for example, are only evaluated on one attribute, the alternative eliminated in the second step are evaluated on two attributes and so on. Low variability in information processed per alternative is considered an indicator for compensatory decision behavior.

The third aspect of decision behavior explicitly deals with the *information search pattern* of a decision maker. Two prototypical search patterns were distinguished: interdimensional and intradimensional. A decision maker showing interdimensional search behavior will investigate information per alternative. Prior to considering a next alternative all relevant attributes of the alternative under consideration will be evaluated first. This is why interdimensional search behavior is also called alternative-based search behavior. Intradimensional search patterns, also called attribute-based search patterns, consider alternatives within a specified dimension. Intradimensional search processes are characterized by the evaluation of one attribute across all alternatives. For example, in a Mouselab context the pattern of search can be determined by examining the alternative and attribute associated with the n^{th}+1 box opened in relationship with the alternative and attribute associated with the n^{th} box opened. If the n^{th} + 1 box opened is within the same alternative as the n^{th} box opened, thus involving a different attribute of the same alternative, then the transition from the n^{th} box to the n^{th} + 1 box can be considered an instance of an interdimensional pattern of search. However, when the n^{th}+1 box opened is within the same dimension, but a different alternative, the transition can be considered an instance on an intradimensional search pattern. The Mousleab output can be used to calculate a measure of interdimensional versus intradimensional search. This measure is "given by the number of intradimensional single step transitions minus the number of intradimensional single step transitions divided by the sum of the two numbers" (Payne 1976, p. 376). A value of +1.00 refers to a pattern consisting of only interdimensional transitions, whereas a value of -1.00 refers to a search pattern consisting of only intradimensional transitions. Interdimensional search patterns are consistent with compensatory decision processes.

In context of the three general aspects of decision behavior presented above, Payne and colleagues developed seven explicit measures to test their hypotheses concerning strategy selection in decision making. Biggs and colleagues (Biggs, 1979; Biggs *et al.*, 1985) used the measures developed by Payne (1976), while adding three additional measures to distinguish among different decision strategies. Table 2.7 shows these dependent measures represented per aspect. Because the additional measures developed by Biggs and colleagues explicitly classify decision behavior according to the way information is processed, an additional aspect of decision behavior, called 'type of information processing', is added.

TABLE 2.7: Dependent Measures, employed by Payne *et al.* and Biggs *et al.*, per Aspect of Decision Behavior

Aspect	*Dependent Measures*	*Source*	*Number*
Total amount of processing	▪ The total number of times information cues were accessed for a particular decision.	(Payne *et al.*, 1988)	1A
	▪ Amount of available information searched.	(Payne, 1976), (Biggs *et al.*, 1985)	1B
	▪ The average time spent per item of information acquired.	(Payne *et al.*, 1988)	2
Selectivity in information acquisition and processing	▪ Proportion of the total time acquiring information that was spent on cues involving the most important attribute of a particular decision problem.	(Payne *et al.*, 1988)	3
	▪ Proportion of time spent on probability information as opposed to information about payoff values.	(Payne *et al.*, 1988)	4
	▪ Variance in the proportion of time spent on each alternative.	(Payne *et al.*, 1988)	5
	▪ Variance in the proportion of time spent on each attribute	(Payne *et al.*, 1988)	6
	▪ Variability in the amount of information searched per alternative.	(Payne, 1976), (Biggs *et al.*, 1985)	6B
Sequence of information acquisitions	▪ The relative use of alternative-based versus attribute-based processing (Search Index (Payne, 1976)).	(Payne *et al.*, 1988), (Biggs *et al.*, 1985)	7
Type of information processing	▪ Number of explicit eliminations of alternatives before choice episode.	(Biggs *et al.*, 1985)	8
	▪ Ratio of dependent evaluations to total evaluations. (Dependent evaluations involve comparing one alternative to another on a specific attribute, whereas independent evaluations involve evaluations of an alternative on a specific attribute, by comparing it with some implicit or explicit intrinsic criterion)	(Biggs *et al.*, 1985)	9
	▪ Number of compensatory stations made before choice episode.	(Biggs *et al.*, 1985)	10

It should be noticed that these measures are closely related to the elements of the classification scheme for decision strategies as explained in chapter two.

2.5 Behavioral decision making: research findings

Because the field of behavioral decision making research covers a vast amount of studies, associated to a broad range of topics, it will be nearly impossible to provide a complete overview of their results and findings. Even the broad range of behavioral decision making studies already referred to in the course of this chapter, is a small subset of all research performed in this area. Besides this, producing such a comprehensive overview is beyond the aim of this study. However, to enhance understanding of the concepts elaborated on in this chapter, we consider it useful to briefly present some findings of studies that investigated the influence of decision problem characteristics on decision strategy selection.

A series of experimental results indicates that decision strategies are sensitive to the complexity of a decision problem (e.g. (Biggs *et al.*, 1985; Billings & Marcus, 1983; Payne, 1976; Payne *et al.*, 1993)). For example, decision makers facing choice sets including two alternatives were found to use compensatory types of decision strategies, such as the weighted additive decision rule (Payne *et al.*, 1993), whereas decision makers faced with more complex decision problems, including more alternatives, were found to prefer noncompensatory decision strategies, such as elimination-by-aspects (Tversky, 1972), or in terms of Payne *et al.* “Taken together, the research on number of alternatives and number of attributes is very consistent in demonstration contingent decision behavior. People respond to increases in task size both by selective attention to information and by shifts in decision strategies. Simpler, noncompensatory strategies are used increasingly as task size increases” (1993, p.37). Similarly, decision behavior is found to be sensitive for: time pressure, response mode, how information is displayed to the decision maker, similarity of alternatives, the quality of the option set, the existence of reference points, and the wording of a decision problem (Payne *et al.*, 1993).

2.6 Summary

Because the focus of this study is on factors that influence decision behavior this chapter introduced and explained the concepts, theories and methods from behavioral decision making theory considered fundamental for this research. The notion of decision strategy was explained since decision strategies will be used in this study to model decision behavior. To create a frame of reference for understanding decision behavior the effort-accuracy framework was introduced. Cognitive effort and decision accuracy appear to be important factors on explaining decision behavior. On studying decision behavior two questions become relevant: 1) how can decision behavior be captured, and when captured, 2) how can decision behavior be characterized? Four methods for capturing decision behavior were introduced, whereas the two methods most relevant for this study are explained in detail. How decision behavior can be characterized is answered through the introduction of the decision process measures most common in behavioral decision making literature. Finally, some behavioral decision making research findings were presented.

The next chapter will discuss decision support systems research and elaborate on the DSS studies considered fundamental for this research project. Each DSS study presented will be dealt with in context of the concepts, theories and methods introduced in this chapter.

CHAPTER 3

DSS RESEARCH

3.0 Introduction

This chapter aims at introducing the fundamental DSS studies for this dissertation. To put theses studies in context, the evolution of the DSS research models, as developed by Todd and Benbasat (1999), will be used as a frame of reference and will be reiterated in the first part of this chapter. The second part will elaborate on the fundamental DSS studies for this research project. Each relevant DSS study will be dealt with in context of the concepts, theories and methods introduced in the previous chapter. In conjunction with a description of each DSS employed, the following questions will be answered: 1) How did the DSS influence decision behavior? 2) How was decision behavior captured? 3) How was decision behavior measured? And, 4) What are the most important findings?

3.1 DSS research literature

Two strands of research on decision support systems for preferential choice decision making are of particular relevance for our research question: the ones put forward by Peter Todd and Izak Benbasat, and by Pai-Cheng Chu and Eric E. Spires. Regarding the combination of research on behavioral decision making and information systems research, the DSS research projects of Todd and Benbasat can be considered a cornerstone with contributions to both fields. By a series of research projects Todd and Benbasat (e.g. (1991, 1992, 1994a, 1994b, 1999, 2000)) contributed significant to our current knowledge regarding the antecedents of decision strategy selection under conditions of automated decision support.

Chu and Spires (2000) contributed to the field of DSS research because of the methodology they employed to record and analyze decision behavior. Whereas Todd and Benbasat rely on verbal protocol analyses to register decision behavior, Chu and Spires integrated a database environment in their DSS to store all actions performed by the decision makers using the system. The data stored in this database was used to analyze the processes underlying decision making.

The DSS studies performed by both Todd and Benbasat and by Chu and Spires will be reviewed in depth in this chapter.

3.2 Evolution of DSS research models

The description of the evolution of DSS research models, developed by Todd and Benbasat (1999), can be used as a frame of reference for positioning DSS research. Todd and Benbasat used the four models presented in figure 3.1 to show the evolution of theoretical understanding of the relationship between DSS and decision-making performance. The variables presented in the various models help to explain how and why DSS influences decision performance. Model 2a suggests that *DSS capabilities* directly influence *decision performance* and does not deal with different types of users, decision tasks, decision aids, and work environments. An overview of DSS research, provided by Eiereman *et al.* (1995), shows that studies testing this direct relationship are not univocal in their results.

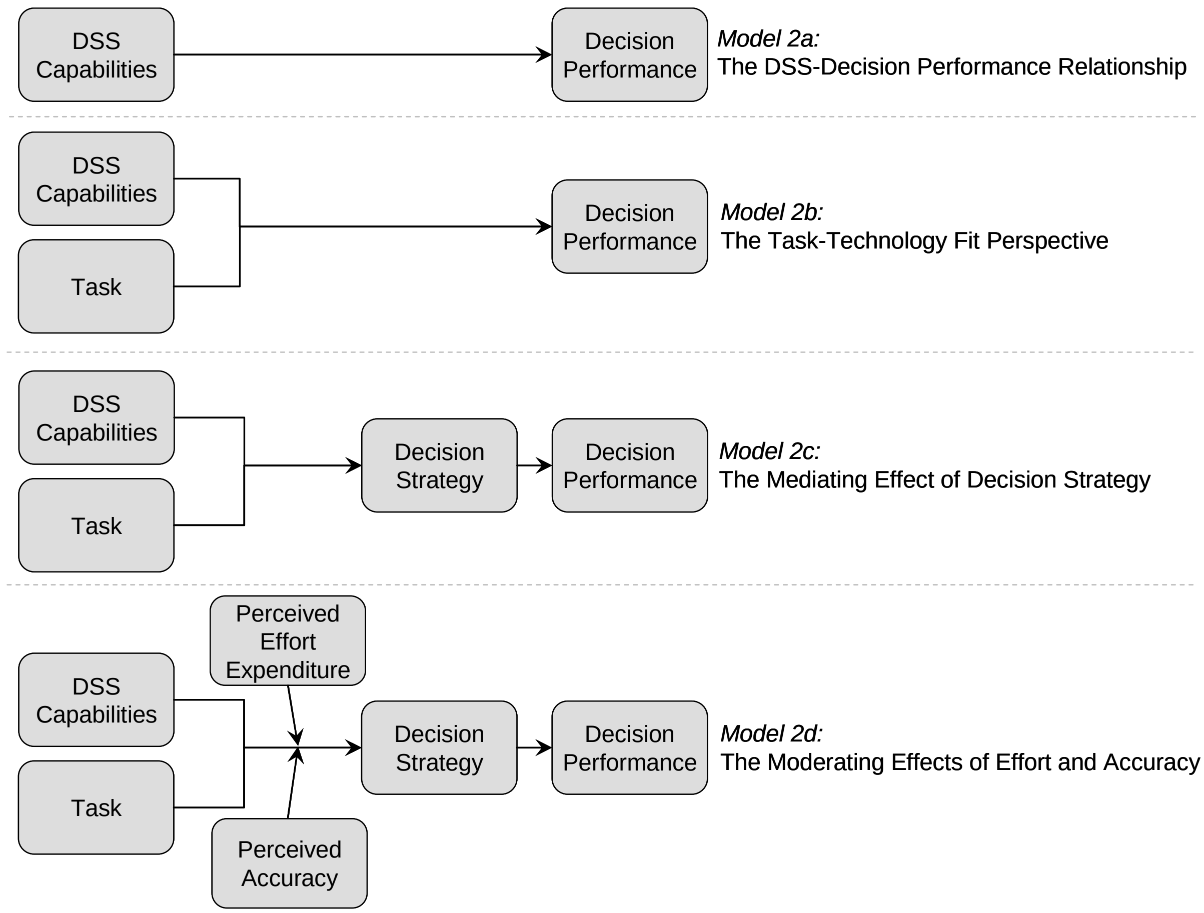

FIGURE 3.1: Evolution of the DSS-Performance relationship (Todd & Benbasat, 1999)

The task-technology fit perspective, presented in model 2b, suggests that decision performance is influenced by the nature of the *decision task* to be executed and the type of *decision support* provided. Task-technology fit focuses on the degree to which the characteristics of a DSS match user task needs (Goodhue, 1995). Research based on this model found that the influence of DSS capabilities on decision performance is contingent upon the match between the requirements of the task and the capabilities provided. For example, Goodhue and Thompson (1995) found support for the notion that decision performance is a function of task-technology fit. The greater the alignment between DSS capabilities and the requirements of the task, the more effective the DSS will be.

Model 2c suggests that the influence on decision performance of both DSS capabilities and the task to be executed is mediated by decision strategies. Jarvenpaa (1989) argued that DSS research should not only focus on the 'end products of decision making', such as decision quality or decision time, but should also examine the decision processes that link information to decision outcomes. The decision process was integrated into DSS research models by the use of decision strategy as mediating variable (Jarvenpaa, 1989; Todd & Benbasat, 1991). Research showed that decision strategy is an important intervening variable in the relationship between DSS features and decision outcomes (Jarvenpaa, 1989).

Model 2d is an extension of model 2c integrating the assumptions of the effort-accuracy framework. According to this model *perceived effort expenditure* and *perceived accuracy* both influence decision strategy selection under conditions of automated decision support. These two factors are presented as mediating variables. A series of DSS studies (Chu & Spires, 2000; Todd & Benbasat, 1991, 1992, 1994a, 1994b, 1999, 2000; Wang & Chu, 2004) proved that the principles of the effort-accuracy framework are valid under conditions of automated decision support also. As such, effort and accuracy considerations can be used to explain how a DSS will be used.

3.3 Effort and accuracy under conditions of automated decision support

Although the assumptions concerning the notion of *accuracy* remain unchanged, the assumptions concerning the notion of *effort* must be modified under conditions of automated decision support. Whereas effort in behavioral decision making research is primarily associated to ‘cognitive effort’, DSS research employs an extended interpretation, not limited to cognitive effort alone. In DSS research the physical acts (e.g. mouse clicks) needed to operate a DSS are also included in the notion of effort, or as Todd and Benbasat (1992) propose: “The effort considerations of the designer must incorporate both the effort required of the decision maker to interact with the DSS and the effort required to process the information generated by the system. If these factors are properly taken into account, then it is possible for the use of a DSS to lead to higher quality decisions” (p.390).

For example, Todd and Benbasat (1999) explicitly integrate command usage on explaining a difference in effort needed for the execution of the WADD across two different levels of decision support. Because both levels of support provide the functions needed to fully automate the cognitive effort required to execute the WADD strategy, cognitive effort can not be used as effort differentiator here. However, the number of system commands needed to implement this strategy varies across the different levels of decision support, allowing for their use as effort differentiator. Such an approach does not limit its focus to cognitive effort, but clearly integrates command usage in the effort construct.

3.4 Decision strategies in DSS research

Although empirical studies in DSS research specifically focused on four decision strategies: (weighted) additive (WADD) strategy, additive-difference (ADDIF) strategy, conjunctive (CNJ) strategy, and elimination by aspects (EBA) (e.g. (Chu & Spires, 2000; Todd & Benbasat, 1991, 1992; Wang & Chu, 2004)), the two strategies most commonly studied are: WADD and EBA (Todd & Benbasat, 2000). The reasoning behind the focus on these two strategies is in the fact that they represent prototypical compensatory and noncompensatory approaches, as well as that the WADD and EBA strategy are relatively easy to automate. Particularly the WADD strategy can be automated to varying degrees, allowing for the examination of a decision maker’s sensitivity to different levels of decision support that require different combinations of individual effort and DSS command usage (Todd & Benbasat, 1999).

3.5 Mouselab and DSS research

To fully understand the DSSs discussed in the subsequent paragraphs of this chapter it does make sense to bear in mind the principles underlying the design of Mouselab (see § 2.4). Mouselab is not a decision support system but rather decision laboratory software, primarily developed to monitor decision behavior. However, the information display method (e.g. (Todd & Benbasat, 1991, 1992, 1994a, 1994b, 1999, 2000)), as well as the computerized process tracing method integrated in Mouselab (e.g. (Chu & Spires, 2000)) served as a frame of reference for the design of the DSSs employed in support of the DSS studies discussed below.

3.6 Prior DSS research: Todd and Benbasat

In a series of DSS studies (1991, 1992, 1994a, 1994b, 1999, 2000), conducted in a time frame of ten years, Todd and Benbasat investigated the role of computer-based decision aids on decision strategy selection. Their findings substantially contributed to our understanding of decision behavior under conditions of automated decision support. On explaining how DSS capabilities influence decision behavior and performance, Todd and Benbasat considerably rely on the effort-accuracy framework.

In context of the effort-accuracy framework, Todd and Benbasat used the notion of elementary information processes (EIPs) to estimate effort expenditure and explain the influence of automated decision aids on decision behavior. Decomposing decision strategies in EIPs allowed Todd and Benbasat to determine the reduction in effort expenditure when specific EIPs are performed by automated decision aids. The decomposition of decision strategies in their constituent series of EIPs is explained by Todd and Benbasat in different research papers (e.g. EBA & ADDIF (Todd & Benbasat, 1994b) and WADD (Todd & Benbasat, 2000)). Because these decompositions also function as a frame of reference for this research we will elaborate on the decomposition of two exemplary decision strategies: the Additive Compensatory[5] (AC) strategy and the Elimination by Aspects (EBA) strategy. It should be noted that Todd and Benbasat deviate from the set of EIPs as proposed by Bettman *et al.* (1990) (see also table 2.2). Whereas Bettman *et al.* use a single EIP (=*read*) for any data acquisition effort, Todd and Benbasat differentiate between a read from an external source (=*read*) and a read from the decision maker's memory (=*retrieve*). Todd and Benbasat also discern an additional EIP called *store*, representing the effort needed to store a data element. Because the estimates of EIP load presented below "are meant to illustrate the *relationships* between the strategies" (Todd & Benbasat, 2000, p.93) the number of EIPs distinguished is less relevant, provided that the same set of EIPs is used for all decomposition processes.

A decision maker implementing an AC strategy will evaluate one alternative at a time along all the relevant attributes. Attribute importance can be expressed by assigning weights to the relevant attributes. To calculate the AC score for a particular alternative the following sequence of operations must be performed by the decision maker: *read* the first attribute value, *combine* this attribute value with its weight, repeat this process for each attribute of the alternative, calculate the AC score for this alternative by *summing* the *products* of the attribute

[5] Todd and Benbasat use the term (AC) strategy instead of weighted additive (WADD) strategy. According to the explanation of the AC strategy provided by Todd and Benbasat (1999, 2000), the AC strategy is similar to the WADD strategy. However, since Todd and Benbasat use the term 'AC strategy' we will continue to use this abbreviation on explaining their DSS research.

values and weights. The sequence of EIPs needed to examine a single attribute is shown in table 3.1.

TABLE 3.1: Sequence of EIPs Associated with the Examination of a Single Attribute (Additive Compensatory (AC) strategy) (Todd & Benbasat, 2000, p. 95)

Sequence	*Elementary Information Process (EIP)*
1	*move* to the specific attribute value
2	*read* the attribute value
3	*retrieve* attribute weight from long-term memory
4	*multiply* attribute value and weight
5	*retrieve* the current alternative score (from short-term memory)
6	*add* weighted attribute score to current alternative score
7	*store* the updated alternative score

In order to evaluate one alternative these seven steps must be repeated for each of the alternative's attributes available at the moment of evaluation. Full implementation of an AC strategy on a decision set representing a ten alternatives (rows, r=10) by eight attributes (columns, c=8) problem implies a total number of 598 EIPs. Evaluation of one alternative involves the seven afore mentioned steps to be performed for each of the eight attributes, resulting in a number of 56 EIPs per alternative. To calculate an AC score for each of the ten available alternatives requires 560 EIPs. Once the AC scores are computed the next step in the AC strategy will be to determine which of the alternatives has the highest AC score. To create a point of reference the decision maker can designate the last processed alternative as the one with the highest AC score and compare the remaining alternatives with this temporary highest score. This requires the decision maker to: *store* a pointer to the last processed alternative as well as *store* its AC score. Subsequently the remaining alternatives are compared to this 'highest' score requiring the decision maker to: *retrieve* the score of the current best alternative, *compare* this score to the AC score of the alternative under evaluation, *store* the alternative with the highest score, and *store* the new best alternative score. These four steps are repeated nine times (alternatives –1). The general formula for calculating the number of EIPs needed to apply an AC strategy reads as follows: 7*(alternatives*attributes)+2 (storing the highest AC value and associated alternative)+4 *(alternatives –1).

The AC strategy belongs to the category of compensatory decision strategies. To compare the cognitive load of a compensatory strategy with a noncompensatory strategy, the effort related to the elimination by aspects (EBA) strategy will be elaborated on below.

Comparison of attribute values to some threshold level is the essence of the EBA strategy. Any alternative that does not meet the threshold level for any one of its attributes will be eliminated. The evaluation of a single attribute requires four EIPs: *move* to the specific attribute value, *read* the attribute value, *compare* attribute value to threshold, and *eliminate*[6] alternative if the attribute value does not meet the specified threshold level. Attributes are

[6] Although not any comparison will lead to an elimination of an alternative we assume the eliminate EIP as a fixed step in the evaluation process of an alternative. Herby we concur to the approach employed by Todd and Benbasat (Todd & Benbasat, 1994b).

selected in hierarchical order of importance, starting with the most important attribute. For any attribute only one threshold needs to be retrieved. Obtaining the thresholds for a ten alternatives by eight attributes (10x8) decision problem requires eight EIPs (number of attributes). An important effort consuming process in the EBA strategy is the tracking of alternatives that have already been deleted as a result of preceding comparisons against the threshold specified. In order to avoid *re*processing of attribute values of alternatives that has already been eliminated it will be necessary to track the status of an alternative prior to evaluation. Except for the first attribute selected, checking the status will be necessary for all other alternatives to be reviewed within the remaining attributes. The number of EIPs required for tracking the status can be computed as follows: ((attributes-1)*alternatives). In our example a total number of (8-1)*10=70 EIPs will be necessary to track the status. The total number of EIPs required to implement an EBA strategy for an r*c[7] matrix is: (1*c)+(1*(c-1)*r)+(4*(r*c)). In case an EBA strategy will be applied to a ten alternatives by eight attributes (10x8) selection task, a total number of 8+70+320=398 EIPs will be required.

A major assumption underlying the afore presented EIP calculations is that all alternatives are only examined once. The results of these calculations must be considered estimates of EIP load and are by no means absolute. The primary purpose of these calculations is to illustrate the relationships between the strategies (Todd & Benbasat, 2000).

According to the effort-accuracy framework an unaided decision maker who places a significant weight on cognitive effort will choose for the lower effort demanding EBA strategy. The effort-accuracy balance can shift when decision makers are supported with decision aids that reduce cognitive effort by automating one or more EIPs. The impact of automated decision aids on decision behavior can be explained using the assumptions of the effort-accuracy framework, whereas the effort reducing effects of automated decision aids can be made explicit by means of the afore mentioned formulas.

3.6.1 The DSS developed by Todd and Benbasat

Todd and Benbasat developed several DSSs to support their research on preferential choice decision making (1991, 1992, 1994a, 1994b, 1999, 2000). Their DSSs used a command based interface and presented information in a matrix form, comparable to the way information is presented in spreadsheet programs. The set of decision aids used in their 1999 and 2000 research projects can be considered the common denominator of all relevant automated decision aids developed by Todd and Benbasat, and will as such be considered a frame of reference for the description of their DSS projects provided in this section. This reference set is presented in table 3.2.

TABLE 3.2: DSS Command Descriptions (Todd & Benbasat, 1999, p. 363)

Command	*Description*	*Syntax*
OPEN	Uncovers a specified cell, row [*)] (attribute) or column (alternative).	Open row, or column, or cell e.g. OPEN 6 F
CLOSE	Covers a specified cell, row or column that has been previously opened.	CLOSE row, or column, or cell e.g. CL 6 F

[7] r is the number of alternatives (rows) and c is the number of attributes (columns).

TABLE 3.2: DSS Command Descriptions (Todd & Benbasat, 1999, p. 363)

Command	*Description*	*Syntax*
DROP	Causes a specified row or column to be deleted from the matrix.	DROP row or column e.g. DR 1
CONDITIONAL DROP	Drops alternatives contingent upon the value of an attribute.	DROP row {operator} threshold e.g. DR 1 > 250
CREATE	Creates a new column into which user specified values can be entered.	CREATE column label e.g., CREATE Weights
CALCULATE	Performs a specified arithmetic operation on any pair of rows or columns.	CALCULATE Column 1 (+,-,*,/) Column 2 e.g., CALC A*B
ROW TOTAL	Sums all the values of each alternative and places the results in a new row.	RTOTAL
GLOBAL	Performs arithmetic operations to combine the values in one column with all other columns. Current values in those columns are overwritten.	GLOBAL (+,-,*,/) column label e.g., GLOBAL * Weight
UNDO	Reverses the effect of the previous command. Successive undo commands progressively undo prior operators for up to six steps.	UNDO

*) Alternatives are represented in columns, the rows of the decision matrix represent attribute values.

The commands provided allowed decision makers (subjects) to manipulate the information in the decision matrix.

Implementation of an AC strategy, using the decision aids presented in table 3.2, requires the following sequence of commands:

1. CREATE Weight
   The CREATE Weight command adds a column to the matrix into which attribute weights can be stored. After creating this “weights-column” the decision maker will be able to assign user-specific attribute weights.
2. GLOBAL * Weights
   The GLOBAL command can be used to calculate the weighted attribute scores by multiplying all attribute values in the decision matrix with the weights entered in the additional weights-column.
3. ROW TOTAL
   The ROW TOTAL command sums the weighted attribute values per alternative, providing a weighted total score for each alternative.

The preferred alternative will be the alternative with the highest weighted total score. These commands reduce the implementation of an AC strategy to three system processing steps: WEIGHTS, GLOBAL, and ROW TOTAL. All calculations will be performed by the decision aids reducing the cognitive effort level to a minimum (only the EIPs related to ‘retrieving’ the weights from memory and determining which alternative has the highest AC score are needed).

The key command in supporting the eliminations by aspects strategy is the CONDITIONAL DROP. Calculating the number of system commands needed to implement a full EBA strategy is not as straightforward as calculating the number of systems commands needed for the implementation of an AC strategy, because the number of commands needed is dependent on both the threshold levels specified by the decision maker and the attribute values of the relevant attributes in the decision matrix. A decision maker applying very tight criteria may be able to specify a threshold level that leaves only one alternative after a single CONDITIONAL DROP. Even in a situation that one CONDITIONAL DROP will be enough, which can be considered extreme, one might expect that the trade off between two additional system commands (= effort), and a higher level of accuracy, will be decided in favor of increased accuracy. In the end, compared to an EBA strategy, the additional effort needed for the implementation of an AC strategy can be considered marginal (one versus three system commands respectively). When the decision aids described are considered in context of the effort-accuracy framework, a decision maker acting under conditions of automated decision support will most likely choose for the implementation of the *AC* strategy.

To show the impact of the DSS developed by Todd and Benbasat on cognitive effort reduction, the EIPs needed for the implementation of the two strategies considered prototypical for compensatory and noncompensatory decision strategies, AC and EBA respectively, under both the ‘aided’ and ‘unaided’ condition, are shown in table 3.3.

TABLE 3.3: EIPs Required for Decision Strategies, Assuming a 10 Alternatives by 8 Attributes Decision Set (adapted from (Todd & Benbasat, 2000))

Decision Strategy	*Unaided*	*Aided*	*Cognitive Effort Reduction*
Additive Compensatory (AC)	598	8*)	590
Elimination-by-Aspects (EBA)	398	8	390

*) Because tracking and processing are fully supported by the DSS, only 8 recall processes are needed to ‘recall’ a weight for each available attribute.

3.6.2 Process tracing method and dependent variables employed by Todd and Benbasat

Todd and Benbasat primarily employed VPA for data acquisition. To infer on decision behavior, five so called strategy operators were developed by Todd and Benbasat. Four of these operators, (1) independent evaluation, (2) dependent evaluation, (3) elimination statements, and (4) compensatory statements, were introduced in their 1994 paper, whereas the fifth operator, (5) total statements, was introduced in their 1999 paper.

Independent evaluations are statements which compare an attribute value to some externally identified criterion. Independent in this context stands for the fact that the evaluation of an alternative is made independent of another alternative. Statements like “Apartment N is small”, “Car B is expensive”, or “The DVD-player of Philips is within my budget of $250”, are all examples of independent evaluations. Independent evaluations are characteristic of noncompensatory decision strategies(Todd & Benbasat, 1994b).

Dependent evaluations imply a pair wise comparison between two alternatives based on a single attribute. Statements like “The DVD-player of Philips is cheaper than the player of Sony”, or “Apartment B is bigger than apartment C”, are both examples of dependent evaluations. Dependent must be interpreted as dependent on other alternatives in the decision set. Dependent evaluations are characteristic of compensatory strategies in general, and an exemplary characteristic of the additive-difference strategy specifically.

Elimination statements. If a decision maker explicitly drops an alternative from the decision matrix prior to a complete evaluation, it will be considered an elimination statement. For example, “This car is not red so it does not make sense to consider it any longer”. Actually this operator considers all alternatives that are eliminated before all attribute values are evaluated. A relative large number of elimination statements is an indicator for noncompensatory decision behavior.

Compensatory statements involve “the aggregation and/or tradeoff of two or more attributes for a single alternative “(Todd & Benbasat, 1994b, p. 46). Examples of compensatory statements are: “Although the price of apartment A is high, it is near the campus and has a well equipped kitchen”, and “Although the sum of attribute values of apartment B is the highest of all alternatives, it is very expensive”. Compensatory statements are characteristic for compensatory strategies.

Total statements. This operator stands for the total number of statements made by a decision maker and is indicative of the overall amount of information processed in completing the decision task (Todd & Benbasat, 1999). According to Todd and Benbasat the number of total statements made should be higher when compensatory strategies are employed, since elimination strategies will reduce the number of alternatives, leaving fewer possibilities to execute statements. A decision matrix containing ten alternatives embodies the potential of performing a compensatory statement on each of these alternatives (10 statements), however, when the number of alternatives is reduced through the application of an EBA strategy, for example to three alternatives, the potential of applying statements is also reduced.

3.6.3 Research findings Todd and Benbasat

The DSS research projects of Todd and Benbasat found strong support for the notion that decision makers tend to adapt their decision behavior to the type of DSS capabilities provided (1991, 1992, 1994a, 1994b, 1999, 2000). The results of their experiments indicate that effort consideration “is the major determinant of strategy selection” (Todd & Benbasat, 1999, p. 359). More specific, they found that increasing the level of compensatory decision support will induce compensatory decision behavior (Todd & Benbasat, 1999, 2000). The results of their experiments confirm the notion that decision behavior can be influenced by means of automated decision aids.

3.7 Prior DSS research: Chu and Spires

The effort-reducing role of automated decision aids, and the influence of these aids on decision strategy selection plays an important role in the DSS research performed by Chu and Spires. In context of this study the DSS research executed by Chu and Spires (2000) is considered important not only because they contributed to our insights on the effects of DSSs on decision behavior, but rather because of the method they employed to trace decision behavior. As will be explained in the next chapter, the decision process tracing method used by Chu and Spires was an important driver for the development of the DSS environment employed in this research project. Although Chu and Spires investigated the effects of both effort and quality on strategy selection in their DSS study (2000), the discussion of their research presented below will consider the decision process aspects only, since the primary focus of this study is on decision behavior and not on decision outcomes.

3.7.1 The DSS developed by Chu and Spires

The DSS developed by Chu and Spires allowed preferential choice problems to be displayed in matrix form. An impression of the decision screen developed by Chu and Spires is shown in figure 3.2.

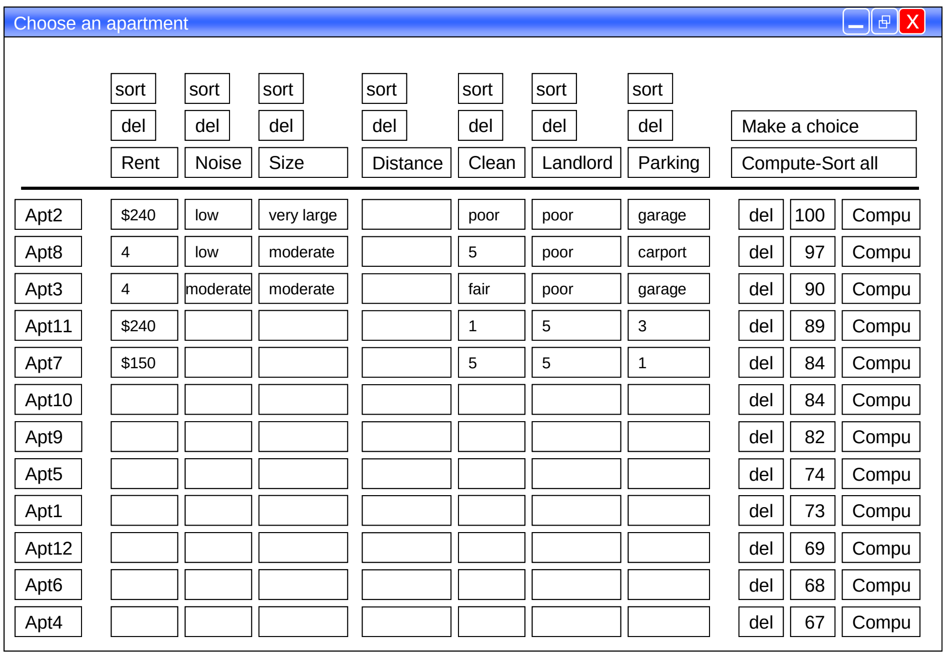

FIGURE 3.2: Sample Screen of the Windows-based Decision Aid developed by Chu and Spires (2000, p.279)

The body of this matrix contains cells, representing all available alternative-attribute combinations. Each cell contains a value that is hidden in the initial status of the matrix. A decision maker can access the value of a cell by a mouse click on the cell. The software allows cell values to be presented in two formats: numeric and text. Clicking the cell for the first time reveals the text value, the numeric value could be revealed by an additional click on the cell. Clicking the cell again will revert it to its hidden state. A cell can be in one of the three states: hidden, open-text, or open-numeric.

Table 3.4 shows the functions that were provided by the system. The decision aids constituted a fully functional DSS. The functions DEL and SORT support the implementation of noncompensatory strategies (e.g. Elimination by Aspects and Lexicographic). Whereas the COMPU command supports the partial implementation of the weighted additive (WADD) strategy, its implementation is fully supported by the COMPU-SORT-ALL command. The system was nondirective (Silver, 1990), decision makers using the system were free in their choice which strategy to apply, so “it imposed no control over a participant’s decision strategy” (Chu & Spires, 2000, p. 275). The system offered the flexibility to pursue various strategies.

The experiments conducted by Chu and Spires included aided and unaided decision tasks. Under the unaided condition the decision matrix was presented to the participants, while no decision aids were made available (apart from the Make a Choice command). Participants acting under the 'aided' condition had all the functions presented in table 3.4 at their disposal (See also figure 3.2).

TABLE 3.4: Decision Aid Functions DSS Chu and Spires (2000)

Command	*Description*
SORT	Sorted alternatives in descending order according to the values of an attribute.
DEL (attribute)	Caused all the values associated with a given attribute to disappear from the display. Clicking the same button again reversed the delete.
DEL (alternative)	Caused all the values associated with a given alternative to disappear from the display. Clicking the same button again reversed the delete.
COMPU	Computes a weighted score for an alternative according to the weighted additive formula. Clicking the COMPU button also triggers additional functionality needed to specify the attribute weights. A decision maker can choose for accepting the default weights (1 for all attributes), or provide differential weights. The computed weighted score will be shown next to the COMPU button.
COMPU-SORT-ALL	This command executes similarly to the COMPU command, except that it computes weighted scores for all alternatives simultaneously and sorts all alternatives in descending order according to the scores. The alternative with the highest score will be placed on top of the decision screen.
MAKE-a-CHOICE	Records the alternative chosen.

Table 3.5 shows an illustration of the EIP computation method as applied by Chu and Spires[8]. To show the impact of the DSS developed by Chu and Spires on cognitive effort reduction, the EIPs needed for implementation of the two prototypical decision strategies WADD and EBA, under both the 'aided' and 'unaided' condition, are shown in table 3.6.

[8] This overview is limited to the WADD and EBA strategy since these two strategies are considered exemplary for compensatory and noncompensatory decision strategies respectively, and will also be sufficient to show Chu and Spires' interpretation of the "EIP language".

TABLE 3.5: Decision Strategies and Related EIPs. Adapted from (Chu & Spires, 2000, p. 289)

EIP Computation Method Chu and Spires
The EIP set contains the following primitives: *read*, *retrieve*, *move*, *subtract*, *add*, *combine* (*multiply*), *compare*, *eliminate*, and *store*. The number of alternatives in a decision matrix is represented by *m*, and *n* the number of attributes.

Weighted-Additive (WADD) strategy

EIPs for the WADD strategy are as follows:

1. EIPs for computing a weighted score for one alternative: *move* to attribute A, *read* A, *retrieve* weight W_A, *multiply* A by W_A, and *store* the result. Five operations are involved. Repeat the process for all attributes. *Add* attribute scores to obtain a total score. *Store* the total score as x_1. Thus, the EIPs required to compute a weighted score for one alternative are $5*n+(n-1)+1$.
2. EIPs for computing a weighted score for all alternatives: m* $(5*n+(n-1)+1)$.
3. EIPs for finding the alternative with the highest score: *retrieve* weighted score x_1, *retrieve* weighted score x_2, *compare* x_1 and x_2, *eliminate* the alternative with the lowest score. Four operations are involved. This process is repeated until one alternative remains. The EIPs required are $4*(m-1)$.
4. Total EIPs: m* $(5*n+(n-1)+1)+(4*(m-1))$. For a problem with 12 alternatives and seven attributes, the total number of EIPs is 548.
5. With the aid, only seven EIPs (retrieving attribute weights) are required.

Elimination-by-Aspects (EBA) strategy

1. The EBA computation for the EBA strategy is based on the formula given by Todd and Benbasat (1994b): $(1*n)+(1*(n-1)*m)+(4*(m*n))$. The three components represent retrieving, tracking, and evaluating operations, respectively. For a problem with 12 alternatives and 7 attributes, the total number of EIPs is 415.
2. With the use of the decisions aid, tracking is not necessary (DEL buttons eliminate unsatisfactory alternatives). Also, the use of the binary search*) technique reduces the number of cells evaluated. In the worst scenario, for each attribute, four cells are accessed and evaluated. EIPs required for evaluation are (4*(4*n)). Thus with the aid, the total number of EIPs is $(1*n)+(4*(4*n))$, or 119.

*) Search a sorted attribute range by repeatedly dividing the search interval in half. Begin with an interval covering the whole array. If the attribute value of the alternative accessed in the middle of the interval is less than the threshold, narrow the interval to the upper half. Repeatedly check until both attributes of the last interval are opened or only one alternative remains. In case of a worst case scenario a decision set containing twelve alternatives must be divided into halves four times, requiring four attributes to be accessed.

TABLE 3.6: EIPs Required for Decision Strategies, Assuming a 12*) Alternatives by 7 Attributes Decision Set.

Decision Strategy	*Unaided*	*Aided*	*Cognitive Effort Reduction*
Weighted-Additive (WADD)	548	7	541
Elimination-by-Aspects (EBA)	415	119	296

*) The decision task employed by Chu and Spires included a decision matrix containing 12 alternatives and 7 attributes.

3.7.2 Process tracing method and dependent variable employed by Chu and Spires

Where Todd and Benbasat used verbal protocols to trace decision behavior, Chu and Spires integrated a database environment in their experimental DSS to record all details of the experimental sessions. Decision time, user interaction with the system, command buttons clicked and the choice made were all chronologically recorded and used to infer about the decision strategies applied by the users of the system. The DSS developed by Chu and Spires integrated some of the core functionality of Mouselab. Whereas Mousleab was primarily developed to support behavioral decision making experiments, and includes dedicated software to develop experiment specific user interfaces, the primary aim of the system developed by Chu and Spires was automated decision support. In fact they integrated the Mouselab functions for information acquisition and information search in a more sophisticated user interface (Windows) and added automated decision aids to support a variety of decision strategies.

To test their hypotheses concerning the influence of decision aids on decision behavior Chu and Spires employed three dependent variables[9]:

1. *Information acquisition*: the proportion of the available cells accessed.
2. *Variability in the amount of information accessed per alternative* measured as the standard deviation of the percentage of available information searched per alternative.
3. The *pattern of information search* measured as:

$$\textit{Search Index} = \frac{\textit{Alternative Transitions -/- Attribute Transitions}}{\textit{Alternative Transitions} + \textit{Attribute Transitions}}$$

Operationalization of these three variables happened in a way similar as defined by Payne (1976) (see also § 2.4.3).

3.7.3 Research findings Chu and Spires

The experiments performed by Chu and Spires proved that decision support aids influence decision behavior in such a way that it is consistent with the basic assumptions of the effort-accuracy framework. For example, Chu and Spires found support for their hypothesis stating that decision makers acting under conditions of automated decision support show more WADD-like decision behavior than unaided decision makers. They also found support for their

[9] The fourth dependent variable employed by Chu and Spires, decision proximity, concerned a decision outcome variable and was not introduced to measure decision behavior.

hypothesis assuming a positive relationship between task complexity and the use of decision aids for the implementation of the WADD strategy.

3.8 Summary

This chapter discussed the fundamental DSS studies for this research. Because DSS research is grounded in behavioral decision making theory, the DSS studies discussed are explained in context of the concepts, theories and methods introduced in chapter two. For each study presented the notion of decision strategy, the method employed for capturing decision behavior, the operators used for characterizing decision behavior, as well as the most important findings are elaborated on. By addressing these issues this chapter developed a point of departure for an investigation aiming at the improvement of the methods and measures employed in DSS research so far. Such an investigation will be the focus of the next chapter.

CHAPTER 4

FUNCTIONAL REQUIREMENTS ENHANCED DSS ENVIRONMENT

4.0 Introduction

The development of an enhanced DSS environment is recognized as an important contribution of this study. This chapter builds upon the research explained in the previous chapters to develop a framework for the design of such an enhanced DSS environment. To create a context for this development process a set of so called design principles will be introduced first. Subsequently, the opportunities for improvement of DSS research concepts, systems and methods will be investigated. The objective of this investigation is to develop the functional requirements for an enhanced DSS environment. However, the first part of this chapter will address an important issue concerning process tracing methods. As explained in the previous chapter, two different process tracing methods are employed in the fundamental DSS studies underlying this research: verbal protocol analysis (VPA) and computerized process tracing (CPT). This chapter will start with a comparison of VPA and CPT. Not only to justify our choice for CPT, but rather to create a point of departure for thinking about the improvement of DSSs.

4.1 Process tracing methods: VPA versus CPT

VPA and CPT are both common data acquisition techniques in DSS research. For example, Todd and Benbasat primarily relied on VPA as a method for data acquisition in most of their DSS research projects (1991, 1992, 1994a, 1994b, 1999, 2000). Mouselab (Payne *et al.*, 1993), Search Monitor (Brucks, 1988), Information Search Laboratory (ISLab) (Cook, 1993) and P1198 (Andersson, 2001) are all examples of CPT tools that have been developed to support research in judgment and decision making. Although most of these CPT tools have been applied in DSS research (Cook, 1993), this study will primarily focus on the implementation of the CPT tool developed by Chu and Spires (2000) (see also § 3.7.2), because this tool is developed to support one of the fundamental studies underlying this research.

In order to explore the possibilities for enhancing the application of process tracing tools in DSS research, the scope, pros, cons and limitations of both VPA and CPT will be elaborated on below.

4.1.1 VPA versus CPT: Scope

Svenson (1979) argued that when process tracing techniques are used to map cognitive processes, it is necessary to know *what* content or information is processed and *how* it is processed. This reasoning is in line with the proposition of Einhorn and Hogarth (1981) that decision behavior is comprised of three interrelated sub processes: (1) information acquisition (*what*); (2) information evaluation (*how*)/action (*decision*); and (3) feedback and learning. Because this study does not focus on dynamic experimental task environments (Biggs *et al.*, 1985) feedback and learning sub processes will not be considered. The primary focus will be on the role of VPA en CPT in tracing information acquisition and evaluation.

When it comes to determining the effort related to information search and information processing, it should be noticed that according to so called explicit behavioral models of strategy effort, the distinction between acquiring and processing information is less relevant. Explicit behavioral models monitor information acquisition and represent a base-line model of effort in that the details of processing are ignored. An important premise of these models is that the specific type of processing done on the information acquired makes little or no difference in determining decision effort (Bettman *et al.*, 1990). However, in context of DSS research aiming at enhanced insight on the influence of automated decision aids on decision behavior, we consider a base-line approach as proposed by explicit behavioral models as an impediment for micro level DSS studies. Especially for the design and development of DSSs it is important to know how decision behavior will be influenced through decision aids providing information processing support.

To support the investigation of the role and use of VPA and CPT in DSS research, a detailed overview of the fundamental DSS studies for this research is provided in table 4.1. For each study included in table 4.1 the dependent variables employed and the process tracing method used are presented. The dependent variables are characterized according to their focus on: information acquisition (*what*), information processing (*how*), the decision outcome (*choice*), or on the combination of all three.

TABLE 4.1: DSS Research Projects, Dependent Variables and Process Tracing Methods

Research Papers		***Dependent Variables***			***Process Tracing***	
Year	***Author(s)***	***Information Acquisition (what)***	***Information Processing (how)***	***Action (choice)***	***VPA***	***CPT***
1991	Todd and Benbasat	• Information used • Variability of attributes examined per alternative	• Direction of search • Eliminations prior to choice • Ratio of dependent to total evaluations • Compensatory statements		Yes	No
Remarks: Although the decision aid employed in this research project comprised a computerized information display board, only VPA was used as process tracing method. Todd and Benbasat expressed: “All data reported were based on the use of concurrent verbal protocols” (1991, p. 110). The two dependent variables explicitly mentioned in the text of this paper are: “direction of search” and “overall strategy” (p. 99). From the appendix of this paper we derived that overall strategy was operationalized using the variables mentioned above.						
1992	Todd and	• Unique units of			Yes	No

TABLE 4.1: DSS Research Projects, Dependent Variables and Process Tracing Methods

Research Papers		***Dependent Variables***			***Process Tracing***	
Year	***Author(s)***	***Information Acquisition (what)***	***Information Processing (how)***	***Action (choice)***	***VPA***	***CPT***
	Benbasat	information referenced • Total units of information referenced • Number of alternatives analyzed in detail				
1994b	Todd and Benbasat		• Independent evaluations • Dependent evaluations • Elimination statements • Compensatory statements		Yes	No
1994a	Todd and Benbasat		• Independent evaluations • Dependent evaluations • Additive statements • Elimination statements		Yes	No
1999	Todd and Benbasat		• Independent evaluations • Elimination statements • Compensatory statements • Total statements		Yes	No

TABLE 4.1: DSS Research Projects, Dependent Variables and Process Tracing Methods

Research Papers		*Dependent Variables*			*Process Tracing*	
Year	***Author(s)***	***Information Acquisition (what)***	***Information Processing (how)***	***Action (choice)***	***VPA***	***CPT***
2000	Chu and Spires	• Proportion of available information used • Variability in the amount of information accessed per alternative • Search index		• Decision outcome	No	Yes
2000	Todd and Benbasat		• Independent evaluations • Elimination statements • Compensatory statements		Yes	No
2004	Wang and Chu	• Proportion of available information used • Variability in the amount of information accessed per alternative • Search index		• Decision outcome • Amount of time spent on decision	No	Yes

Although VPA is considered valuable for tracing both information acquisition (*what*) and information processing (*how*) (Abelson & Levi, 1985), the focus of VPA in the DSS research projects presented in exhibit 4.1 has particularly been on information processing. VPA is mentioned as a method to infer on information acquisition behavior only in the early DSS research projects (1991 and 1992) of Todd and Benbasat. Since their 1994 research, including their most recent DSS studies, VPA has only been used to infer on information processing behavior.

Research comparing concurrent verbal protocol traces with those from a computer search process tracing method confirmed this shift as sensible, because verbal traces were found to capture information acquisition behavior less completely than CPT methods did (Biggs *et al.*, 1993). As can be derived from exhibit 4.1[10], CPT tools are used in DSS research to tap *what* content or information is processed, whereas verbal protocols are used to trace *how* information is processed. Roughly speaking one can argue that CPT tools have been useful primarily for examining information *acquisition* behavior, whereas VPA has been useful primarily for examining information *processing* behavior.

4.1.2 VPA versus CPT: pros, cons and limitations

Providing a general evaluation of the available process tracing techniques is common in research projects that rely on process tracing for data acquisition (e.g. (Abelson & Levi, 1985; Biggs *et al.*, 1985; Ford *et al.*, 1989; Payne *et al.*, 1993; Svenson, 1996)). Regarding the evaluation of process tracing techniques in DSS research the papers of Todd and Benbasat (1987), Cook (1993), Cook and Swain (1993), and Biggs *et al.* (1993) are of special interest because they directly evaluate the use of VPA against CPT tools. The most important application and methodological issues concerning both VPA and CPT are presented in tables 4.2 and 4.3 respectively. It should be noticed that these overviews are based on a review of the literature mentioned above.

TABLE 4.2: Advantages and Limitations of Verbal Protocol Analysis (VPA)

	Verbal Protocol Analysis
Advantages	***Rich data (Biggs et al., 1993):*** The major advantage of VPA is that it produces rich data about knowledge and reasoning processes used during the performance of a judgment/decision task. Verbal protocols provide the greatest data richness, and are considered the most powerful of all process tracing tools for discovering the dynamics of problem definitions, hypothesis formation, and information search in less structured contexts (Todd & Benbasat, 1987).
Limitations	***Concurrent verbal reports may be incomplete (Biggs et al., 1993):*** Experienced subjects can use highly over learned processes that operate automatically and will not be expressed while thinking aloud. Coding schemas must be developed in such a way that all relevant data will be captured. If a coding schema does not provide codes for all relevant statements done by a subject, the result will be an incomplete representation of the decision process (Todd & Benbasat, 1987). ***Validity:*** The validity of the data recorded is only as good as the ability of the decision maker to examine

[10] To the best of our knowledge table 4.1 is a complete representation of all research projects aiming at the investigation of the influence of DSSs on the decision behavior of decision makers performing a preferential choice task.

TABLE 4.2: Advantages and Limitations of Verbal Protocol Analysis (VPA)

	Verbal Protocol Analysis
	introspectively his or her cognitive processes effectively (Cook & Swain, 1993). The presence of an instructor that reminds the decision maker to think aloud is not typical of real life decision situations. ***Obtrusive:*** Since decision makers are highly sensitive to even minor changes in task environments (Einhorn & Hogarth, 1981) the 'thinking aloud' performed during the execution of a decision task can be considered an obtrusive factor influencing the decision process (Biehal & Chakravarti, 1989; Cook & Swain, 1993). Verbalization may be cognitive demanding. Although research investigating the influence of thinking aloud on decision processes and outcomes did not show unequivocal results (Biehal & Chakravarti, 1989; Todd & Benbasat, 1987) it should be noticed that strict rules must be applied to avoid thinking aloud influence the decision task. ***Subjectivity (Biggs et al., 1993):*** Although the coding and interpretation of the (same) protocols can be done by more than one person (intercoder agreement), coding and interpreting protocols are considered a somewhat subjective process. ***Costs of protocol analysis (Todd & Benbasat, 1987):*** The nature and quantity of data generated in a protocol makes analysis difficult and time consuming, which causes samples usually to be very small (commonly between 2 and 20). Small sample sizes make the application of standard statistical procedures difficult and could lead to lower than desired statistical power (Todd & Benbasat, 1991).
Scope	Both information acquisition (*what*) and information processing (*how*).

TABLE 4.3: Advantages and Limitations of Computerized Process Tracing (CPT)

	Computerized Process Tracing
Advantages	***Increased sample size:*** More practical (less labor intensive) to collect data from a large number of subjects, permitting statistical analyses not appropriate for verbal protocol data because of sample size limitations. Increased statistical power (Cook & Swain, 1993). ***Unobtrusive:*** A computer can unobtrusively track the amount, sequence, and type of information viewed, as well as the time related to the actions performed. If the experimental task to be performed and the DSS used are typical of realistic decision situations it will be possible to capture natural, uncontaminated (participants are not required to verbalize their higher-order cognitive processes) process traces (Cook & Swain, 1993).

TABLE 4.3: Advantages and Limitations of Computerized Process Tracing (CPT)

	Computerized Process Tracing
	Objective: Based on prototypical models of information search developed in the field of judgment and decision making research (e.g. search index by Payne and colleagues (1993), decision rules of Svenson (1979)) it will be possible to develop computer algorithms that are able to code and statistically test the data objectively (Cook & Swain, 1993). ***Data format:*** Data can be captured in a machine-readable format, ready for processing and analysis. ***Instructor:*** Participants are not distracted by the presence of an instructor. There will be no active role of the researcher in the experimental session (Cook & Swain, 1993).
Limitations	***Structured task:*** Only decision tasks that can be structured to fit the software can be performed (Cook & Swain, 1993). ***(External) Validity:*** CPT tools focus on decision process research within a computerized environment. Results are only generalizable to decision situations that are in concert with the focus of the research environment. For the purpose of capturing decision behavior the DSS interface can include special CPT functions. The design of the user interface must be in such a way that these functions do not interfere (unobtrusive) with the user's natural decision processes (Cook & Swain, 1993).
Scope	Primarily information acquisition (*what*). (Limited information processing (*how*) e.g. search index)

4.1.3 VPA or CPT?

It has been argued that information display boards and verbal protocols are complementary methods (e.g.(Biggs *et al.*, 1993; Payne *et al.*, 1993; Svenson, 1979)). When this notion of complementarity is considered in the context of DSS research, it is important to distinguish between the use of (1) information display boards; (2) automated information display boards, and (3) CPT tools. Although CPT tools are considered to be automated information display boards, an important feature of CPT tools is the availability of process tracing software that can be used to record all decision process data as well as to investigate information search behavior (Biggs *et al.*, 1993). The difference between option two and three is that automated information display boards do *not* integrate process tracing software. Given this distinction, the complementary use of process tracing methods in DSS research is limited to the simultaneous use of VPA and automated information display methods. The simultaneous use of VPA and CPT in DSS research is sparse, if not lacking. It should be noticed that Todd and Benbasat used automated information display boards in their DSS research projects, however, they did not use process tracing software and fully relied on VPA to derive information acquisition behavior[11].

The advantages and limitations presented in Exhibits 4.2 and 4.3 provide a trivial explanation for the lack of simultaneous use of VPA and CPT in DSS research. A major advantage of CPT tools, nearly unlimited sample sizes, will be undone by a choice for the simultaneous use of VPA because of its implications regarding sample sizes. A researcher considering the use of a multi-method process tracing approach, encompassing both VPA and CPT, has to balance the value of the additional data acquired by CPT against the sample size limitations imposed by the use of VPA. Given the fact that most research budgets will not be unlimited, and that VPA can also be used to infer on information acquisition behavior, it will not be obvious to assign additional resources for the development of CPT tools given the relative high costs related to the use of VPA.

In search for a more scientific explanation for the limited simultaneous use of both methods DSS related research literature was reviewed. This review led to the conclusion that research studying this phenomenon is very sparse. To the best of our knowledge we know of only one study that simultaneously applied VPA and CPT to infer on the validity of both process tracing methods. In their paper called *Methodological Issues in Judgment and Decision-Making Research: Concurrent Verbal Protocol Validity and Simultaneous Traces of Process*, Biggs *et al.* (1993) examined two dimensions of concurrent protocol validity. They investigated (1) whether verbalization affects process and outcome by comparing verbal protocol traces with CPT logs (reactivity), and (2) whether concurrent verbal protocols are complete (completeness) by comparing "concurrent verbal protocol and computer traces that were simultaneously obtained in a treatment in which subjects verbalized as they acquired information from the computer" (Biggs *et al.*, 1993, p. 187). Although the findings of the study performed by Biggs *et al.* are not immediately generalizable to all kinds of judgment and decision-making processes, their study is considered relevant in context of this research for three reasons: (1) it addresses general validity issues concerning VPA and CPT, (2) it supports the scientific positioning of both methods by bringing together relevant issues regarding VPA and CPT in an empirical context, and last but not least, (3) it offers a point of departure for the exploration of possible CPT tool enhancements. The major findings of the study by Biggs *et al.* will be briefly presented below.

Concerning a hypothesized reactivity[12] of computer search to verbalization Biggs *et al.* found that verbalization increased decision time, however, verbalization did not affect amount of information acquired, acquisition pattern, or accuracy of decisions[13]. A BOTH condition was used to test completeness of both verbal and computer process traces. This condition made it possible to compare simultaneous verbal and computer traces of information acquisition behavior. Concerning completeness Biggs *et al.* found evidence that verbal protocols do not provide complete traces of the amount of information acquired by the decision maker. Regarding the value of combining CPT and VPA, Biggs *et al.* concluded:

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[11] The two papers regarding the DSS research projects that considered information usage both mention the use of VPA to derive information usage measures. "All data reported were based on the use of concurrent verbal protocols (Todd & Benbasat, 1991, p. 110) and "All information usage measures are taken from an analysis of verbal protocols that were recorded concurrently with the experimental session (Todd & Benbasat, 1992, p. 382)."

[12] Reactivity was tested by comparing the relevant means of the COMPUTER condition versus the BOTH condition. In the COMPUTER condition, subjects accessed information using a CPT tool, the BOTH condition provides two simultaneous traces of information acquisition (verbal and computer).

[13] "Thus, although verbalization may impact decision process beyond increasing decision time, this effect remains undetected without more powerful methods of process tracing (Biggs *et al.*, 1993, p. 199)."

"The third issue is whether combining computer search and concurrent verbal protocols results in data about acquisition and use that are as complete as would result from applying each method independently. Computer search provides a complete trace of information acquisition from experimental materials while concurrent verbal protocols provide insight into information use. Although verbalization did not affect the information acquisition trace provided by computer search, computer search decreased the relative proportion of verbalized evaluations in the verbal traces, which may limit the insights provided by concurrent verbal protocols[14] [footnote added]" (1993, p. 200).

Given these research findings, in combination with the effort and related costs associated with the simultaneous use of VPA and CPT, it will not immediately be obvious that a combination of both methods is the adequate answer for any judgment and decision making research project that requires process tracing. However, the findings presented in the study performed by Biggs *et al.* do have important implications for decision research. Concerning the positioning and use of VPA and CPT they propose:

"First, if information acquisition is of primary interest and if computer search activities can be naturally integrated into performing the primary task, computer search is preferred to concurrent verbal protocols. Second, if information use or retrieval from long-term memory is of primary interest, concurrent verbal protocols are preferred to computer search. Thus, computer search may be enhanced by adding verbalization to task. Furthermore, the combined method provides complete acquisition data whereas completeness of the verbal protocol data is not assured" (1993, p.200).

Based on the evaluation of process tracing methods expounded in the previous paragraphs of this section, we have chosen to employ CPT in this research for the following reasons:

1) Our aim is to stay as close as possible to established research methods in judgment and decision making theory. In drawing general conclusions about decision strategies applied, the method that was initially developed by Payne (1976), and completed by Payne, Bettman, and Johnson (1993) (see § 2.4.3), will be used as point of departure for the method developed in this study. This method heavily relies on information acquisition behavior. Given this focus a choice for CPT can be justified from both a scientific and practical point of view.
2) Since the development and first implementation of Mousleab in 1986 (Payne *et al.*, 1988), CPT is well established in judgment and decision making research. The principles underlying Mouselab are also implemented in CPT tools that were employed in DSS research (Chu & Spires, 2000; Wang & Chu, 2004).
3) Computer search activities can be naturally integrated into performing the primary task.
4) CPT tools allow us to increase the number of participants in our experiments.
5) The use of computerized process tracing methods do have the potential to enhance so called "*micro-level approaches to cognitive engineering of DSS design [italics added]*" (Todd & Benbasat, 1999, p.371). In their 1999 study Todd and Benbasat propose: "Such micro-level approaches to the cognitive engineering of DSS design are important not

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[14] Biggs *et al.* found evidence that practice with the computer prior to performing the combined activity may reduce this effect, and propose that further study of the ability of practice to prevent the reactivity of verbal protocols to computer search is needed prior to an endorsement of the combined method.

> simply because they make a DSS easier to use, but because such ease of use is critical making DSS more useful" (1999, p.371).

4.2 Design principles for the development of functional requirements enhanced DSS environment

The development of functional requirements for an enhanced DSS environment will be performed in context of a set of design principles. These principles can be considered guidelines for the investigation into the opportunities for DSS enhancement.

Our choice for the use of CPT tools logically implies the following design principle: *the DSS environment should integrate a CPT tool for capturing decision behavior*.

The three questions addressed in the previous chapter: 1) how does a DSS influence decision behavior? , 2) how is decision behavior captured? , and 3) how is decision behavior measured? , can also be used to guide the investigation into DSS improvements. The DSS to be developed should add value in such a way that it includes enhanced functions, methods and models compared to the systems used in prior DSS research. The first question can be translated in two principles concerning the DSS user interface: *provide support for multi-alternative, multi-attribute preferential choice decision making*, and *the user interface should be improved compared to user interfaces developed in support of prior DSS research*.

The issue of capturing decision behavior, included in the second question, induces an investigation aiming at the improvement of CPT models. In context of this study improvement of CPT models can be realized in two ways: 1) through development of new CPT methods to determine existing operators for measuring decision behavior, and 2) through development of CPT methods that allow for the introduction of new operators for measuring decision behavior. The first option implies a focus on the development of more efficient and effective styles for capturing the data needed to determine *existing* measures of decision behavior. The second option implies a focus on support for *new* measures to characterize decision behavior. Point of departure for this second option will be an important conclusion of the comparison of VPA against CPT: CPT provides very limited support for acquiring data on information processing behavior. Given this conclusion, an opportunity for CPT model improvement will be the integration of a method for capturing information processing behavior. The development of such a method can be considered a prerequisite for the design of new measures aiming at characterizing information processing behavior.

Both options are covered by the following design principle: *the CPT model should be improved compared to the CPT models developed in support of prior DSS research.*

The last question, regarding operators for measuring decision behavior, is closely related to the development of an improved process tracing model, since operators for measuring decision behavior must be embedded in the CPT environment. For example, the second option explained above specifically aims at providing support for new measures. Although new measures for characterizing decision behavior can be used as input for the investigation of CPT model improvements, the development of new measures is not considered an issue to be addressed in context of the development of functional requirements for a DSS. To prevent a chicken and egg discussion we have chosen to use the general notion of 'integration of information processing behavior' as point of departure for our investigation for CPT tool improvement, whereas the resulting functional requirements will be used in chapter seven (Method) as a context for the development of specific operators for measuring decision behavior.

The last principle logically follows from the nature and purpose of this study: *the DSS to be developed should support the interpretation of research findings in context of prior DSS research*. This principle implies that system design will not start form scratch but will elaborate on functions and methods that are established in DSS research considered fundamental for this study. Actually, the design should not be disruptive, but rather a continuation of prior designs.

An overview of the design principles guiding the development of functional requirements for an enhanced DSS environment is provided in table 4.4.

TABLE 4.4: Design Principles Functional Requirements Enhanced DSS

Number	*Description*
1	Integration of a CPT tool for capturing decision behavior.
2	Support multi-alternative, multi-attribute preferential choice decision making.
3	Improvement of the DSS user interface.
4	Improvement of the CPT model.
5	Support the interpretation of research findings in context of prior research.

The design principles numbered one (integrated CPT tool), two (preferential choice) and four (continuation) can be considered boundary conditions for the design of DSS improvements (principle three and four). These three principles create a context for the design processes aimed at the development of improved decision support functions (user interface), and the development of enhanced methods to trace decision behavior (CPT). Design principle number four (continuation) will be dealt with at the end of this section, since it only implies a compliancy check regarding prior research.

4.2.1 Design principle one: integration of CPT tools for capturing decision process data

The discussion on process tracing techniques (see § 4.1.3) ended with an explanation of our choice for the application of CPT. Point of departure for the development of process tracing functions employed in this study will be the CPT solution developed by Chu and Spires (2000). This decision is driven by three reasons: 1) The focus of the DSS research performed by Chu and Spires was also on multi-alternative, multi-attribute preferential choice problems; 2) to infer on decision strategies implemented by the subjects fulfilling the experimental task, they employed the same measures as Payne and colleagues (1993) did, this implies that the basics of a method that is well established in research on judgment and decision making was implemented in their process tracing solution, and 3) the design of the DSS developed by Chu and Spires is based on state of the art technology (Graphical User Interfaces).

The implication of this design principle is that the DSS to be developed must integrate a database environment to store process tracing data as well as the software needed to capture all decision process traces. The choice for CPT as a method for data acquisition is a boundary condition for the design of DSS improvements, because it both imposes limitations as well as creates opportunities for improvements at the same time. For a detailed review of related factors driving these limitations and opportunities we refer to paragraph 4.1.2.

The corresponding functional requirement for this design principle reads as follows: *The experimental DSS should integrate a CPT environment.*

4.2.2 Design principle two: support multi-alternative, multi-attribute preferential choice decision making

The experimental DSS to be developed must cover the functions needed to support multi-alternative, multi-attribute preferential choice decision making. Theoretically this requirement implies that all thirteen decision strategies distinguished by Svenson (1979), and described in paragraph 2.1.1, must be supported by the experimental DSS to be developed. However, the DSS developed in this study will primarily focus on supporting the WADD and EBA strategy for the same two reasons the fundamental DSS studies underlying this research primarily focused on these two strategies: 1) both strategies are considered prototypical for compensatory decision behavior (WADD) and noncompensatory decision behavior (EBA), and 2) because both strategies are relatively easy to automate (Todd & Benbasat, 1999) (see also § 3.4). If we consider these two strategies as point of departure, the decision aids designed by Todd and Benbasat (see table 3.2) and Chu and Spires (see table 3.3) can be regarded as a minimum scenario for the development of the DSS interface to be applied in this study. An important issue to be dealt with is whether an explicit choice for the integration of decision aids that support these two exemplary strategies (WADD and EBA) will be an impediment for the implementation of other decision strategies. If this would be the case then it can be interpreted as a kind of decisional guidance (Silver, 1990). However, when we consider the common denominator of decision aids used by Todd and Benbasat (table 3.2) and Chu and Spires (table 3.3) as frame of reference, this set does not limit the selection of decision strategies to the WADD strategy or EBA strategy. The calculation functions provided, in combination with the functions that make it possible to specify threshold values for attributes, as well as the functions that support the assignment of attribute weights, allow for the implementation of nearly any strategy specified by Svenson (1979). For example, a decision maker willing to implement *the minimum difference lexicographic rule*, can do so by first creating three additional rows (R1, R2 and R3), using the CREATE command, copy two alternatives to R1 and R2 respectively, using the CALCULATE command, and use the CALCULATE command again to calculate the attribute differences (R3=R1-R2).

The corresponding functional requirement for this design principle reads as follows:
The experimental DSS should provide the decision aids needed to support preferential choice problem solving, at least in such a way that the decision maker is free in its choice which decision strategy to apply.

4.2.3 Design principle three: improvement of DSS user interface

The context for an elaboration on DSS improvement is adequately addressed by the issue of micro-level analysis as explained in paragraph 1.7. The importance of enhancement of the “micro level toolkit”, supporting DSS research, is emphasized by Todd and Benbasat several times (e.g. 1999 and 2000). It is also important to recognize that the DSS and process tracing method developed by Chu and Spires (2000) will be point of departure for our search for improvements, and that the issues to be addressed in this paragraph must also be considered in context of the enhancements elaborated on in the paragraph (§ 4.2.4) on CPT model improvements.

An investigation of the DSS developed by Chu and Spires (2000) in context of the findings of the fundamental DSS studies discussed in the previous chapter as well as in context of the pros and cons of process tracing methods dealt with in the first part of this chapter, revealed that the number and type of decision aids integrated in their user interface can be considered an important topic for DSS improvement.

Compared to the DSS developed by Todd and Benbasat (1999)[15], Chu and Spires included a limited set of decision aids in the user interface of their DSS (see tables 3.2 and 3.3 for an overview of the commands used in the relevant DSS research projects). Apart from the fact that Chu and Spires did not explicitly explain why they chose for the decision aids as employed, we consider the driving factors underlying the design of Todd and Benbasat's DSS most rigorous from a scientific point of view. The functions that were built into the DSS developed by Todd and Benbasat have theoretically been derived from knowledge on preferential choice strategies and were empirically validated through testing (Todd & Benbasat, 1991, appendix 2). The decision aids implemented were derived by decomposing the four exemplary choice strategies (WADD, ADDIFF, CONJ and EBA) into their constituent information processes, according to the method described by Bettman *et al.* (1990). All decision support functions developed by Todd and Benbasat are related to one or more of to the elementary information processes a subject would perform in pursuing a specific decision strategy.

The commands built into the DSS could be used to support various aspects of preferential choice strategies. A significant feature of the DSS developed by Todd and Benbasat is that a specific strategy can be supported in multiple ways, given the commands available. The user is not forced to proceed in a predetermined way once a choice for a specific decision strategy is made by the decision maker (Todd & Benbasat, 1992). Due to the limited set of commands used by Chu and Spires, this issue is less developed in their system. For example, explicit support for the EBA strategy is not provided in Chu and Spires' DSS, while Todd and Benbasat developed the CONDITIONAL DROP command to support an EBA strategy. Whereas Chu and Spires fully support the implementation of the WADD strategy by means of one single function (COMPUTE-SORT-ALL), Todd and Benbasat chose to support the implementation of this strategy by means of three different functions[16]. The CREATE command facilitates the creation of a vector containing attribute scores, the GLOBAL command computes the weighted attribute scores for all alternatives, and finally, application of the ROW TOTAL command provides a weighted total score for each alternative. By automatically triggering the sequential execution of these three commands, what the COMPUTE-SORT-ALL in fact does, valuable details concerning the potential support a DSS can offer in reducing cognitive effort will not be registered. Todd and Benbasat (1994b) explain how decision strategies can be discussed in terms of three different effort components: (1) processing effort (associated with comparison and computation within and among alternatives), (2) attribute recall effort (associated with the retrieval of information about attributes, such as importance weights and threshold values, from long term memory) and (3) tracking effort (associated with the storage and subsequent retrieval of information about alternatives, e.g. status or alternative weights). If we are able to relate

[15] The DSS as described in Todd and Benbasat's 1999 research paper will be our reference. The development process of their DSS was already described in appendix 2 of their 1991 research paper.

[16] Under the condition of HIGH AC (additive compensatory) support (Todd & Benbasat, 1999).

specific decision aids to the effort components mentioned above, it will be possible to measure the effort reducing effects of DSS functions in terms of the three components specified. For example, the question: Do subjects use the DSS to reduce processing effort or do they use it to reduce tracking effort, can hardly be answered if all the steps necessary to execute a specific strategy are triggered by a single command. After all, a user interface offering just one function that fully automates the desired decision strategy does not allow for much differentiation in support desired by the decision maker.

The appropriate number and variety of decision aids is especially important for the DSS research community. By manipulating the number and variety of functions incorporated in the user interface of a DSS, a researcher will be able to track the effects of these manipulations on decision behavior. Insight in the effects of these manipulations can help the researcher or system developer to determine which functions reduce cognitive effort and as such enhance our understanding of how decision makers can best be supported (Cook & Swain, 1993). Knowing what kind of support is needed and desired by decision makers will be of value for the DSS research community when it comes to improving automated decision aids, or as Todd and Benbasat put it:

"Our research has focused on the effort associated with employing different choice strategies and the role of decision aids in changing those strategies with an eye towards inducing decision makers to work smarter. The implications for this at micro level have been to develop some fundamental techniques for the analyses of DSS. As part of this we have outlined a decomposition method for DSS designers to estimate the potential effects of DSS use on effort and strategy selection ….. to allow them to direct behavior by manipulating restrictiveness and providing guidance via relative effort. Such *micro-level approaches to cognitive engineering of DSS design* [italics added] are important not simply because they make a DSS easier to use, but because such ease of use is critical making DSS more useful. Making technologies more useful is critical to user acceptance and assessment of the value of IT" (Todd & Benbasat, 1999, p. 371).

More detailed support functions will also offer the possibility to enhance our insight in how information is processed, and thus our understanding of decision behavior. Given the fact that the primary objective of a DSS will not be enhancement of our insights into decision behavior, but instead improve decision making, the designer of an experimental DSS must balance the additional value of detailed support functions against the external validity of the experimental decision situation. Providing many detailed support functions will make it possible to split up decision behavior in its constituent elementary processing units, and in turn enhance our insight in decision behavior by allowing the researcher to investigate how information was processed on a very detailed level. However, providing too much detailed support increases the risk of building unrealistic DSSs as well as the risk of influencing decision behavior due to increased effort levels required to implement a decision strategy (in the end a COMPUTE-SORT-ALL requires less effort than the sequential execution of CREATE, GLOBAL and ROW TOTAL). To be used a DSS must provide a net reduction in effort (Todd & Benbasat, 1992). On determining the level of detail in decision support provided the external validity of the experimental DSS must balanced against its ability to capture sufficient information processing details to infer on decision strategies employed. To deal with this issue we have chosen to develop a user interface that integrates the common denominator of the decision aids developed by both Chu and Spires (2000) and Todd and Benbasat (1999). This approach addresses two improvements: (1) concerning the user interface developed by Chu and Spires, the level of detail in decision support as well as the variety in decision support functions will be increased, offering the opportunity to capture more details regarding information processing behavior, (2) concerning the experimental DSS developed by Todd and Benbasat, CPT, instead of VPA, will be used to trace decision behavior. In fact, this second issue implies that the decision aids developed by Todd and Benbasat will be placed in a CPT environment.

The first functional requirement regarding this design principle reads as follows:
The common denominator of the decision aids employed by Todd and Benbasat and Chu and Spires should function as point of departure for the design and development of the automated decision aids to be used in this research project.

4.2.4 Design principle four: improvement of the CPT model

The development of CPT model enhancements is closely related to the issues addressed in the previous paragraph and can not be considered independent of so called micro level DSS studies as addressed by Todd and Benbasat (1991). To fulfill our aim for CPT tool improvement the DSS environment developed by Chu and Spires is investigated in context of both the findings of the fundamental DSS studies discussed in the previous chapter, and the evaluation of process tracing methods presented in the first part of this chapter.

The evaluation of process tracing methods (see § 4.1) revealed that VPA is the preferred method for capturing information *processing* behavior (how), whereas CPT is preferred for capturing information *acquisition* behavior (what). Although each method permits researches to draw the same general conclusions about decision strategies (e.g. compensatory versus noncompensatory behavior) (Biggs *et al.*, 1985; Biggs *et al.*, 1993; Payne *et al.*, 1978), a multi-method strategy, combining VPA and CPT, appears to be the best approach (Biggs *et al.*, 1985; Biggs *et al.*, 1993; Payne *et al.*, 1993; Payne *et al.*, 1978). However, due to the limitations of each method, explained in paragraph 4.1.2, multi-method approaches are sparse, if not lacking, in DSS research. Given our choice for the use of CPT tools, which are primarily information acquisition focused, we investigated the possibilities to enrich computerized process traces with data concerning information processing behavior (multi-method!).

Especially in the context of DSS research it must be possible to capture how information is processed because information processing is at the heart of automated decision support. By using decision support functions the major part of the information processing needed to execute a strategy can be transferred from the decision maker's mind to the DSS. It is the decision maker that chooses specific DSS functions for the purpose of information processing support. The aim of the explanation provided below is to underpin our proposition that it will be possible to enhance CPT tools with methods that also allow for tracing information *processing* behavior. Such an enhancement would reduce the need for multi-method process tracing approaches. The basic principles of this method will be included in the functional requirements guiding the development of our experimental DSS.

Remember that Chu and Spires (2000) used the same variables as Payne (1976) did to infer on decision strategies applied by the decision makers participating in their experiment:

1. *Information acquisition*: the proportion of the available information accessed.
2. *Variability in the amount of information accessed per alternative*, measured as the standard deviation of the percentage of available information searched per alternative.
3. The *pattern of information search* measured as:

$$Search\ Index = \frac{Alternative\ Transitions\ \text{-/-}\ Attribute\ Transitions}{Alternative\ Transitions\ +\ Attribute\ Transitions}$$

All three measures were calculated using the process tracing data that was stored in the CPT database of their DSS. The process traces revealed which cells were accessed by a subject, supporting the calculation of the first two variables. The third variable, search index, was computed using the process tracing data revealing the order in which the cells of the decision matrix were opened. It is important to recognize that only a mouse click on a cell of the decision matrix causes information to be marked as “accessed”, or as Chu and Spires put it: “Participants accessed the value of a cell by clicking the cell” (2000, p.273). Basically, this part of the CPT environment works in exactly the same way as Mouselab does. However, this Mouselab-alike approach, that only marks information as “accessed” when the decision maker explicitly clicks on a cell, ignores the fact that information can also be accessed by means of automated decision support functions. The consequences of ignoring this data will be shown on the basis of the following example.

Consider a ten alternatives by eight attributes decision matrix in its initial status (all cells are closed). Activating Chu and Spires’ COMPU function will compute a weighted score for an alternative according to the weighted additive (WADD) formula. Because this function does not require explicit mouse clicks on relevant cells, the status of the attribute values of the alternative chosen will remain “not accessed”. According to this approach, execution of the COMPU command does not influence both the variables *information use* and *variability*. The same is true for the *search index* measure. Regarding the calculation of this index Chu and Spires explained: “Like Payne (1976), we measured participant’s search patterns as follows:

$$Search\ Index = \frac{Alternative\ Transitions\ \text{-/-}\ Attribute\ Transitions}{Alternative\ Transitions\ +\ Attribute\ Transitions}$$

where alternative (attribute) transitions represent the number of instances in which the i^{th}+1 piece of information accessed was of the same alternative (attribute) as the i^{th}” (2000, p.280). However, the execution of a COMPU command does not require explicit mouse clicks (transitions) to access information, so the search index will not be influenced by its execution.

This approach, primarily focusing on information acquisition and search behavior, ignores a valuable source of information that is typically available in automated DSS environments: information processing data. By establishing a direct link between a DSS function executed (e.g. COMPU), and the information accessed, processed and produced by this function, additional insight in decision behavior can be provided. For example, execution of the COMPU command in context of the decision matrix described above implies that eight attribute values are processed in order to calculate the weighted additive score for the alternative selected. This means that all available information on the alternative selected is accessed (use and variability), and is processed across all dimensions (interdimensional/alternative-based).

Although the example given above refers to DSS research employing CPT tools, establishment of the direct link between an automated decision aid, and the information accessed and processed by this aid, is also appropriate to a research context using VPA. The following example by Todd and Benbasat, regarding an analysis of verbal protocols, shows the consequences of ignoring potential relevant information:

"A "run[17]" [footnote added] is used as the basic unit of analysis since the strategies focus on evaluations of alternatives or attributes. When the number of attributes and alternatives are not equal, the number of pairwise transitions can take on different meanings. If, for example, a subject first examined all values for rent in a 20-alternative problem, that would be considered one run but 20 pairwise transitions. If the decision maker then looked at three alternatives in detail, the pairwise count would yield 24 transitions (8*3), while the run score would be three. Overall the pairwise analysis would indicate a neutral search pattern ((20-24)/44) while the run score would indicate a tendency towards alternative based processing ((1-3)/4). We believe this latter measure better reflects the behavior of subjects and takes into account that the major focus of the strategies is on attributes or alternatives and not simply pairs of values" (1999, p. 99).

Given this example, would we draw the same conclusion (alternative based information processing is one of the characteristics of compensatory decision models (Biggs *et al.*, 1985)) if we were also able to include the amount of information used in our analysis? The decision matrix contains 20 (alternatives) * 8 (attributes) = 160 information elements. The number of information elements used in the example given is: 24 (3 alternatives all cues) + 17 (17 alternatives only one cue) = 41, indicating that 26% of the available information was used by the decision maker. Assuming that compensatory decision strategies require a complete acquisition of information cues (Biggs *et al.*, 1985), a percentage of 26% is more likely an indication of noncompensatory information processing than an indicator for compensatory information processing.

To the best of our knowledge we are not aware of any DSS research project that explicitly addresses a direct link between automated decision aids and the information used and processed by these aids.

Regarding research projects that employ VPA it should be noticed that it will be possible to develop a coding scheme that captures this link. However, given the drawbacks of VPA, establishment of such a link in a protocol coding schema will only add to the drawbacks of VPA. For example, asking a subject to explicitly mention which information is used, processed and produced by each DSS function executed will make the verbalization more obtrusive, the task more complex and less realistic, the coding schema less surveyable, and the coding and data processing more effortful. An exploratory investigation of the protocol coding schema presented by Bettman and Park (1980) delivered that this scheme does not provide mechanisms that directly link the information used to statements expressed by the decision maker. For example, a statement like "I will calculate the sum of all attribute values of brand X", will, according to this coding schema, be coded as "B9: One brand, more than one attribute, compensatory combination or tradeoff of attributes". Appropriate to this coding schema, this statement stands for compensatory information processing. However, which information is processed can not be derived from this code. Consider a decision set using eight attributes to define the available alternatives, and a decision maker that calculates an additive score for alternative X and alternative Y. The additive score for alternative X is calculated early in the decision process, while the additive score for alternative Y is calculated in the final stages of the decision process. Somewhere between the expression of these two "I will calculate the sum of all attribute values of brand X/Y" statements, the decision maker decided to eliminate four dimensions from the decision set. So, for alternative X 100% of the available information is processed, while for alternative Y only 50% of the available information is processed. Despite the fact that amount of

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[17] $$Run = \frac{\text{Number of "Attribute" Runs -/- Number of "Alternative" Runs}}{\text{Total Number of Runs}} * 100$$

information processed is an important measure regarding the distinction between compensatory and noncompensatory information processing (Payne *et al.*, 1993), the protocol coding schema presented by Bettman and Park (1980) does not catch this difference and will value both statements equally as compensatory statements.

When verbal protocols are used to *reconstruct* a decision process it will in retrospect be possible to derive which information was used and processed by which decision aid. Reconstruction requires the verbal protocols to be synchronized with the data presented on an information display. This reconstruction method only allows for an indirect (or implicit) establishment of the link described. This indirect method was employed by Todd and Benbasat only to derive which information was used by the subjects that were aided by a DSS, or as they put it “In each case these commands replace some set of operations that the subject would otherwise be required to perform; thus, they allow information to be factored into the choice process without ever being *explicitly* [italics added] referenced by the subject” (1992, p.382). Again, this implicit method will also add to the drawbacks of VPA.

None of the DSS research studies presented in table 4.1 that employed CPT described a method to record the link between DSS functions and the information used, processed and produced by these functions, or even made notice of it.

We propose that the implementation of a direct link between a DSS function and the information accessed, processed and produced by this function (from now on we will call this Function-Information-Processing link the FIP-link) will make it possible to capture both information *acquisition* and information *processing* behavior by means of a single process tracing method.

Process traces captured through the FIP-link enable the data to be analyzed from two complementary perspectives: (1) which information was processed, and (2) whether processing took place within or across dimensions.

The first perspective implies that it becomes possible to enhance the calculation method of the *information use* measure. Due to the FIP-link it will not only be possible to capture the information accessed through explicit mouse clicks across the automated information display boards, but also to integrate the information accessed through the execution of DSS functions.

The second perspective implies a focus on how information is processed: alternative-based or attribute-based. The FIP-link captures the number of information cues that are processed *inter*dimensionally as well as *intra*dimensionally due to the execution of a DSS command. For example, consider a decision matrix containing ten apartments, each described by eight attributes and a decision maker solving an apartment selection problem. This decision maker first decides to eliminate two dimensions (e.g. kitchen quality and distance to campus) from the decision matrix before using the COMPU function to calculate the weighted additive score for the alternative called A1. Due to the FIP-link it is known that six of the eight available attribute values of A1 are accessed, and that the information accessed is processed in an *inter*dimensional manner. Suppose this decision maker subsequently sorts all alternatives on rent in descending order, using the SORT command. Again, due to the FIP-link it is known that the SORT function caused the attribute rent to be accessed across all alternatives, and that the information accessed is processed *intra*dimensionally. When the process traces resulting from the actions performed by this decision maker are analyzed, the following numbers can be calculated: unique information cues accessed = 15 (6 due to the COMPUTE, and 9 due to the SORT on rent), information cues processed *inter*dimensionally = 6 (COMPUTE), and information cues processed *intra*dimensionally = 10 (SORT). Suppose this data was used to calculate the search index, the result would be (6-10)/(6+10)= -.25, indicating slightly more attribute-based than alternative-based information processing.

The explanation provided in this paragraph shows that under conditions of automated decision support CPT tools not only allow for capturing data on information acquisition behavior, but also on information processing behavior. In order to improve CPT models the following functional requirement must be met:

The experimental DSS should provide the mechanisms needed to record the link between a DSS function and the information used, processed and produced by this function.

4.2.5 Design principle five: support the interpretation of research findings in context of prior research

The nature of this design principle implies that it will not result in the definition of additional system requirements; however, it rather deals with the execution of a so called 'compliancy check' regarding the functional requirements developed in the previous paragraphs. In order to interpret our research findings in context of prior behavioral decision making as well as prior DSS research, it will be important that the functionalities of the experimental DSS to be developed have a solid reference in theory concerning these research disciplines. To determine compliancy with prior research we checked whether the argumentation underlying the development of the other four design principles was grounded in theory. This check focused on three important questions:

1) Does the DSS support decision strategies that are recognized in behavioral decision making research?
2) Does the user interface of the DSS include decision aids that were recognized in prior DSS research?
3) Does the DSS support the development of measures that are based on methods which are well established in behavioral decision making research?

The first two questions are closely related because both Todd and Benbasat (1991) and Chu and Spires (2000) used the decision strategies recognized by Svenson (1979) as input for the design and development of their automated decision aids. The decision rules developed by Svenson (1979) are the frame of reference for much of the research done in the field of behavioral decision making (e.g. (Billings & Marcus, 1983; Bockenholt *et al.*, 1991; Ford *et al.*, 1989; Huber, 1980; Payne, 1982; Payne *et al.*, 1993; Russo & Dosher, 1983; Stone & Schkade, 1991)). Added the fact that the common denominator of the decision aids developed by both Todd and Benbasat (1999) and Chu and Spires (2000) will be point of departure for the design and development of our experimental DSS, the first two questions can be confirmed.

The method to infer on decision behavior initially developed by Payne (1976) has become more or less the standard for measuring information acquisition behavior (Abelson & Levi, 1985; Biggs *et al.*, 1993; Einhorn & Hogarth, 1981; Lohse & Johnson, 1996; Payne *et al.*, 1978; Schkade & Johnson, 1989; Svenson, 1979). Because this method will be used as point of reference for this study as well as that the functional requirements developed in this chapter allow for integration of this method in our research design, the third question can be confirmed as well.

4.3 Summary

This chapter addressed two important issues concerning the DSS environment to be developed in support of this study: 1) the choice for a process tracing tool, and 2) the development of the functional requirements for this DSS environment. On development of these functional requirements, improvements concerning both the DSS user interface and CPT models are established. Enhancement of the DSS user interface is realized through a synthesis of the decision aids that were developed in support of the different DSS studies that are considered fundamental for this research, whereas the design of the so called Function-Information-Processing-link (FIP-link) contributed to CPT tool enhancement. This FIP-link records the link between automated DSS functions and the information used, processed and produced by these functions. The applicability of CPT tools can be extended through implementation of this link because it allows for additional styles to capture information acquisition behavior, as well as for the integration of measures for capturing information processing behavior. So far, CPT tools were only considered to be applicable for capturing measures on information acquisition behavior. By development of these enhancements, this chapter delivered the first step in realizing the first contribution recognized for this study: development of an enhanced DSS environment. The final step concerning this contribution, actual development of the DSS environment, will be realized in the next chapter. This chapter also developed a point of departure for realizing the second contribution recognized for this research: development of an extended measuring instrument to capture decision behavior. The enhanced CPT model presented in this chapter allows for the development of new measures for capturing information processing behavior. These measures will be elaborated on in chapter 7 (method).

CHAPTER 5

THE EXPERIMENTAL DECISION SUPPORT SYSTEM

5.0 Introduction

The aim of this chapter is to introduce the experimental DSS that has been developed to support this research. This will be done by satisfying the functional requirements, as defined in the previous chapter, as precisely as possible. The sections of this chapter will be arranged according to the major components of a DSS: (1) user interface, (2) model subsystem, and (3) data subsystem (Benbasat & Nault, 1990; Bennet, 1983; Power, 2002; Sprague, 1980; Turban & Aronson, 2001). The user interface is the part of the system that permits the decision maker to interact with the system, allowing for bi-directional communication between a system and its users. The model subsystem will make available the decision models that support the purpose of a DSS. With respect to the purpose of the DSS presented (support of preferential choice decision making), the model system will encompass a library of functions that support the implementation of the decision strategies that were described in the preceding chapters. The data subsystem of the DSS developed serves two functions: (1) it contains the data needed to fulfill the decision task (alternatives and attribute values), and (2) it includes the structures needed to record the full decision processes executed by the participants working with the DSS. This second function implies that the computerized process tracing (CPT) tool is considered to be part of the data subsystem.

The functional requirements developed in the previous chapter will be addressed per major DSS component. The categorization of the requirements into the three DSS components is presented in table 5.1.

TABLE 5.1: Functional Requirements Grouped into DSS Components

DSS Component	*Functional Requirements*
User Interface	▪ The experimental DSS should provide the decision aids needed to support preferential choice problem solving, at least in such a way that the decision maker is free in its choice which decision strategy to apply.
Model Subsystem	▪ The common denominator of the decision aids employed by Todd and Benbasat and Chu and Spires should function as point of departure for the design and development of the automated decision aids to be used in this research project.
Data Subsystem	▪ The experimental DSS should integrate a CPT environment. ▪ The experimental DSS should provide the mechanisms needed to record the link between a DSS function and the information used, processed and produced by this function.

Prior to an elaboration on the functionality included in each of the three DSS components, some details concerning the development process will be discussed briefly. Finally, in the he last section of this chapter, the impact of the DSS developed on effort reduction will be demonstrated.

5.1 The development process

The experimental DSS was developed using the Oracle database environment and development tools (Designer and Developer). The data subsystem was implemented in an Oracle 8 database. The system fully supported a multi tier application architecture, including decentralized DSS clients and a centralized database server. Both the DSS application and the data model were multi user. Basically there were no restrictions concerning the number of concurrent users.

The system was developed by a single qualified Oracle professional. Development of the system started in March 2003. The first versions of the software became available in May 2003 and were tested by the author. Prior to running the pre-test sessions of the experiment, the software was tested during two dedicated pilot sessions in which respectively seven and eight subjects participated. Software bugs were reported and documented and were all resolved as soon as possible. Remarks regarding the software expressed by the subjects attending these pilot sessions were also documented. These remarks were evaluated and when considered relevant converted into functionality. All bugs were fixed prior to the pretests of the experiment.

5.2 The user interface

The graphical user interface (GUI) of the DSS is a so called Windows user interface. All DSS functions included in the user interface can be executed using the mouse as pointing device. A screenshot reflecting this GUI is presented in figure 5.1.

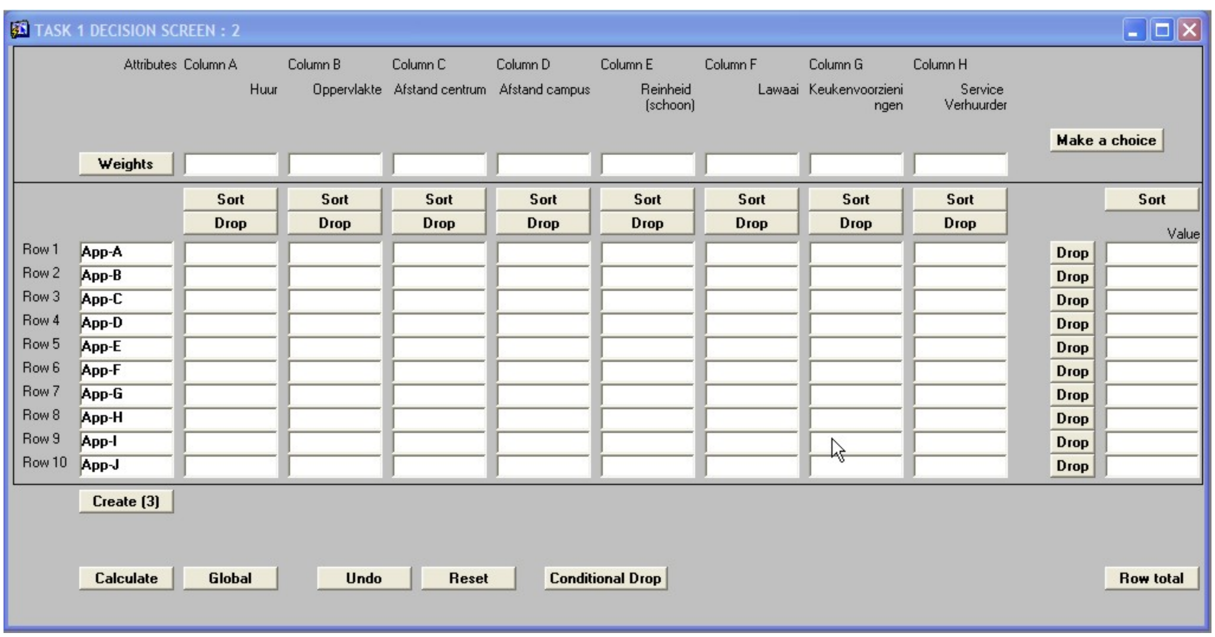


FIGURE 5.1: Screenshot DSS User Interface Experiment 1

The user interface can roughly be subdivided into two parts: (1) the digital information display board, providing access to the data subsystem, and (2) the set of buttons, representing the automated decision aids available, that provides access to both the data and the model subsystem. The digital information display board, at the heart of the user interface, is used to display the choice problems. This information display facilitates the presentation of a choice set containing ten alternatives. Alternatives are represented as rows, whereas attributes are represented as columns. Each cell of the decision matrix contains the value for a particular alternative along a particular attribute. In the initial status, all cell values of the decision matrix are hidden. In order to reveal information about a specific alternative, a decision maker must explicitly choose which information to access. In this sense the functioning of our DSS is comparable to the functioning of the DSS developed by Todd and Benbasat (1999) as well as to the functioning of the DSS developed by Chu and Spires (2000).

Participants can reveal cell values by either a mouse click on a specific cell or by executing specific decision aids. A mouse click on a cell caused the underlying attribute value to be accessed. Similar to Chu and Spires (2000), we chose for the option to present cell values in two different formats: numeric or text. A first click on a cell causes the underlying numeric value to be presented, a second click on the same cell reveals its text value. Clicking the cell again will change it to its hidden state. Once a cell is opened, its value remains revealed. During the decision process any cell can be in any of the three statuses described: closed, revealed-numeric, or revealed-text. A decision maker can repeat the sequence described as many times as desired.

The user interface did not impose control over a participant's actions, and offered the flexibility to pursue any decision strategy desired. Neither the use of specific functions nor the order in which functions were activated was limited. The DSS was nondirective (Parikh *et al.*, 2001; Silver, 1990).

The design of the user interface also addressed issues regarding user friendliness. The opportunities of Windows-technology are employed to make the GUI as intuitive as possible. Choice options, for example, are nearly all facilitated by so called 'drop-down-menus' which dynamically adapt to the choice options available. To prevent unintended actions, all commands that influenced the data of the decision set must be confirmed before they are executed. Different colors are used to make the status of the data presented as clear as possible. For example, the font color of the original numeric values is black, whereas the font color of all calculated values is blue.

The interface is developed in such a way that the effort required to make use of it is kept to a minimum, commands can be executed by means of a simple mouse click, and the number of commands is kept small (Todd & Benbasat, 1994b).

The set of functions included in the user interface will be the focus of the next paragraph.

5.3 The model subsystem: automated decision aids

This paragraph will elaborate on the working of the automated decision aids included in the DSS user interface. Each of the buttons shown in exhibit 5.1 represents an automated decision aid. The compilation of functions provided was driven by the following functional requirement:

The common denominator of the decision aids employed by Todd and Benbasat and Chu and Spires should function as point of departure for the design and development of the automated decision aids to be used in this research project.

Although it is not our aim to repeat the argumentation underlying the inference of this functional requirement, we do consider it important to emphasize that we consider the level of detail in decision support provided by Todd and Benbasat (1999) as the appropriate level. On studying the commands explained below, one should bear in mind that the decision aids provided by Todd and Benbasat are our point of departure. The unique DSS functions developed by Chu and Spires (2000) are added to this reference set. Only those functions are added which are not covered in some way or another by the DSS functions developed by Todd and Benbasat. Finally, a few new functions are added that we developed ourselves.

Table 5.2 shows an overview of the automated decision aids included in the user interface of the experimental DSS. The column 'source' shows the origin of the DSS functions. Some of the functions presented were used by both Todd and Benbasat (T&B) and Chu and Spires (C&S). In case a function was described by both research groups, the marker "U" is an indicator showing which interpretation we used for the development of our DSS. For example, the OPEN command was used by both Todd and Benbasat and Chu and Spires. However, whereas Todd and Benbasat used a command based user interface, Chu and Spires made use of a GUI. Our interpretation of the OPEN command was driven by the description given by Chu and Spires.

In case all three sources for a specific function are marked at the same time, this means that although a decision aid was described by both research groups, we chose for a working of the function that deviates from the description provided by Todd and Benbasat of Chu and Spires. For example, the WEIGHTS command is not explicitly mentioned by both Todd and Benbasat and Chu and Spires, however, both research groups described how weights could be entered either as part of a process triggered by a single command (COMPUTE-SORT-ALL) or as part of the execution of a command with a more general purpose (e.g. CREATE).

TABLE 5.2: DSS Functions Provided

DSS Function	***T&B***	***C&S***	***New***	***DSS Function***	***T&B***	***C&S***	***New***
OPEN	X	U		CALCULATE	X		
CLOSE	X	U		SORT		X	
SEQUENCE			X	WEIGHTS	X	X	X
DROP COLUMN/ROW	X	X		GLOBAL	X		
CONDITIONAL DROP	X			MAKE a CHOICE		X	
ROW TOTAL	X			UNDO	X		
CREATE	X			RESET			X

Each of the functions presented in table 5.2 will be described and explained below. Please note that the working of the decision aids that were already established in DSS research by Todd and Benbasat and Chu and Spires was based on an interpretation of the description given by these researchers. Although most of these descriptions left little room for misinterpretations, a few of them could be interpreted less univocal. Because we did not have the software used by both research groups at our disposal, the less univocal descriptions were interpreted as literally as possible.

The explanation of the functions presented below is supported by a website (www.feweb.vu.nl/dssresearch) including multimedia objects that, when triggered, show the working of the DSS functions explained. The descriptions provided below include references to these objects. The website contains objects of all the DSS functions included in the enhanced DSS developed in support of Experiment 1.

OPEN / CLOSE:

The working of the OPEN and CLOSE commands is already explained in the paragraph that elaborated on the user interface of the DSS. The OPEN and CLOSE commands do not have dedicated buttons in the user interface, but can be triggered by a mouse click on a cell of the decision matrix. Each mouse click on a cell changes the status of the cell taking into account the following cycle:

First click: OPEN numeric
Second click: OPEN text
Third click: CLOSE
This cycle can be repeated as many times as desired.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> OPEN/CLOSE)

SEQUENCE:

The working of the SEQUENCE function will be explained by means of the following example. Consider table 5.3.

TABLE 5.3: Example Sequence

Alternative	*Attribute : Rent*	*Sequence*
1	6	3
2	5	4
3	10	1
4	7	2

If we consider all attribute values for rent it becomes clear that alternative number three has the highest score (10), whereas alternative number two has the worst score on rent (5) (assuming that higher attribute values are better). Regarding rent, alternative number three occupies the number one position in the sequence of all available values on rent.

When a cell is opened, the SEQUENCE command can be used to determine its sequence within the attribute range of the dimension specified. Just like the OPEN and CLOSE commands, the user interface does not provide dedicated buttons for the execution of the SEQUENCE commands. The sequence of an opened cell can be determined by the following combination of keys: CTRL+Left-Mouse. By holding down the CTRL-key while clicking on an opened cell, the sequence number of the attribute value of the cell selected will be presented. As long as the pointing device is positioned across the cell selected, and the CTRL-key is pressed, the sequence number will be shown. When the pointing device moves outside the cell, or the CTRL-key is no longer pressed, the value presented in the cell will switch back to the value as presented before the SEQUENCE function was activated.

It is also possible to present the sequence numbers of more than one cell at the same time. By holding down the SHIFT-key, while simultaneously clicking on cells that are already opened, the sequence number of each cell clicked on is presented. When the SHIFT-key is no longer pressed, all cell values will switch back to the values as presented before this SEQUENCE

command was executed. In fact, the working of the SHIFT+Left-Mouse is comparable to the working of the CTRL+Left-Mouse, as to that the latter is only applicable to one cell, whereas the first is applicable to more than one cell.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> SEQUENCE)

DROP ROW

Pushing the DROP ROW button causes an alternative to be eliminated from the decision matrix. A DROP ROW button is positioned behind each available alternative.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> DROP ROW)

DROP COLUMN

A dimension can be eliminated from consideration by pushing the DROP COLUMN button. For each dimension available a DROP COLUMN button is provided at the top of the decision matrix. Any dimension dropped can be restored by clicking the DROP COLUMN button again.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> DROP COLUMN)

CONDITIONAL DROP

The CONDITIONAL DROP command causes alternatives to be eliminated contingent upon the value of an attribute. After pushing the CONDITIONAL DROP button, a sub window will be opened in which the characteristics of the CONDITIONAL DROP can be entered (see figure 5.2). By means of so called drop-down-lists, the following parameters can be specified: 1) relevant dimension, 2) operator (domain: =; <; >; <=; >=), and 3) threshold value.

For example, the following specification: ‘price > 6’, causes all alternatives with an attribute value greater than 6 on the dimension price to be eliminated from the decision set.

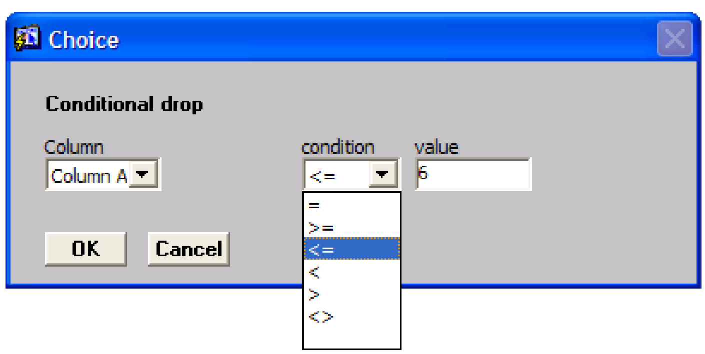


FIGURE 5.2: Screenshot Conditional Drop Command

(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> CONDITIONAL DROP)

CREATE

The CREATE function creates a new row into which user specified values can be entered as well as the results of a CALCULATE command can be stored. The maximum number of rows to be created is three. Each row created will be assigned a unique row number. Because this row number can be used as parameter in both the GLOBAL and CALCULATE command, this

command must be considered in context of the explanation of these two commands. The rows created will be positioned at the bottom of the decision matrix.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> CREATE)

WEIGHTS

The WEIGHTS function allows for the assignment of attribute weights. On activating this function a sub window will be opened showing all attributes and related input fields that can be used to enter the weights. The sum of the attribute weights entered must be one. The system checks whether this condition is met. In the initial status all weights are equal.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> WEIGHTS)

CALCULATE

The calculate command performs a specific arithmetic operation on any pair of rows, inclusive the additional rows and the weights row. The results of a CALCULATE operation can only be stored in the additional rows created through the CREATE command, so a subject must first create at least one additional row before the CALCULATE function can be executed.

After pushing the CALCULATE button a sub window, allowing for the specification of the operation to be performed, will be opened (see figure 5.3). By means of drop-down-lists, the following parameters can be specified: 1) row number of the additional row into which the results must be stored, 2) the first row to be used in the arithmetic operation, 3) operator (domain: *, /, +, -, %, ^), and 4) the second row to be used in the arithmetic operation.

For example, the following specification: ‘R11=R1-R2’ causes the difference in attribute values between row one (R1) and row two (R2) to be stored in the first additional row (R11) created.

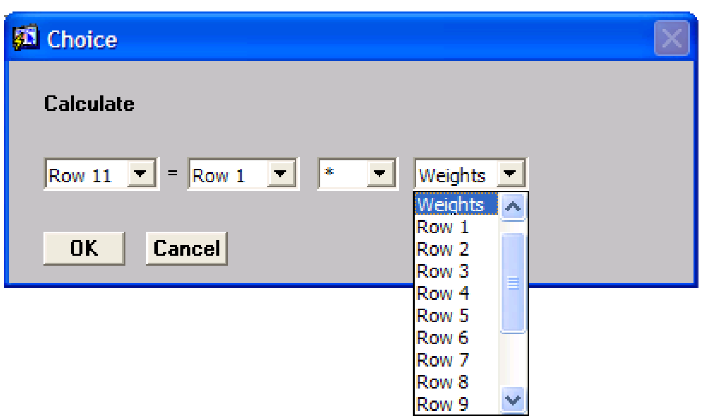


FIGURE 5.3: Screenshot CALCULATE Command

(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> CALCULATE)

GLOBAL

The GLOBAL function performs an arithmetic operation that combines the values of a specified row with all other rows available in the decision matrix. On activating the GLOBAL command, a sub window will be opened (see figure 5.4) that allows for the specification of the following GLOBAL command parameters: 1) operation to be performed (domain: *, /, +, -, %, ^), and 2) the additional row to be used in the arithmetic operation. After execution of the GLOBAL command the current values of the decision matrix will be overwritten.

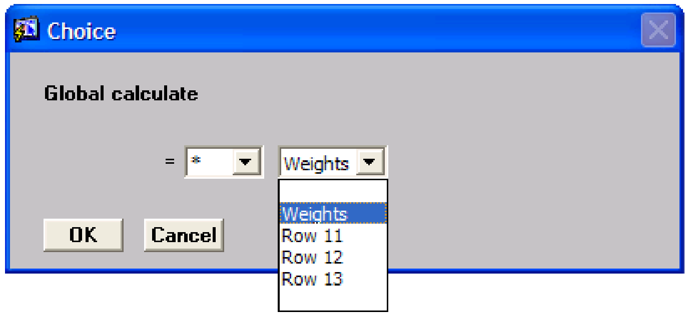


FIGURE 5.4: Screenshot GLOBAL Command

For example, consider the following decision matrix:

	Attr-1	*Attr-2*	*Attr-3*	*Attr-4*	*Attr-5*	*Attr-6*	*Attr-7*	*Attr-8*
Weights	0.10	0.10	0.20	0.10	0.20	0.15	0.10	0.05
Row-1	8	6	8	5	2	8	6	5
Row-2	7	7	8	9	6	6	5	9

After execution of the GLOBAL command with the following specification: '* weights' the decision matrix will be as follows:

	Attr-1	*Attr-2*	*Attr-3*	*Attr-4*	*Attr-5*	*Attr-6*	*Attr-7*	*Attr-8*
Weights	0.10	0.10	0.20	0.10	0.20	0.15	0.10	0.05
Row-1	0.80	0.60	1.60	0.50	0.40	1.20	0.60	0.25
Row-2	0.70	0.70	1.60	0.90	1.20	0.90	0.50	0.45

(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> GLOBAL)

ROW TOTAL

For each available alternative the sum of the attribute values can be calculated using the ROW TOTAL command. Each row total will be shown in the field that is positioned behind the attribute values describing an alternative. Activating the ROW TOTAL command implies that the row totals will be calculated for all alternatives still available in the decision matrix. Attribute values of the dimensions that are deleted from the decision matrix will not be counted for. A cell does not necessarily have to be opened in order to be counted for in the execution of the ROW TOTAL command. For example, consider a decision matrix in its initial status, so all cells are closed. After execution of the ROW TOTAL command, the cells will stay closed, but the row total fields at the end of each alternative line will show a row total for each alternative.

Row totals will be presented as long as the values of the decision matrix are in accordance with the row totals calculated. If, for example, a column is deleted from the decision matrix after a row total has been executed, the row total values will be eliminated since these totals have become inaccurate due to the elimination of a column.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> ROW TOTAL)

SORT

Performing a SORT command causes the available alternatives to be sorted based upon the attribute values of the dimension selected. Regarding the order a decision maker can choose for ascending or descending. If row totals are calculated, it will also be possible to sort all alternatives based upon the row total values.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> SORT)

UNDO

The UNDO command reverses the effect of the previous command executed. Successive execution of this command progressively undoes prior operations. The number of UNDO commands to be executed is unlimited, the full sequence of commands performed can be undone. Only so called button commands can be undone, an UNDO will not reverse OPEN and CLOSE actions (these functions are not triggered by a button, but instead by a mouse click).
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> UNDO)

RESET

Execution of the RESET command will bring back the user interface in its initial status. All cells of the decision matrix will be closed, the additional rows will be removed, and attribute weights will be set to default values (equal weights).
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> RESET)

MAKE A CHOICE

The objective of the MAKA A CHOICE command is to record a decision maker's final choice. A sub window will be opened which allows for the specification of an alternative. After the choice has been confirmed the decision screen will be closed.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 1-> MAKE-A-CHOICE)

5.4 The data subsystem

The data subsystem encompasses two separate parts: the task data subsystem and the process tracing subsystem. Each of these subsystems serves a different purpose. The task data subsystem contains the data representing the choice set. All alternatives and defining attribute values are stored in this subsystem. Each OPEN command, for instance, accesses the task data subsystem to fetch the attribute value requested.

The process tracing subsystem includes the logic and structures needed to store all decision process traces. In fact, this subsystem represents our CPT tool. An important driver underlying the development of the logic and structure of this subsystem is the following functional requirement:

The experimental DSS should provide the mechanisms needed to record the link between a DSS function and the information used, processed and produced by this function.

The challenge in implementing this requirement is in the dynamic aspect of this link. Just recording which actions are performed by a participant will not be sufficient. For any information processing DSS function, the input used as well as the output produced by this function need to be captured. The input is needed to infer on information acquisition and processing behavior, the output is needed because it can be the input for the next function to be performed. For example, consider the following decision set:

	Price	***Color***	***Size***	***Weight***
Alt-1	8	6	8	5
Alt-2	7	7	3	9
Alt-3	6	5	7	7
Alt-4	4	7	2	10

Suppose a decision maker performs a CONDITIONAL DROP command, using the following parameters: ‘Color <= 6’. Execution of this command causes the color attribute for all alternatives to be accessed (= information acquisition) and to be compared against the threshold specified (= intradimensional information processing). Due to this CONDITIONAL DROP command two alternatives will be eliminated: Alt-1 and Alt-3. Suppose this decision maker does not attach much value to the low scores on size (=information acquisition) for the remaining alternatives and decides to DROP the size column. Finally, this decision maker decides to compute a ROW TOTAL for the remaining alternatives (= interdimensional information processing). It should be noticed that this ROW TOTAL command does not deal with the attribute size (= information acquisition), because this dimension was eliminated in the previous step.

To capture the dynamics of the FIP-link we developed and implemented a data model that not only provides the structures needed to record the actions performed by the participants, but also the structures needed to record the input-processing-output logic. The latter is realized by storing the status of the full decision matrix after execution of each DSS function. The data model provides in a status indicator for each alternative-attribute combination of the decision set. Consider a ten alternatives by eight attributes decision set (10X8), including 80 alternative-attribute combinations. Each combination can have one of the following five statuses: 1=closed, 2=opened numeric, 3= opened text, 4= opened calculated, and 5=deleted. As a result of the execution of each DSS function the following traces will be stored: 1) the DSS function performed, 2) the attribute values of each alternative in the decision set, and 3) the status of each alternative-attribute combination. Taken together these process traces offer a rich source for inferring on decision behavior. The data model of the system is included in appendix 1.

5.5 Impact on effort reduction

The automated decision aids included in our DSS aim at reducing the cognitive effort related to the implementation of decision strategies. The impact of decision aids on effort reduction can be estimated using a calculation method developed by Todd and Benbasat[18] (1994b). To investigate the impact of automated decision aids on the reduction of cognitive effort Todd and Benbasat explicated the processing demands of the EBA strategy and the WADD strategy under different conditions of decision support. Three different groups of processing demands are recognized in their method: attribute recall, tracking and processing. Attribute recall stands for the effort needed to acquire the relevant attribute values. Tracking includes the EIPs needed to determine the status of an alternative, for example, whether the alternative has been eliminated or not, and processing includes the EIPs needed to process the information acquired. The related EIPs for each of the different categories of processing demands for the EBA and WADD strategy are presented in table 5.4.

TABLE 5.4: EIPs per Category of Processing Demands

	Attribute Recall	***Tracking***	***Processing***
EBA	*Retrieve* attribute threshold from memory	*Read* status of attribute (alternative eliminated or not) Only for the first attribute to be processed it will not be necessary to track the status.	*Move* to new attribute *Read* attribute value *Compare* to threshold *Eliminate* alternative if threshold is violated
Formula	1*Att*)	1*(Att-1)*Alt	4*(Att*Alt)
WADD	*Retrieve* attribute weights from memory	*Retrieve* current best score *Compare* to alternative score *Store* pointer to alternative with highest score *Store* new best score	*Move* to attribute *Read* attribute value *Multiply* attribute value and attribute weight *Retrieve* current score *Add* weighted attribute score to current score *Store* new current score
Formula	1*(Att*Alt)	4*(Alt-1)+2	6*(Att*Alt)

*) Att=Number of attributes; Alt=Number of alternatives.

To show the impact of the DSS presented in this chapter on effort reduction imagine two different levels of decision support: low WADD support and high WADD support. The commands available under each of these levels are presented in table 5.5.

Table 5.6 presents the impact of the different levels of decision support on the effort required to execute the EBA as well as the WADD strategy. The exemplary calculations are based on a decision matrix containing ten alternatives, each described by eight attributes. The estimates presented in table 5.6 are valid under the assumption that the DSS functions are used in the appropriate way to support the strategies mentioned.

[18] See also § 3.6.

TABLE 5.5: Decision Support Commands per Level

Low WADD Support	***High WADD Support***
DROP	DROP
CONDITIONAL DROP	CONDITIONAL DROP
	WEIGHTS
	GLOBAL
	ROW TOTAL
The general purpose commands OPEN, CLOSE, SORT, UNDO and RESET are available under both conditions.	

TABLE 5.6: Impact of Decision Aids on Cognitive Effort

	Elimination by Aspects (EBA)				***Weighted Additive (WADD)***			
Component	Attribute Recall	Tracking	Processing	**Total**	Attribute Recall	Tracking	Processing	**Total**
Formula	1*Att	1*(Att-1)*Alt	4*Att*Alt		1*Alt*Att	4*(Alt-1)+2	6*(Alt*Att)	
Unaided	8	70	320	**398**	80	38	480	**598**
Low WADD support	8	0	0	**8**	80	38	480	**598**
High WADD support	8	0	0	**8**	8	1	0	**9**
				Command Usage				
Low WADD support	CONDITIONAL DROP (8 times)			**8**				NA
High WADD support	CONDITIONAL DROP (8 times)			**8**	WEIGHTS, GLOBAL, ROW TOTAL and SORT (of row totals).			**4**

The numbers in table 5.6 show that under the condition of high WADD support the difference in cognitive effort expenditure between both strategies will be negligible. Regarding the use of decision aids both strategies require different functions. An EBA strategy can be implemented using the CONDITIONAL DROP. Under the assumption that a CONDITIONAL DROP command will be used for each available alternative[19], this command needs to be activated eight times. Application of a WADD strategy requires the following sequence of commands: WEIGHTS to enter the relevant attribute weights, GLOBAL to calculate the weighted attribute values for the complete decision matrix, ROW TOTAL to compute the weighted additive scores for all alternatives, and finally SORT the weighted additive scores.

[19] The assumptions underlying EIP-calculations explained in § 3.6 are valid in this context also.

5.6 Summary

This chapter introduced the DSS environment developed in support of this study. Development of this environment took place according to the functional requirements evolved in the previous chapter. Each of the major DSS components: user interface, model subsystem, and data subsystem, is explained in detail. The last part of this chapter presented an analysis concerning the influence of the DSS on effort reduction. This impact analysis will be used in the next chapter as input for hypothesis development.

CHAPTER 6

RESEARCH MODEL and HYPOTHESES

6.0 Introduction

This chapter will introduce the research model and related hypotheses to be tested in this study. Our research model, presented in figure 6.1, aims at integrating those factors that are, according to both behavioral decision making and DSS theory, recognized to influence decision strategy selection. Whereas automated decision support as influencing factor was already introduced in chapter three, two additional influencing factors, emanating from behavioral decision making research, will be introduced and explained in this chapter: 1) characteristics of the decision problem, and 2) characteristics of the decision maker.

For the purpose of this research Todd and Benbasat's 'final' model (model 1d, see also § 3.2), including the moderating effects of effort and accuracy, will be adopted, and extended by integrating context effects and cognitive style. Because the focus of this research is on the grey colored constructs, as presented in figure 6.1, this chapter will only develop hypotheses on the associations among these constructs.

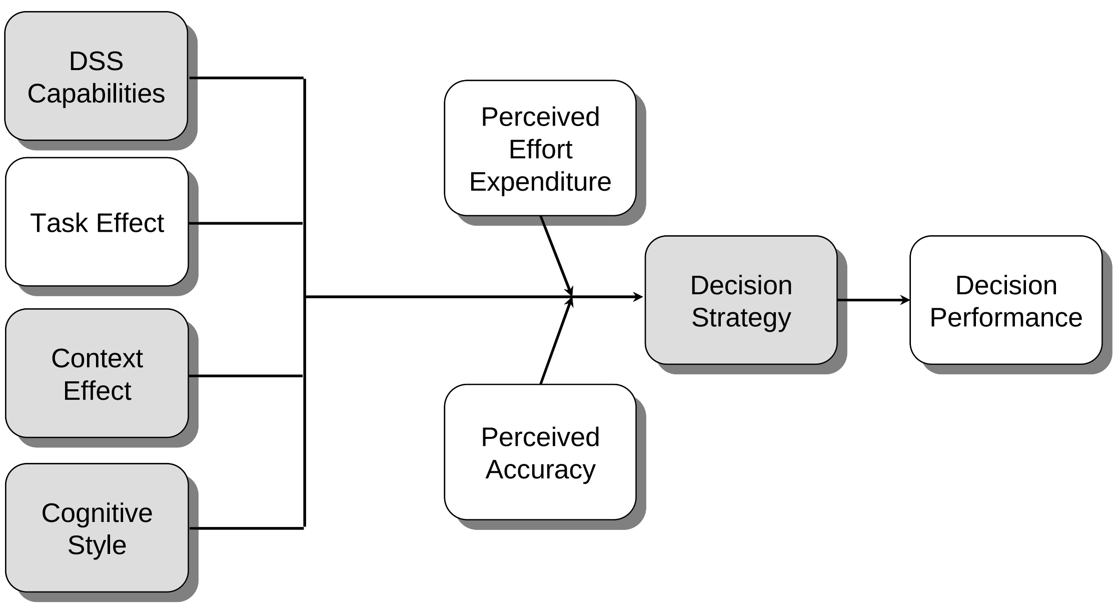


FIGURE 6.1: Research Model
(Based on Todd and Benbasat's model 1d "the moderating effects of effort and accuracy" (1999, p.359). The model is extended with *context effect* and *cognitive style*.)

Prior to an explanation of the variables, and their relationships, the fundamental assumptions underlying this study will be presented first.

6.1 Model assumptions

An important premise is that the decision maker is presumed to be boundedly rational (Simon, 1957; Taylor, 1975). The decision maker's pursuit of making more effective decisions is restricted by limited cognitive capabilities (Keen & Morton, 1978). Rationality is bounded not only by limitations on human information processing capacities but also by individual difference such as age, education and knowledge. The notion of bounded rationality is omnipresent in traditional DSS research (Todd & Benbasat, 1992). A decision maker's cognitive limits can be expanded by the use of automated decision aids (Keen & Morton, 1978).

Another major assumption underlying this research is related to the fundamentals of the effort-accuracy framework. It is assumed that the selection of decision strategies is primarily driven by considerations concerning both the perceived cognitive effort and perceived accuracy related to various decision strategies (Payne *et al.*, 1993). The level of cognitive effort needed to reach a decision using a particular decision strategy, as well as the relative accuracy levels of various strategies, is contingent upon task environments.

6.2 Decision support

When considered in context of the effort-accuracy framework, two essential propositions can be made regarding the influence of automated decision aids on decision behavior (Todd & Benbasat, 2000): (1) if, all other things being equal, the use of decision aids causes the implementation of a specific decision strategy to be less effortful than other strategies, a decision maker will more likely employ this less effortful strategy than other decision strategies, and (2) if two decision strategies are equally effortful, a decision maker will be inclined to implement the decision strategy that is perceived to be the most accurate.

To map the implications of these two assumptions on the DSS presented in the previous chapter, effort estimates as presented in table 5.6 will be used. Table 6.1 shows the changes in effort needed to implement the EBA and WADD strategy under different levels of decision support as well as the effort differential between both strategies.

TABLE 6.1: Impact of Decision Aids on Effort

	EBA strategy		***WADD strategy***		***Differential (WADD -/-EBA)***	
Level of Support	Cognitive Effort	Command Usage	Cognitive Effort	Command Usage	Cognitive Effort	Command Usage
Low WADD	8	8	598	NA	590	NA
High WADD	8	8	9	3	1	-5
DSS effect					-589	

According to the numbers in table 6.1 a decision maker acting under LOW WADD support will most likely perform an EBA strategy, because it will be 590 units more effortful to employ a WADD strategy than an EBA strategy. However, under the HIGH WADD support condition the effort differential is negligible which implies that a decision maker acting under this condition will most likely be inclined to employ a WADD strategy. Prior DSS research that investigated this relationship found support for this proposition (Todd & Benbasat, 1999, 2000).

If we consider the functions of our experimental DSS in context of both the numbers presented in table 6.1 and the findings of prior research, it will be most likely that the WADD support provided in our experimental DSS will induce compensatory information processing behavior, therefore we hypothesize:

H1: *The level of compensatory decision support available positively influences the use of compensatory decision strategies.*

6.3 Characteristics of the decision problem: alternative similarity

Concerning the two categories of decision task characteristics: task effects and context effects, we are focusing here on context effects, or more specific: on the influence of alternative similarity on decision behavior. Investigation of the influence of task effects on decision behavior is well established in DSS research. For example, Chu and Spires (2000) reported that task complexity positively influenced the use of compensatory decision support aids. They operationalized task complexity by varying both the number of alternatives and attributes. The simple task had two alternatives and four attributes, whereas the complex task had twelve alternatives and seven attributes. Task effects were also manipulated in some of the experiments of Todd and Benbasat. To investigate the value of automated decision aids under different levels of cognitive load, Todd and Benbasat manipulated the number of alternatives and found support for decision maker adaptability to problem size and to automated decision support (1991; Todd & Benbasat, 1994a). Finally, Wang and Chu (2004) also manipulated the number of alternatives (20 versus 100 alternatives) and found support for the influence of the number of alternatives and decision support provided on decision behavior.

Alternative similarity refers to the similarity of alternative choices within a decision set. Alternatives described on the same dimensions are similar to the extent that their attribute levels are close together (Stone & Schkade, 1991). For example, a choice set containing cars with a price difference of only $100 between the cheapest and most expensive car will, regarding to the dimension price, make the cars more similar than those in a choice set showing a variance of $5000 on this dimension. Similarity of alternatives can also refer to the extent to which alternatives are equally ‘desirable’ at first sight (in this case prior to the application of a decision rule) (Best & Ursic, 1987; Bockenholt *et al.*, 1991).

Many managerial decision problems are characterized by a large number of similar alternatives. For example, retailers arrange their stores into peer groups based on attributes like location, size, and customer demographics and develop metrics to compare each store with their most similar peers (Joseph *et al.*, 2003). A store manager willing to perform a benchmark analysis will have to select a reference store from his peer group. The stores in this peer group will show a high degree of congruence. Bank loan officers often have to choose among equally attractive companies in order to grant business loans (Biggs *et al.*, 1985). Decision problems with similar alternatives are also known to play a role in new product introduction decisions (Payne *et al.*, 1993) and the problem of cannibalization in product lines (Batsell & Polking, 1985).

Alternative similarity can also increase due to the nature of decision processes itself. To reduce complexity of decision processes, people generally tend to use a two-stage decision model where editing of the available alternatives into a simpler representation characterizes the activities in the first stage, and the second stage is characterized by a thorough evaluation of a limited subset of alternatives (Bettman & Park, 1980). According to Payne (1982) "The editing phase is seen as the primary source of context effects in decision making: The same set of options might be edited in different ways depending on the context in which it appears" (p. 384). One can imagine that the editing performed in the first stage of the decision process can result in a decision set containing more similar alternatives. Consumers, for example, looking for a new computer will not be able to analyze in detail all systems made available via the Internet, but instead will use criteria to compose a limited set of alternatives that can be evaluated in detail (Levin *et al.*, 2000). This reduction process will most likely be guided by criteria that filter out the alternatives that do not meet the expectations of the decision maker, resulting in a consideration set containing options that are more similar than the alternatives available in the initial set.

Alternative similarity affects the information-processing strategies leading to choice (Payne *et al.*, 1993). Ease of comparison between alternatives, for example, is influenced by similarity (Shugan, 1980). Bockenholt *et al.* (1991) found that decision makers considered more information when the attractiveness differences between two alternatives were small rather than large. The additional information was needed to make the equally attractive alternatives less ambiguous. Decision makers confronted with choices among similar alternatives are more likely to apply compensatory rather than noncompensatory decision strategies (Biggs *et al.*, 1985). If attributes of two alternatives significantly differ and one alternative is dominant, only few comparisons will be necessary to make a choice. In this case, noncompensatory strategies will minimize the cost of thinking by quickly eliminating the dominated alternatives. Noncompensatory strategies may require more comparisons than compensatory strategies if the attributes of two alternatives have similar values. It is difficult to eliminate alternatives based on small differences in attribute values. However, "in a situation where there are small dimensional differences across alternatives, the combining of weights is likely to provide a basis for making a choice after one pass through the alternatives. Thus, compensatory strategies would tend to minimize the cost of thinking in choice situations involving similar alternatives" (Biggs *et al.*, 1985, p.972). Therefore, we hypothesize:

H2: *The level of alternative similarity positively influences the use of compensatory decision strategies.*

What will happen under conditions of alternative similarity? Does alternative similarity require more information processing on the part of the decision maker? Payne (1982) proposes that the cognitive effort associated with making a choice may also be a function of similarity. Prior research, (e.g. (Helgeson & Ursic, 1993; Todd & Benbasat, 1992) found that a decision maker's perceived cognitive effort limits the use of more compensatory decision strategies. According to the effort-accuracy framework (Payne *et al.*, 1993) the use of the more effort demanding compensatory strategies will be dominant over the use of noncompensatory decision strategies only when the effort to execute the former is not greater than the effort required for the latter. Automated decision aids supporting compensatory strategies reduce the cognitive load induced by application of these strategies and stimulate their use. We therefore assume an interaction effect of context effects (alternative similarity) and the level of compensatory support on the use of decision strategies.

> **H3**: *The effect of alternative similarity on the use of compensatory decision strategies is positively influenced by the level of compensatory decision support.*

6.4 Characteristics of the decision maker: cognitive style

Decision strategy selection is influenced by both problem and problem-solver characteristics (Beach & Mitchell, 1978; Benbasat & Taylor, 1978). Problem-solver characteristics can be expressed by means of psychological or cognitive styles. ”Cognitive style refers to the process behaviour that individuals exhibit in the formulation or acquisition, analysis, and interpretation of information or data of presumed value of decision making” (Sage, 1981, p. 642). According to Benbasat and Taylor (1978) the three cognitive styles that appear to have the greatest relevance for MIS design are: 1) complexity, 2) field independence-dependence (high analytic/low analytic) and 3) analytic-heuristic styles. Complexity pertains to structural characteristics of perception and thinking (Zmud, 1979). The field independence-dependence dimension has to deal with an individual’s ability of perceiving data independent of its context. Individuals can be classified as perceiving data as either “(1) patterns of data which are relatively independent of their context (high-analytic), or (2) discrete items embedded in their context (low-analytic)” (Bariff & Lusk, 1977, p.822). Analytic-heuristic refers to thinking modes that can be classified as systematic (discovering algorithmic solutions by searching the data for causal relationships) or heuristic (searching data by trial and error ad hoc hypothesis testing) (Bariff & Lusk, 1977). Van Bruggen *et al.* (1998) propose that cognitive style forms a continuum ”with the two opposite types of decision makers at the extremes: high-analytical and low-analytical” (p.647). We have chosen to integrate these two opposite styles in our research model with the purpose of investigating their influence on decision strategy selection. Compensatory strategies are, amongst other factors characterized by complete acquisition of available information (Biggs *et al.*, 1985; Payne, 1976). In contrasting the decision behavior of low-analytic and high-analytic individuals, research findings show that high-analytics seek more information (Goodenough, 1976) and outperform low-analytics in structured decision tasks (Zmud & Moffie, 1983). In line with these findings we therefore assume an effect of cognitive style on the use of decision strategies.

> **H4**: *High analytical cognitive style positively influences the use of compensatory decision strategies.*

6.5 Research model

Figure 6.2 shows the research variables, their associations and the related hypotheses.

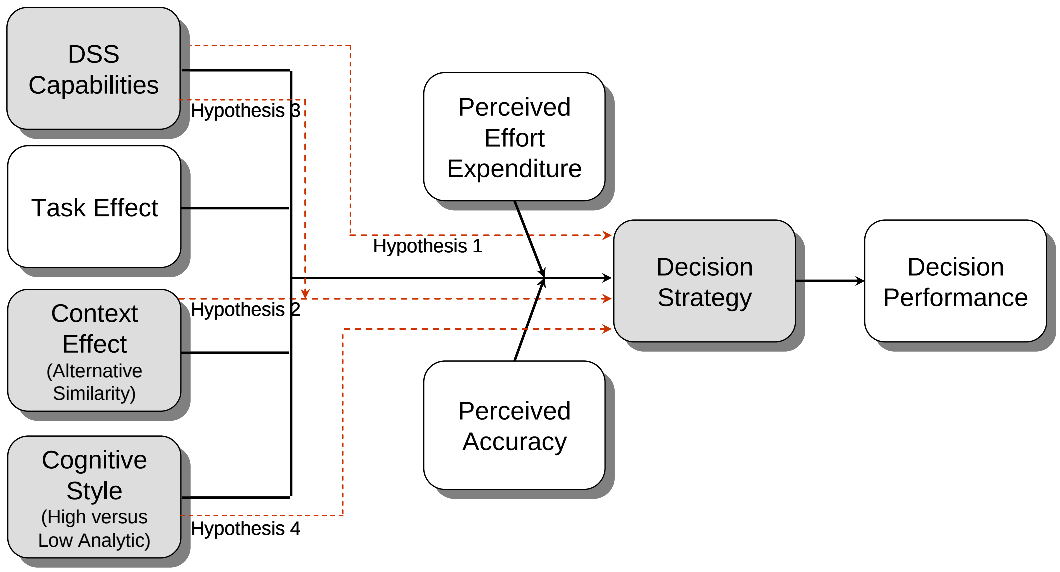


FIGURE 6.2: Research Model

6.6 Summary

This chapter developed the research model and related hypotheses. The hypotheses developed assume that each of the following factors: automated decision support, alternative similarity and cognitive style, influences the selection of decision strategies. How the hypotheses developed in this chapter will be tested is the focus of the next chapter.

CHAPTER 7

METHOD EXPERIMENT 1

7.0 Introduction

To examine the hypotheses developed in the previous chapter, a laboratory experiment was conducted in October 2003. The experimental design is a 2x3 between subjects factorial in which alternative similarity (low & high condition) varied across three levels of DSS support (no compensatory support, moderate compensatory support, high level of compensatory support). This chapter will describe in detail how the experiment was conducted. The decision task, the subjects and the manipulations, as well as the experimental procedures and apparatus will be discussed. Finally, the details of the procedures that were executed to verify the completeness of the computerized process tracing data and the accuracy of the software routines that calculated the dependent variables will be presented. We have chosen to deal with these two issues in this chapter because both the process traces (input) and the results of the calculation routines (output) are key to our analyses. The procedures driving these issues are fully embedded in the software, and as such not easy to verify, that is why it is appropriate to pay additional attention to their verification.

7.1 Decision task

Participants were supposed to perform a multi-alternative, multi-attribute preferential choice task, in which the objective was to select a one-bedroom apartment, a task similar to those employed by Payne (1976), Todd and Benbasat (1991, 1992, 1994a, 1994b, 1999, 2000) and Chu and Spires (2000). This task was chosen for three reasons: 1) a large proportion of the participant population is familiar with selecting a single room apartment, 2) participants do not need specialized knowledge to execute the task, and 3) this task provides continuity with prior research and a basis for comparative analysis.

The structure of the choice matrix employed in this experiment was identical to the matrices used by Todd and Benbasat (1994a, 1994b, 1999, 2000) and included ten alternatives each described by eight attributes. The eight attributes employed in this experiment were particularly chosen from the set of dimensions used in prior studies (Chu & Spires, 2000; Payne, 1976; Todd & Benbasat, 1991, 1992, 1994a, 1994b, 2000). Table 7.1 shows the attributes used.

Each individual attribute value could be presented in two formats: numeric and text. Participants could switch between numeric and text presentation using the default DSS functionality. The initial numeric values used in the choice tasks were expressed on a 10 point numeric scale similar to those found in consumer reports. An associated text value was assigned to each numeric value, for example, the text value ‘Very Good’ relates to the numeric score ‘9’ on the attribute named ‘Kitchen’. An overview of the datasets employed in this experiment, including both the numeric and text values used, is included in appendix 2.

To increase the external validity of the choice matrices used in this experiment data on student rooms gathered from websites of housing agencies specialized in student accommodations[20] was used to develop and review the final data sets.

No time constraints were imposed and participants were free to use as much or as little information as they wanted.

TABLE 7.1: Attributes Used in Decision Task

Attribute	*Description*
Rent	Monthly rent in euros.
Size	Size of the apartment in square meters.
Distance City Centre	Time in minutes needed to walk from the apartment to city centre.
Distance Campus	Time in minutes needed to walk from the apartment to university campus.
Cleanliness	Cleanliness of the apartment.
Noise	Environmental noise penetrating the apartment.
Kitchen	Kitchen quality.
Landlord Service Attitude	Service level provided by landlord expressed in a tenant's autonomy to hire subcontractors to fix problems.

7.2 Participants and treatment assignment

All participants were graduate and undergraduate business administration students. Participants were enrolled from an elective class in Decision Support Systems at the Faculty of Economics and Business Administration of the *Vrije Universiteit* Amsterdam. Participants volunteered to participate in return for partial class credit. In total 186 individuals participated.

Assignment to the different treatment combinations took place through random assignment without replacement. The software automatically assigned each participant to a specific treatment during the log on procedure that provided access to the experimental DSS environment.

7.3 Manipulations

The manipulations of the experiment were the level of compensatory decision support and the level of alternative similarity. The operationalization of both manipulations will be explained below.

7.3.1 Level of compensatory decision support

The level of compensatory decision support was manipulated by the availability of automated decision aids included in the decision support system. Three levels of compensatory decision support were distinguished: *none*, *moderate* and *high*. A detailed overview of the

[20] www.opkamers.nl (May 21, 2003), www.kamernet.nl (May 21, 2003), www.studentenkamers.nl (May 21, 2003), and www.kamergids.com (May 21, 2003).

decision aids available under each of the three levels of decision support provided is presented in table 7.2.

TABLE 7.2: Decision Aids Available under Each Condition

	Level of Compensatory Decision Support		
Commands	***NONE***	***MODERATE***	***HIGH***
Open/Close	√	√	√
Sequence	√	√	√
Drop Row	√	√	√
Drop Column	√	√	√
Conditional Drop	√	√	√
Sort	√	√	√
Undo	√	√	√
Reset	√	√	√
Create	-	√	√
Weights	-	√	√
Calculate	-	√	√
Global	-	-	√
Row Total	-	√	√
Make a Choice	√	√	√

As can be derived from table 7.2, each ‘higher’ compensatory support condition also includes the decision aids provided in the ‘lower’ conditions.

Under the condition of ‘*no* compensatory’ support a decision maker could only make use of functionality that automate EIPs associated with noncompensatory decision rules. In fact, this '*no*-condition' offered full support for the application of the so called elimination by aspects (EBA) strategy. In the experimental DSS this strategy was supported with a CONDITIONAL DROP button, enabling automated support for the elimination of alternatives that do not meet the threshold level entered by the decision maker.

The *high* compensatory support condition automated nearly all the processes needed to execute the weighted additive (WADD) strategy. Under this condition, the application of a WADD strategy through the experimental DSS requires the use of three commands: WEIGHTS, GLOBAL and ROW TOTAL. Pushing the WEIGHTS-button allowed the decision maker to assign weights to the relevant attributes. Calculation of weighted attribute values for any relevant alternative in the decision set could be effectuated by using the GLOBAL command. After a GLOBAL has been performed, the WADD score per alternative could be computed using the ROW TOTAL command. Using these three commands to implement a WADD strategy will reduce the associated cognitive load to a minimum level.

Introduction of the *none* and *high* condition was necessary to allow comparisons of this experiment with the experiment performed by Chu and Spires (2000). The *moderate* level of compensatory decision support was introduced to examine a decision maker's sensitivity to different levels of support each requiring different combinations of individual effort and automated support (Todd & Benbasat, 1999). Whereas the *none* and *high* compensatory decision support conditions offer support for a specific decision strategy (EBA and WADD respectively) there is no clear support for a single strategy under the moderate condition. Next to the CONDTIONAL DROP, WEIGHTS and ROW TOTAL commands, the moderate condition offered a CREATE and a CALCULATE command. The GLOBAL command was not available under this condition. The CREATE command made it possible to create additional rows into which user specific values could be entered. In turn, the CALCULATE command made it possible to perform specified arithmetic operations on any pair of rows (alternatives). The results of a CALCULATE could be stored in the additional rows created by means of the CREATE command. Choosing for the implementation of a WADD strategy required more effort under the moderate condition because the steps supported by a GLOBAL command would have to be performed manually. For example, the computation of a WADD score for all alternatives requires the execution of the following command sequence for each alternative: CALCULATE (weights * alternative) followed by a ROW TOTAL. Acting under this moderate support condition a decision maker will, to a greater extent than under the other two conditions, have to balance effort versus accuracy.

7.3.2 Alternative similarity

Prior research (Best & Ursic, 1987; Biggs *et al.*, 1985; Bockenholt *et al.*, 1991; Helgeson & Ursic, 1993; Roe *et al.*, 2001) that focused on the effects of *alternative similarity* distinguished three different criteria to operationalize similarity of alternatives. The first criterion, called attribute variance, focuses on the variance in the values on the attributes across alternatives. Alternatives become more similar as this variance decreases (Payne *et al.*, 1993). For example, consider two different choice sets C_1 and C_2, each including three attributes: rent, size, and noise. The attribute values for the alternatives included in both choice sets are presented in table 7.3.

TABLE 7.3: Criteria Alternative Similarity

	Choice Set C_1				***Choice Set C_2***			
	Rent	***Size***	***Noise***	***Mean***	***Rent***	***Size***	***Noise***	***Mean***
Alt-1	4	5	8	*5.67*	5	7	7	*6.33*
Alt-2	8	9	3	*6.67*	6	7	6	*6.33*
Alt-3	3	9	7	*6.33*	6	6	7	*6.33*
Alt-4	9	6	5	*6.67*	5	6	8	*6.33*
Variance	*6.50*	*3.19*	*3.69*		*0.25*	*0.25*	*0.5*	
SD	*2.55*	*1.79*	*1.92*		*0.50*	*0.50*	*0.71*	
Maximum Difference	*6*	*4*	*5*		*1*	*1*	*2*	

The variance in attribute values of choice set C_2 is significantly lower than the variance in attribute values of choice set C_1, indicating that the alternatives included in C_2 are more similar.

The second criterion, called maximum difference, was used by Biggs *et al.* (1985) and is closely related to the first criterion. Biggs *et al.* set a maximum to the difference between alternatives on a dimension in their 'similar' treatment, or as they put it: "For "similar" tasks, the maximum difference between companies on a cue was 3 points (on the 11-point scale), and of the 30 possible pairwise comparisons (21 in the 7x3, and 9 in the 3x3), 19 had differences of 1 point or less" (p. 977). The maximum difference in choice set C_2 is 2, whereas the maximum difference in C_1 is 6. A pairwise comparison of all attribute values on rent in C_1 delivers that only two comparisons result in a difference of 1 point or less (Alt-1 versus Alt-3, and Alt-2 versus Alt-4). However, all pairwise comparisons on rent in C_2 result in a difference of 1 point or less.

The third criterion, called attractiveness of alternatives (Bockenholt *et al.*, 1991), considers the overall attractiveness of the alternatives in a choice set. The unweighted average of the attribute values of an alternative is considered an appropriate measure for expressing the overall attractiveness of an alternative (Best & Ursic, 1987; Bockenholt *et al.*, 1991; Helgeson & Ursic, 1993). As can be derived from table 7.3 all alternatives in choice set C_2 are equally attractive, again indicating that the alternatives in C_2 are similar.

The attribute values in the decision set employed under the 'similar alternatives' condition were manipulated such that all three criteria explained above were met. The variances in the attribute values for all attributes under the 'similar alternatives' (M_{similar}= 0.61; SD_{similar}= 1.37) condition were significantly lower than the average under the 'not similar' condition ($M_{\text{not similar}}$= 4.10; $SD_{\text{not similar}}$=0.18,), $t(14)=7.154$, $p< .01$. The maximum difference between alternatives on an attribute under the 'similar' condition was 2 points, whereas this maximum difference under the 'not similar' condition was 8 points. Under the 'similar' condition more than 80% of the pairwise comparisons of all alternatives on an attribute resulted in a difference of 1 point or less, whereas this number was only 40% for the 'not similar' condition. The attractiveness scores were equal (5.625) for all alternatives under the 'similar' condition, under the 'not similar' condition the attractiveness scores varied between 5.63 and 7.00. The attractiveness scores under the 'similar alternatives' condition (M_{similar}=5.625, SD_{similar}=.000) differed significantly from the attractiveness scores under the 'not similar' condition ($M_{\text{not similar}}$=6.290, $SD_{\text{not similar}}$=.513), $t(18)=4.097$, p=.001.

The direction of the attribute differences was varied in such a way that none of the alternatives in both datasets dominated the other alternatives.

7.4 Measures

Next to the two independent variables explained in the previous section (*alternative similarity* and *compensatory decision support*) the third independent variable of interest in this study is *cognitive style*. How cognitive style is measured will be explained in this section. However, before we will elaborate on the operationalization of cognitive style we will first focus on the operationalization of the dependent variable of interest in this research project: decision strategy employed.

7.4.1 Decision strategy

Measuring the actual decision strategy applied by a decision maker is a difficult job. Besides the fact that decision makers rarely use decision strategies in their pure forms (Bettman & Park, 1980; Häubl & Trifts, 2000) any attempt to look inside the brains of a decision maker, in order to determine which strategy was applied during the pre-decision process, will at most result in an approximation of the actual strategy applied. *Decision strategy* applied by the decision makers will be deduced from the log data stored in the CPT database and will be measured using data on both information acquisition and information processing behavior.

To determine information acquisition behavior we adopted the same method as Chu and Spires (2000) applied. This method, based on information search patterns, does not claim to measure the actual decision strategy applied but proposes to infer a decision maker's inclination to use a specific decision strategy.

A subject's pattern of information search should provide a method for discriminating between alternative decision strategies. Each of the four prototypical decision strategies explained earlier, additive compensatory, additive difference, conjunctive and elimination by aspects, "imply, at least in their common forms, different information search processes" (Payne, 1976, p. 369). To characterize information search patterns we adopted the same measures as Payne (1976), Chu and Spires (2000) and Biggs *et al.* (1985) did:

Amount of information search. Information acquisition can be measured as the proportion of available data in the decision set accessed.

Variability of information search. This measure is the same as employed by Payne (1976): the standard deviation of the percentage of available information accessed per alternative.

Pattern of information search. Payne (1976) developed a so called search index.

$$\textit{Search Index} = \frac{\textit{Alternative Transitions -/- Attribute Transitions}}{\textit{Alternative Transitions} \ + \ \textit{Attribute Transitions}}$$

The search index can be determined by examining the alternative and dimension associated with the n^{th} +1 piece of information accessed by a subject as a function of the alternative and dimension associated with the n^{th} piece of information accessed. *Inter*dimensional transitions, also called alternative transitions, represent information processing across dimensions (or attributes) within a particular alternative. *Inter*dimensional transitions represent the number of instances in which the i^{th} +1 piece of information accessed was of the same alternative as the i^{th}. If the n^{th} + 1 piece of information reviewed was within the same dimension, but a different alternative, then the transition could be designated as *intra*dimensional. Comparable to the methods employed by Chu and Spires (2000) and Bell and O'Keefe (1995) the software used in this experiment logged the number of *inter*dimensional and *intra*dimensional transitions associated with any command performed by the participants.

The information acquisition method is a so called explicit behavioral model of strategy effort (Bettman *et al.*, 1990). Behavioral models monitor information acquisition behavior and represent a base-line model of effort in that the details of processing are ignored. However, as substantiated in the previous chapters, information processing behavior should also be part of analyses on decision behavior. To deal with information processing behavior we developed the so called *processing index*. This measure is calculated as follows:

$$\text{Processing Index} = \frac{\text{Alternative Elements - Attribute Elements}}{\text{Alternative Elements + Attribute Elements}}$$

where the variable *alternative elements* represents the number of information cues that are processed across the dimensions of one or more alternatives due to the execution of a DSS command, and the variable *attribute elements* represents the number of information cues that are processed within a specific dimension. Calculation of this measure is comparable to the calculation method of the search index with this difference that it will not be based on transitions caused by mouse clicks but on information cues processed by an automated DSS function.

A processing index of +1 indicates full interdimensional information processing (alternative based), whereas a process index of -1 is an indication for full intradimensional information processing (attribute-based). The FIP-link developed in chapter four allows for capturing the data needed to calculate this index.

How these four measures are influenced by the individual decision aids included in the DSS provided is explained in appendix 3.

7.4.2 Cognitive style

The dimension used to differentiate between the cognitive styles was field dependence-independence (FDI). FDI, originally proposed by Witkin (1962), is perhaps the most intensively studied cognitive style (Miyake *et al.*, 2001) and well established in information systems research (e.g. (Bariff & Lusk, 1977; Benbasat & Dexter, 1982; Bruggen *et al.*, 1998; Crossland *et al.*, 2000)). The label field-independent is used to “refer to performances which reflect ready ability to perceive objects apart from the context in which they occur, or to overcome an embedding context, or to deal with a field analytically. We use the term field dependent to refer to performances which reflect dominance of perception of an item by the organization of the prevailing field, or relative inability to separate item from field, or to overcome embedding contexts” (Witkin, 1964, p.176). Field dependent, or low analytic[21] individuals, show a high degree of dependence on the structure of the prevailing visual field.

For the operationalization of FDI we used an adaptation of the Thurstone-Gottschaldt Embedded-Figures Test called the Hidden Figures Test (HFT) (French *et al.*, 1963). The HFT is a close variant of Witkin’s Embedded Figures Test (Witkin *et al.*, 1971) and is widely used as a measure of field-dependence-independence (Miyake *et al.*, 2001). This test requires individuals to identify which one of five simple figures is embedded in each of in total 32 complex figures. Figure 7.1 shows a sample item representative of the problems in the Hidden Figure Test.

The sample figures are available for inspection at all times throughout the test. The test encompasses two parallel sections, each including 16 problems. Participants get ten minutes for each section. The sections are administered one after the other, separated by a short break. The problems are approximately equivalent in terms of difficulty and do not become progressively

[21] Literature from psychology uses “field dependence/independence”, whereas the managerial literature appears to prefer “high/low analytic” (Benbasat & Dexter, 1982).

more difficult within or between the two sections. The final score is the number of correct figures identified corrected by a factor for chance. Field dependence-independence will be treated as covariate.

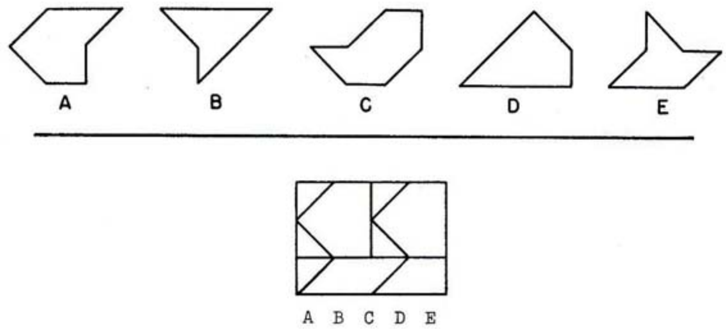


FIGURE 7.1: A Sample Item of the Hidden Figures Test
(The task is to determine which of the five simpler figures is hidden in the more complex figure. The correct answer for this problem is "A". (Adapted from Miyake *et al.*(2001))

7.5 Pre-testing

Prior to the execution of the experiment five pre-test sessions were organized in which a total of 60 individuals participated. During these pre-tests the experimental procedures and associated documents were tested. The output of the pre-tests was also used to verify the accuracy and completeness of the data stored in the computerized process tracing environment. Based on the results of the first pre-test sessions the experimental procedures and the DSS software were only slightly modified. The versions of the documents, procedures and DSS software used during the last pre-test sessions proved to be appropriate for the experiment.

7.6 Experimental procedures and apparatus

The experimental sessions were performed in a dedicated lecture room that was rebuilt into a DSS laboratory, facilitating 40 cubicle-like workplaces. Each workplace was equipped with a personal computer system that was configured to support the execution of the experiment. Images of the lecture room in which the experimental sessions were performed are shown in figure 7.2.

Precautionary measures were taken to prevent the participants being disturbed by other individuals that did not participate in the experiments. For example, an eye-catching "Do Not Disturb" sign was put on the door giving entrance to the DSS-laboratory. During each session the workplaces were not fully occupied to create a fall-back in case one of the personal computers crashed or broke down during as session. Actually this did not happen at all.

In total eight three hour sessions were scheduled in an unbroken time frame of four days. Dedicated web-based scheduling software was used to support the enrollment for the experiment. Each subject could choose which session to attend according to the 'first come, first served' principle.

FIGURE 7.2: Images of the Setting of the Experiment

7.6.1 Instructor, documents and apparatus

All sessions were supervised by an instructor who directed the sessions and provided instructions. Apart from giving instructions and responding to questions the instructor had a passive role. To prevent for 'instructor bias' the same instructor supervised all sessions and proceeded according to a strict instruction script. Prior to each session the instructor prepared the laboratory room by switching on the personal computers and distributing all necessary documents across the workplaces. To prevent for premature reading all documents were laid upside down on the desk tops. A clear document code was printed on the back of each document. This code was referred to in the instructions. Participants were only allowed to turn around and read a specific document when they were explicitly asked or instructed to do so.

One of the documents provided a participation code (user name) and password needed for a log on to the experiment related applications. The participation code printed on this document was also used to integrate all relevant data produced by a participant. For example, to be able to link the results of the Hidden Figures Test (HFT) to the computerized process traces of a specific participant, this unique participation code was printed on the HFT documents as well as recorded in each process trace record stored in the CPT environment. To prevent type errors and complicated log on procedures participation codes were kept as short as possible. A participation code included the character "E" followed by a three digit number ranging from 600 to 800, e.g. 'E600'. To prevent passwords being logically derived, passwords included the character "D" followed by a three digit number that was generated randomly providing values in a discontinuous range between 100 and 200. Each combination of participation code and password was unique, this, together with the fact that such a combination could only be used once, guaranteed that each participant was uniquely registered in any of the relevant systems used. Prior to the execution of the experiment all participation codes and associated passwords were uploaded to the application environment. When a participant entered a wrong participation code/password combination access was denied. Since participation codes played a key role in the experimental procedures, this code and all other essential log on data were printed on a yellow form, so it could be easily distinguished from the other documents used.

7.6.2 Briefing

Participants were asked to come at least ten minutes prior to the planned starting time of a session and waited outside the laboratory room until they were asked to enter the room collectively. Each participant was assigned to a specific workplace. A personalized sign, clearly stating a participant's name and student number, was provided to each workplace, so the participants knew where to sit. Participants were told that all data was processed anonymously, no link was made between a participant's name and participation code.

Each session started with a general briefing. This briefing was used to inform participants about the routine issues concerning the execution of the experiment, such as: switching off mobile phones; how to deal in case of questions; that it was not allowed to communicate with other participants; and what to do when you are ready. Beside the settlement of routine issues this briefing was also used to explain a few points of special interest. Participants were told that a session consisted of two parts. The first part was a plenary part in which all instructions were given by the instructor. During this plenary part all participants worked on the same task at the same time. In the second part of a session the participants continued in their own tempo. The time needed to execute the tasks included in this second part of a session was dependent on the treatments assigned. During this second, individual part, instructions were given by the software. The tasks to be performed were embedded in a kind of workflow application that directed the participants through the steps to be executed. When needed, the workflow instructions clearly referred to the document codes printed on the relevant documents. During the briefing it was also emphasized that no time constraints were imposed. It was explicitly stated that participants could take as much time as they wanted to fulfill the experimental decisions tasks[22]. To avoid participants being pressured for time they were informed about the fact that different tasks with different time needs were assigned, so if another participant finished the tasks earlier this might be due to the nature of the task assigned. The briefing also rehearsed that participants were expected to stay in the laboratory room, at their workplace, until the end of the session[23]. It was explicitly underlined that it was only allowed to use the DSS provided to fulfill the decision task. The use of other tools (e.g. calculators or paper and pencil) was not permitted. The network environment was configured in such a way that it was not possible to start 'unauthorized' applications such as Microsoft Excel or the desktop calculator.

7.6.3 Experimental tasks

After the general briefing participants were asked to read the nondisclosure statement and upon agreement to sign it. The aim of the nondisclosure statement was to prevent participants to carry over details of the experiment to participants that would attend subsequent sessions. Although it was emphasized that no one was obliged to sign the statement, all participants did sign it.

[22] From the pre-test sessions it was known that the maximum time needed to fulfill the experiment was two and a half hours. To avoid rush behavior all participants were asked to schedule a three hours session in advance.

[23] This was also noted prior to the experiment, so participants were asked to take reading material to the sessions of the experiment in case they had to kill the time.

Next, participants were instructed to read the document called ‘general instructions’. This document provided an overview and a brief explanation of all the tasks to be performed during the session. A session involved completion of the following tasks:

1. Hidden Figures Test
2. Tutorial
3. Tutorial Test
4. Decision Task
5. Debriefing Questions.

The ‘general instructions’ document also produced a summary of the points of interest that were explained in the general briefing. While participants were reading this document the instructor collected the nondisclosure statements and verified whether all statements were signed.

If no further questions regarding the setup of the experiment existed the Hidden Figures Test was introduced. After the participants verified whether the subject codes printed on the test forms equaled the subject codes printed on the yellow form including the log on codes, they were requested to read the HFT instruction page. Prior to the execution of the test the instructor repeated the key elements of the test instructions and made sure that no further questions concerning the test existed. Participants got ten minutes to perform the first part of the test, followed by a very short break. During this break it was not allowed to talk. Another ten minutes were clocked for the second part of the test. After finishing the HFT, the final task of the plenary part of a session, participants were asked to close their test set. These test sets were collected by the instructor immediately after the next instructions were provided.

Additional instructions regarding the second part of the session were provided by the instructor. Next, participants were asked to log on to the workflow environment using the codes provided on the yellow form. The software included a treatment assignment procedure that was triggered as part of the log on procedure. After a successful log on an instruction screen appeared showing a code representing the DSS treatment assigned: 0 for *no* compensatory support, 1 for *moderate* compensatory support, and 2 for *high* compensatory support. This code was needed to support the efficient and proper distribution of the DSS tutorials. By looking at a display, showing the DSS treatment code in a very large font, the instructor could easily determine which tutorial to issue to which subject. On receipt of the tutorial document participants could immediately start reading the tutorial.

The tutorial explained each of the commands available within a specific DSS treatment and guided the participants in a step-by-step approach through all the DSS functions at least once. The set-up of the tutorial was such that they primarily focused on a functional explanation of the decision aids provided, no direct linkages were made between the commands and decision strategies. Participants worked through the mechanics of the user interface, no choice strategies were developed during the tutorials. Apart from one additional command the DSS user interface used for the tutorial was equal to the user interface employed in the decision task. For convenience an ‘INITIALIZE’ command was provided in the user interface for the tutorial. This command was referred to only in the tutorial and caused the decision matrix to be brought back in a status ready for the execution of the tutorial instructions. The tutorial document explicitly stated that this ‘INITIALIZE’ command was only available during the tutorial.

A dedicated decision matrix, containing attribute values that were randomly generated, was developed for the tutorial. The alternatives and dimensions of the decision matrix employed in the tutorial were named meaningless, for example ‘Row 1’ or ‘Column A’. The tutorial decision matrix was equal for all treatment groups. Apart from the number of rows and columns the tutorial matrix showed no resemblance with the decision matrix used in the decision task.

Participants could work through the tutorial in their own pace. It was allowed to use the tutorial document as a reference during the subsequent tasks to be performed. Each subject also received a so called ‘DSS Function Card’. This plasticized command reference card provided an overview and a brief description of the commands available under the DSS treatment assigned.

The next step after finishing the tutorial was the execution of a tutorial test. The aim of this test was to investigate the level of participants’ understanding of the DSS functions provided. All tutorial tests were treatment specific generated by the workflow application. Dependent on the DSS treatment assigned a subject got two (*no* compensatory support), four (*moderate* compensatory support), or five (*high* compensatory support) multiple choice questions. Each test for a higher level of DSS support included the questions of the test(s) for the lower level(s) of DSS support. The two questions for the ‘*no* support’ treatment group, for example, were also included in the tests for the ‘*moderate’* and ‘*high* support’ groups. Each question aimed at testing the understanding of specific DSS functions and required participants to perform DSS commands on the tutorial decision matrix. The questions were formulated in functional terms without making explicit references to DSS commands. A decision maker had to decide which DSS commands to use in order to answer the questions of the test. Table 7.4 shows the commands tested per question.

TABLE 7.4: DSS Commands Tested per Tutorial Test Question

Question	*DSS Command*	*No*	*Moderate*	*High*
1	CONDITIONAL DROP, SORT, OPEN(text)	√	√	√
2	SORT, SEQUENCE	√	√	√
3	CREATE, CALCULATE, ROW TOTAL		√	√
4	WEIGHTS, CALCULATE		√	√
5	GLOBAL, SORT			√

A digital test environment[24] was used to administer the test. This test application was embedded in the workflow environment. The results of the tutorial tests were only available to the researchers and were not communicated to the participants during the sessions. Analysis of the test results revealed that question number two was misinterpreted by nearly all participants. This question aimed at testing the understanding of the SEQUENCE function. Participants were asked to determine the sequence of a specific attribute value within a column specified. It appeared that less than 4% of the participants correctly answered this question. Since all answers were recorded in the database of the digital test environment, it was possible to analyze the answers given. An analysis of the answers revealed that 86% of the participants chose for the answer option that was associated with a wrong way of determining the attribute’s sequence. If a subject chose to mentally determine the sequence and didn’t know that the SEQUENCE function performed a continuous count in case of equal attribute values, as was explained in the tutorial, the most likely choice was the option that was chosen by this 86% of the participants. This logic

[24] This digital test environment (DTE) is developed in support of the Decision Support Systems class participants were enrolled from. Participants were familiar with the working of this environment since several tests and exams were taken through this DTE.

convinced us in our conclusion that the chances are very high that 86% of the participants mentally determined the sequence of the attribute requested, and as such did not make use of the SEQUENCE function. Given this conclusion, the results of the tutorial tests will be presented with and without the results of question two. The average[25] marks are presented in table 7.5.

TABLE 7.5: Results Tutorial Tests

	Level of WADD Support					
	Nonr		***Moderate***		***High***	
	M	***SD***	***M***	***SD***	***M***	***SD***
Marks (question 2 included)	4.84	1.26	7.25	1.49	7.78	1.25
Marks (question 2 excluded)	9.52	2.15	9.56	1.43	9.60	1.43
Percentage of participants with a maximum score (10).	95%		93%		89%	

Given the fact that the results of question two are ignored the marks presented in table 7.5 show that on average the tutorial tests were made very good. It should also be noticed that the SEQUENCE function was a general purpose command and did not play a crucial role in the application of any of the decision strategies distinguished. When the results of the tutorial tests are considered an indication for the level of understanding of the DSS commands provided, it is allowed to conclude that the participants were sufficiently prepared to apply the DSS in the final decision task. Another indicator for the appropriateness of the DSS tutorial are the answers to the post experiment survey statement “The tutorial was clear and obvious to me.” (1=fully disagree, 5=fully agree). The average score to this statement was 3.81 (*SD*=1.49).

The next task to be performed was the decision task: the selection of a one-bedroom apartment. Prior to activating the DSS and the related decision matrix supporting this decision task, participants were asked to read a document called ‘decision task description’. This document included an introduction to the decision task, explaining its suggested context and objective. The dimensions of the decision matrix were also explained in this document. The decision task description also rehearsed that no time constraints were imposed.

After a participant submitted its choice by means of the MAKE-a-CHOICE function the DSS application was closed. The final task of the experiment concerned answering a post experiment survey (debriefing questions) which was also administered through the digital test environment. The relevant debriefing questions are presented in appendix 4.

When all tasks included in the experiment were fulfilled a participant was supposed to inform the instructor that he or she was ready. After the instructor made sure that a participant indeed finished all tasks included in the experiment, all documents were collected and the participant was asked to exit the workflow application. Since all documents were numbered, the instructor was able to verify whether all documents were returned. Closing the workflow application implied that the participant’s subject code got the status ‘finished’ in the database and workflow environment. From this moment on this subject code could not be used anymore. Assigning the status ‘finished’ made it impossible to log on to the DSS and workflow

[25] The higher the grade, the better the result. Grades range form 1 (very bad) to 10 (excellent).

environment again using the same subject code. This procedure guaranteed that no one outside the laboratory room had access to the DSS applications and workflow environment.

A participant that finished the experiment was instructed to shut down its personal computer and asked to wait until all participants were ready. Prior to the experiment participants were advised to take reading material to the sessions of the experiments in case they had to kill the time. Participants were allowed to read this material. It was not allowed to communicate with other participants.

After all participants finished the experiment they were offered the opportunity to react on the experiment or, if wanted, to ask questions. As long as the questions were not related to the essentials of the experiment the questions were answered. All sessions were finished within the planned three hours time frame.

7.7 Verification process traces and dependent variables

Regarding the computerized process traces additional checks were performed to verify the reliability of the data. Two issues deserved special attention: 1) *completeness* of the process traces, and 2) *accuracy* of the dependent variables. The first issue aimed at answering the question: "Are all actions performed by a decision maker actually recorded and stored in the process tracing database?" To verify the completeness of the process traces the data of three dummy subjects were added to the DSS environment. Each of these subjects was used to perform a trial decision process. To be sure that the DSS functions were recorded properly all available DSS functions were used at least once across the trial processes. For each dummy subject the treatments assigned and all actions performed were manually registered. A standard query tool[26] was used to access the CPT database and to report the data recorded per dummy subject. An example of the output generated by the query tool is included in appendix 5. The output of the query tool was compared with the manually registered data. It appeared that all relevant data was correctly recorded in the CPT database.

The second issue dealt with the automated procedures for calculating the dependent variables. These procedures were implemented in software that used the process traces as input and produced the key elements for calculating the dependent variables as output. To verify whether these procedures worked in accordance with the rules explained in appendix 3, the dependent variables were manually calculated for a sample of subjects drawn from the total participant population. Fourteen subjects were randomly selected for verification taking into account that from each treatment group at least two subjects were to be selected. The process traces of the fourteen verification subjects were used by two university graduate students to manually calculate the dependent variables. These students used the calculation rules to map the influence of each individual action performed by a participant on the dependent variables. In order to be able to determine the influence of a user action on the dependent variables it was necessary to manually reproduce the decision matrix for each action performed by a subject. The students performing the verification did not know the actual values of the dependent variables as generated by the software in advance.

The verification process developed incrementally. The verification data of each individual verification subject was submitted to the research team. Before a next subject was verified by a student the dataset of the subject already submitted had to be approved by the research team. Together with the students the research team compared the output of the software

[26] Oracle Discoverer Plus 4.1

routines with the manually produced output. If the automated output deviated from the manual output the cause of the deviation was determined by a researcher. In case a deviation was due to an error in one of the software routines, the software was modified nearly immediately and the dependent variables were calculated again using the adjusted routines. The manual output associated to the verification subjects already ‘approved’ were reviewed in context of the new automated output. Modifications in the software were hardly needed, most deviations that occurred were due to the fact that the students overlooked minor issues in the datasets. The students got feedback concerning the cause of the deviation and could use this feedback in the verification of the next participants. The advantage of this incremental approach was that both the learning effects and the modifications of the software were taken along in the subsequent verifications. The incremental approach also prevented from doing needless work.

Based upon the data of the fourteen verification subjects the automated calculation routines were found to be accurate.

7.8 Summary

This chapter explained how the first experiment was conducted. The preferential choice problem employed in this first experiment concerned the selection of a one-bedroom apartment. The choice set included ten alternatives each described by eight attributes. The DSS treatment was operationalized through three different levels of compensatory decision support: none, low, and high. The alternative similarity treatment was realized through the implementation of three criteria. Under the ‘similar’ condition 1) the variances in attribute values across alternatives were lower than under the ‘not similar’ condition, 2) the maximum difference between alternatives on an attribute was 2-points, compared to 8-points under the ‘not similar’ condition, and 3) all alternatives had an equal attractiveness score. Decision behavior was characterized through the following four operators: amount of information search, variability of information search, search index, and processing index. The instrument used to differentiate between the cognitive styles field dependence/field independence was the Hidden Figures Test. The procedures executed to verify the completeness of the computerized process traces, as well as the accuracy of the software routines that calculated the operators for characterizing decision behavior, revealed that both completeness and accuracy were appropriate.

CHAPTER 8

RESULTS EXPERIMENT 1

8.0 Introduction

This chapter will present summaries of the data collected and the results of the statistical treatments used. The characteristics of the participant population and the results of the manipulation checks will be presented first. Subsequently the findings of the multivariate analyses, performed to test our hypotheses, will be presented. Effect sizes and observed power of significant results will be reported in the final section of this chapter.

8.1 Characteristics of the participants

Initially 189 participants attended the sessions of the experiment. Because three subjects did not perform any actions during the execution of the final decision task[27], and one participant quit the session after execution of the hidden figures test, four observations were excluded from the analyses. In total 185 participants (male: 153/female: 32) successfully fulfilled the experimental tasks. The average age of the participants was 22.6 years (*SD*=1.9). More than 62% of the participants reported that they, in some way or another, had been involved in the process of selecting a single bedroom apartment, whereas 51% reported to actually live in rooms at the time the experiment was executed. The results of the post-survey questions show that participants enjoyed the execution of the decision task. The average response to the question: ”I consider the selection of an apartment from the decision set given” (1=very boring, 5= very enjoying) was ‘enjoying’ (*M*=3.74; *SD*= .56).

8.2 Randomization

If we consider the dispersion of cognitive style over the different treatment groups as a measure for the functioning of the randomization process we can conclude that the random assignment procedure functioned properly. Cognitive style was evenly dispersed over the groups.

8.3 Manipulation checks

The manipulation of alternative similarity was examined by performing a *t*-test for equality of means on participant’s responses to the post-survey question: “To which extent do you consider the apartments in the decision set similar?” (1=not similar at all, 5=very similar). The groups differed significantly on the alternative similarity responses in the correct direction, $t(183)=-6.41$, $p<.001$ (Similar: $M=3.31$, $SD=.927$; Not Similar: $M=2.51$, $SD=.758$). We conclude that the manipulation was successful.

[27] An analysis of the CPT data revealed that three subjects immediately chose for “Make a Choice” and hereby closed the decision application. Actually these subjects did not see any value of the decision matrix and were as such not able to make a ‘sensible’ decision.

8.4 Dependent variables

Table 8.1 provides the means and standard deviations for the four dependent variables: Amount of Information Search, Variability of Information Search, Search Index and Processing Index.

TABLE 8.1: Means and Standard Deviations on the Dependent Variables

Treatments		*Amount of Information Search*		*Variability of Information Search*		*Search Index*		*Processing Index*		
		M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	**n**
DSS (level of compensatory support)	*Similarity*									
NONE	No similarity	.92	.15	.06	.11	-.68	.42	-.51	.61	32
	Similarity	.88	.20	.09	.13	-.86	.16	-.58	.52	31
MODERATE	No similarity	.89	.19	.08	.15	-.66	.31	.48	.60	30
	Similarity	.96	.10	.04	.09	-.70	.25	.42	.56	30
HIGH	No similarity	.98	.10	.02	.08	-.58	.46	.68	.55	32
	Similarity	.98	.11	.01	.07	-.49	.51	.74	.40	30

(*Dependent Variables* spans all measure columns.)

The correlations among all dependent variables are represented in table 8.3.

TABLE 8.3: Correlation Matrix Dependent Variables

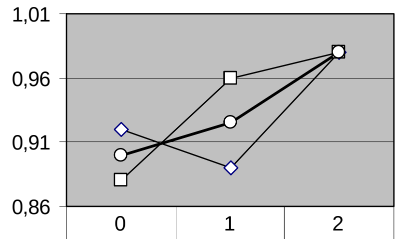
	Amount of Information Search	*Variability of Information Search*	*Search Index*	*Processing Index*
Amount of Information Search	--	$-.884^{***}$	.065	$.230^{**}$
Variability of Information Search		--	-.069	$-.212^{**}$
Search Index			--	$.212^{**}$
Processing Index				--

(**Correlation among variables** spans all columns.)

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

Figures 8.1a-h show a detailed overview of the main and interaction effects of the level of decision support (DSS) and alternative similarity (AS).

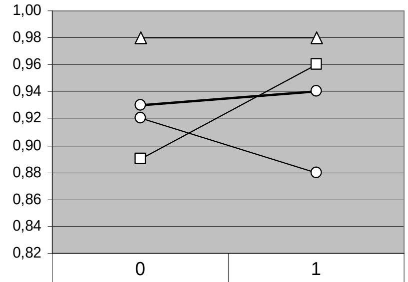
Figure 8.1a: Marginal and Cell Means Amount of Information Search (DSS)



	0	1	2
No Similarity	0,92	0,89	0,98
Similarity	0,88	0,96	0,98
DSS Main effect	0,90	0,93	0,98

DSS

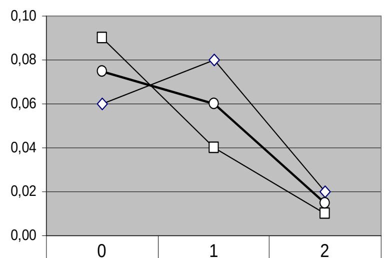
Figure 8.1b: Marginal and Cell Means Amount of Information Search (AS)



	0	1
DSS=0	0,92	0,88
DSS=1	0,89	0,96
DSS=2	0,98	0,98
AS Main Effect	0,93	0,94

Similarity (0=no/1=yes)

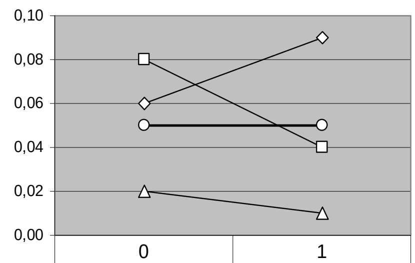
Figure 8.1c: Marginal and Cell Means Variability of Information Search (DSS)



	0	1	2
No similarity	0,06	0,08	0,02
Similarity	0,09	0,04	0,01
DSS Main Effect	0,08	0,06	0,02

DSS

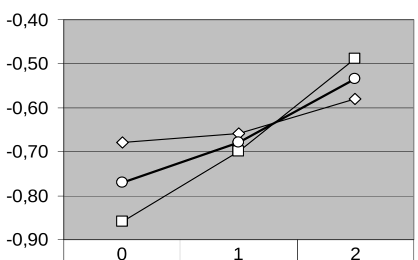
Figure 8.1d: Marginal and Cell Means Variability of Information Search (AS)



	0	1
DSS=0	0,06	0,09
DSS=1	0,08	0,04
DSS=2	0,02	0,01
AS Main Effect	0,05	0,05

Similarity (0=n0/1=yes)

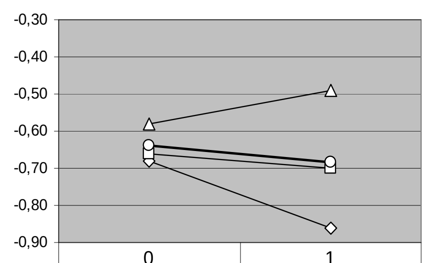
Figure 8.1e: Marginal and Cell Means Search Index (DSS)



	0	1	2
No Similarity	-0,68	-0,66	-0,58
Similarity	-0,86	-0,70	-0,49
DSS Main Effect	-0,77	-0,68	-0,54

DSS

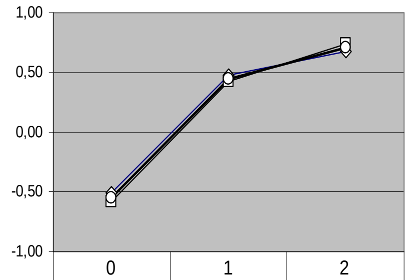
Figure 8.1f: Marginal and Cell Means Search Index (AS)



	0	1
DSS=0	-0,68	-0,86
DSS=1	-0,66	-0,70
DSS=2	-0,58	-0,49
AS Main Effect	-0,64	-0,68

Similarity (0=no/1=yes)

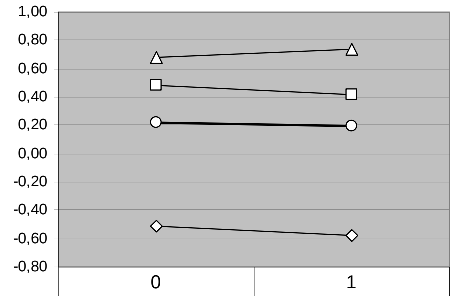
Figure 8.1g: Marginal and Cell Means Processing Index (DSS)



	0	1	2
No Similarity	-0,51	0,48	0,68
Similarity	-0,58	0,42	0,74
DSS Main Effect	-0,55	0,45	0,71

DSS

Figure 8.1h: Marginal and Cell Means Processing Index (AS)



	0	1
DSS=0	-0,51	-0,58
DSS=1	0,48	0,42
DSS=2	0,68	0,74
Main Effect	0,22	0,19

Similarity (0=no/1=yes)

8.5 Test of the hypotheses

A two-way multivariate analysis of variance (MANOVA) was conducted to determine the effect of the DSS and alternative similarity treatments. Cognitive style was treated as a covariate in this analysis and was used to test our fourth hypothesis stating that high analytical cognitive style positively influences the use of compensatory decision strategies. The data did not support this hypothesis, Wilks' Λ =.986, being not significant $F(4,175)$=.618, p=.65. Because the results of this analysis show that cognitive style did not influence the dependent variables, the hypotheses are tested under exclusion of cognitive style. Table 8.4 displays the results without cognitive style. An alpha level of .05 is used for all statistical tests.

TABLE 8.4: Multivariate and Univariate Analyses of Variance of Main and Interaction Effects (without covariate*)

	Multivariate				Univariate							
					Amount of Information Search		Variability of Information Search		Search Index		Processing Index	
	Wilks's Λ	***Df***	**F**	***P***	**F**	***P***	**F**	***P***	**F**	***P***	**F**	***P***
Alternative Similarity (AS)	.99	4	.25	.91	.16	.69	.24	.63	.69	.41	.06	.81
DSS	.47	8	20.11	.00	4.17	.02	4.44	.01	6.35	.00	92.03	.00
DSS*AS	.95	8	1.05	.40	2.01	.14	1.53	.22	1.99	.14	.28	.76

*) The analyses with covariate produced the same results.

Box's M test showed that the variances and covariances among the variables are not the same (Box's M=245.218, p<.001). This implies that the analyses should be interpreted with caution.

Hypothesis 1 stated that the level of compensatory decision support available positively influences the use of compensatory decision strategies. The data supported this hypothesis. The univariate analyses in table 8.4 show that the influence of the level of compensatory decision support on the dependent variables is significant for each of the dependent variables. The data presented in figures 8.1a, c, e, and g show that the group means develop in the right direction.

Hypothesis 2 stated that the level of alternative similarity positively influences the use of compensatory decision strategies. The data did not support this hypothesis, Wilks' Λ = .994, being not significant, F(4,176)=.246. Two specific decision aids are exemplary for the implementation of the noncompensatory EBA strategy: DROP COLUMN and CONDITIONAL DROP. Both commands were available for all groups. The implementation of a one-way MANOVA on the overall data showed no difference in use of noncompensatory commands (EBA strategy) between the different similarity treatments (Wilks's Λ = .99, F(2,184)= .90, p=.41), indicating that alternative similarity did not influence the use of 'non-compensatory' decision aids either.

Hypothesis 3 predicted an interaction effect between the level of compensatory support and alternative similarity that will positively influence the use of compensatory decision strategies. We did not find support for this hypothesis.

8.6 Effects sizes and observed power DSS effects

Table 8.5 presents the effects sizes and observed power for the four dependent variables under the DSS condition.

TABLE 8.5: Effects Size and Observed Power under DSS Condition

Source	***Dependent Variable***	***Partial Eta Squared*** η^2	***Observed Power*** *)
Level of Compensatory Support	Amount of Information Search	.05	.73
	Variability of Information Search	.05	.76
	Search Index	.07	.90
	Processing Index	.51	1.00

*) Computed using α=.05

Table 8.5 shows that the sample size was sufficient to show the effect sizes reported.

8.7 Summary

The results presented in this chapter show that the manipulations were successful. The multivariate analyses of variance (MANOVA) conducted revealed that only the hypothesis concerning the assumed positive effect of *automated decision support* on the selection of *compensatory decision strategies* could be confirmed. The data did not support the hypotheses concerning the effects of *alternative similarity*, the interaction of *DSS* x *alternative similarity*, and *cognitive style* on *decision strategy* selection.

CHAPTER 9

DISCUSSION EXPERIMENT 1

9.0 Introduction

In chapter one, the research question for this dissertation was developed: "*What is the influence of automated decision support and cognitive style on decision strategy selection, in particular under varying levels of alternative similarity?*" This chapter will evaluate and interpret the results of Experiment I in the context of this research question and will include three parts. In the first part the results presented in chapter eight will be discussed with respect to our hypotheses. The second part will discuss the implications of the computerized process tracing (CPT) model developed in chapter four for DSS research, and will more specifically focus on the value of the processing index in capturing information processing behavior. Finally, in the third part of this chapter, the limitations of our findings will be discussed as well as directions for future research will be presented.

9.1 Research findings: main effects

The results of the experiment indicate that the level of compensatory decision support influenced the selection of decision strategies, whereas alternative similarity and cognitive style did not.

9.1.1 DSS effect

The support found for the influence of automated decision aids on decision strategy selection (Hypothesis 1) is in line with prior research findings. Chu and Spires (2000) and Wang and Chu (2004), for example, used three of the four dependent variables that were also employed in this research (amount of information search, variability of information search, and search index) and found a positive relationship between the level of compensatory decision support and the selection of compensatory decision strategies. Regarding Hypothesis 1, the results are also consistent with the DSS research findings of Todd and Benbasat (1994a, 1994b, 1999, 2000), who found evidence that the selection of compensatory decision strategies can be induced by effort-reducing compensatory decision aids.

9.1.2 Alternative similarity and interaction effects

Regarding the effects of alternative similarity on decision behavior the results indicate that alternative similarity (Hypothesis 2) and the interaction of DSS x alternative similarity (Hypothesis 3) both do not influence decision strategy selection. Figures 8.1a-f show a detailed overview of the main and interaction effects of the level of *decision support* (DSS) and *alternative similarity* (AS). Concerning the main effect for alternative similarity the graphs presented in figures 8.1b, d, f and h show a near horizontal line for all four dependent variables. According to our data, there is hardly any effect of the similarity treatment on each of the dependent variables employed in this experiment, indicating that alternative similarity does not influence decision behavior.

A more specific investigation of the graphs shown in figures 8.1a-h, representing the marginal and cell means for the DSS main and DSS*Alternative Similarity effects, delivers at least two notable issues:

1) the lines for the 'similar' and 'not similar' conditions nearly are each other's mirror image, and
2) under the 'high compensatory support' condition (DSS=2), the cell means seem to converge on a single point for all dependent variables.

To support a possible explanation for the lack of an 'alternative similarity' effect both issues will be elaborated on below.

9.1.2.1 Mirror image

An investigation of the graphs presented in figures 8.1a-h reveals that the lines for the 'similar' and 'not similar' conditions nearly are each other's mirror image. Especially when graphs 8.1a-f are investigated in detail for the 'no compensatory support' (DSS=0) and the 'moderate compensatory support' (DSS=1) condition, the mirror image of the lines conveys the impression that the lack of an alternative similarity main effect might be due to the fact that both simple effects canceled each other out, and as such delivered an instance of a "pure interaction" (Keppel & Wickens, 2004, p.206). To determine whether this was the case, a MANOVA was performed on the dataset under exclusion of the 'high compensatory support' (DSS=2). The MANOVA executed did not show significant results for both alternative similarity (Wilks's Λ = .962, $F(4,116)=1.134$, $p=.344$) and the interaction of *DSS x alternative similarity* (Wilks's Λ = .960, $F(4,116)= 1.196$, $p=.316$), indicating that the mirror images are more a matter of chance rather than due to the alternative similarity treatment.

9.1.2.2 Convergence

Figures 8.1a-g show that the cell means for the 'high compensatory support' (DSS=2) condition converge on a single point for all dependent variables, indicating that the influence of alternative similarity is 'dominated' by the high level of decision support. In order to explain this finding we refer to a DSS study by Todd & Benbasat (1999) who also performed a multi-alternative preferential choice DSS experiment using a 4X2 factorial research design. The two factors were: (1) level of additive compensatory support provided, and (2) level of incentives. Todd and Benbasat argued that "performance-based incentives have the effect of motivating individuals to work harder to achieve a high level of performance by increasing the decision-maker's sense of involvement with the task" (p. 360) and hypothesized that: higher levels of incentives will lead to higher use of the AC strategy when partial support for AC is provided, but will have no influence when either complete or no support for AC is provided. Todd and Benbasat did not find support for this hypothesis. Their findings suggest that DSS effects dominate effects due to incentives. In support of their findings Todd & Benbasat argue: "When complete support for AC strategy is not present, decision makers do not have the capability to carry out the strategy regardless of the degree of motivation that may be provided by the incentives. When support for AC is high the strategy becomes so simple to carry out that it will be used regardless of the level of incentives." (p. 370). Our findings concerning alternative similarity are comparable to the research findings of Todd and Benbasat regarding incentives and actually confirm their argumentation. Incentives are considered to increase a decision maker's involvement but do not alter the complexity of the decision task itself. Alternative similarity however, adds complexity to the decision task and will as such only strengthen a decision maker's 'incapacity' to perform a compensatory strategy under conditions of 'no compensatory decision support'. The convergence on a single point of the cell means under the 'high compensatory support' treatment can be interpreted as a confirmation of the so called 'DSS-dominance-effect' addressed by Todd and Benbasat. The implementation of a compensatory decision strategy under the 'high compensatory support' condition was so simple that it will be used regardless of the level of alternative similarity.

According to our data decision strategy selection is not influenced by alternative similarity under conditions of automated decision support. Just like Todd and Benbasat (1999, p. 371) did regarding incentives, we explain the lack of alternative similarity effects in the following way: Without a DSS, the effort needed to implement better strategies dominates the effect of alternative similarity, with a DSS, the effort reduction made possible by a DSS has already influenced the decision maker to use normative strategies, in which case alternative similarity does not play a key role.

9.1.3 Cognitive style

To the best of our knowledge we are not aware of prior DSS research that investigated the influence of a decision maker's analytic capabilities (field dependence/field independence) on decision strategy selection in a multi-attribute preferential choice task setting. This is why not only DSS research literature was reviewed in search for possible explanations of our findings, but instead our scope was broadened to the more general area of MIS research literature. A possible explanation for the lack of a cognitive style effect can be found in MIS research on the so called task-technology fit (TTF). Task-technology fit can be defined as "the correspondence between task requirements, individual abilities, and the functionality of the technology" (Goodhue & Thompson, 1995, p. 218). Goodhue and Thompson (1995) relate the relevance of cognitive style to technology issues and propose a model of the relationship of task-technology fit and individual performance.

According to this model, task characteristics, technology characteristics (e.g. user interface) and individual characteristics (e.g. cognitive style) are antecedents to task-technology fit. Task-technology fit is important because, amongst other things, it influences how technology will be used (Crossland *et al.*, 2000). Goodhue and Thompson (1995) assert that task-technology fit directly affects the performance of an individual using the technology. Task-technology fit and the "effort accuracy framework" (Christensen-Szalanski, 1980; Payne *et al.*, 1993) are both "based on the same basic propositions that a) an individual's performance is affected by how well technology options "fit" his or her task requirements, b) fit operates through its impact on task processes, and c) individuals can evaluate fit and choose technologies on that basis" (Goodhue, 1995, p.1830).

Whereas the TTF framework aims at explaining the use of information technology through a correspondence between task requirements, individual abilities, and the functionality of the technology, the effort-accuracy framework aims at explaining decision behavior through a process of effort and accuracy considerations. Actually, the effort accuracy framework can be used to explain *how* the functionality will be used when technology *fits* the task to be performed.

Characteristics of the decision maker, such as analytic capability, are recognized by the TTF framework to influence the fit between task and technology. For example, extraordinary analytical skills can help bridge a considerable gap between technology and task, whereas limited analytical skills can be an impediment to fulfillment of the same task with the same technology.

A possible explanation for the finding that decision strategy selection was not influenced by cognitive style might be in the fact that our DSS fits the decision task to be performed in such a way that little room was left for cognitive style to influence this specific task-technology relationship. Assuming such a fit, the influence of cognitive style can become completely 'overruled' by the self-explanatory character of the functions provided in the user interface given the task to be performed. Or put it else, it was as obvious for both the high and low analytics *how* to use the DSS to solve the decision task given. This can be a cautious indicator for the fact that our user interface is insensitive for cognitive style.

Cautious, since prior research on the influence of cognitive style on decision behavior is equivocal at least. For example, Benbasat and Dexter (1985) performed a DSS experiment in which they investigated the influence of graphical presentation formats on decision performance and found a significant relationship between field dependence and task performance accuracy, whereas Liberatore *et al.* (1988) report no significant differences in individual performance related to field dependence.

9.2 DSS and CPT model

The development of an experimental DSS that supports micro level analyses of decision behavior was addressed as one of the contributions of this research project. In order to be able to judge the value and validity of the DSS and CPT environment developed in this study in general, and the processing index in particular, the following two steps will be executed:

1) Check for consistency between our findings and prior DSS research findings.
2) Evaluate the values of the processing index in context of the values of the other dependent variables.

9.2.1 Check for consistency

When different DSS experiments, that are established in the same fundamental theories and use comparable measuring instruments, research designs, and decision tasks, deliver consistent research findings, this can be considered a measure for the validity of the apparatus and methods employed in these experiments (Berthon *et al.*, 2002; Hubbard & Armstrong, 1994; Jarvenpaa *et al.*, 1985; Sharda *et al.*, 1988). The so called 'Research Space' framework, developed by Berthon *et al.* (2002), will be used to determine the level of equivalence between this study and the DSS studies considered fundamental for this research. Berthon *et al.* recognize four dimensions that can be used to systemize the conceptualization of replications: *problem*, *theory*, *method* and *context*. "The problem or phenomenon specifies and delimits the focus of the research-Simply it specifies *what* is being investigated. The theory answers questions as to *why* certain phenomena might occur; the method addresses the problem of *how* one might go about generating knowledge about the phenomena; and the context concerns the *who*, *what*, and *where* – the phenomenological context and content of the problem" (p.421). Dependent on the number

TABLE 9.1: Overview of elements replicated (compared to fundamental studies)

Study	*Problem*	*Theory*	*Method*				*Context*	
			Independent Variables	*Dependent Variables*	*Process Tracing Method*	*Statistical Method(s)*	*Participants*	*Decision Task*
Chu and Spires (2000)*)	Investigate the influence of automated decision aids on decision strategy selection	Effort-Accuracy framework	1. Level of compensatory decision support 2. Task effect: complexity	1. Amount of Information Search 2. Variability of Information Search 3. Search Index	CPT	(M)ANOVA	Students	Multi-alternative, multi-attribute, preferential choice problem
Todd and Benbasat (1999)	Investigate the influence of automated decision aids on decision strategy selection	Effort-Accuracy framework	1. Level of compensatory decision support 2. Incentives	1. Independent evaluations 2. Elimination statements 3. Compensatory statements 4. Total statements	VPA	(M)ANOVA	Students	Multi-alternative, multi-attribute, preferential choice problem
This study	Investigate the influence of automated decision aids on decision strategy selection	Effort-Accuracy framework	1. Level of compensatory decision support 2. Task effect: context	1. Amount of Information Search 2. Variability of Information Search 3. Search Index 4. Processing Index	CPT	(M)ANOVA	Students	Multi-alternative, multi-attribute, preferential choice problem

*) The 'decision outcome' part of this study is considered not relevant in this context.

of dimensions modified in a focal study, compared to the target study[28], three different research strategies are distinguished by Berthon *et al.*: *pure replication* (no modifications), *replication with extensions* (one or two dimensions modified), and *pure generation* (three or more dimensions modified). Table 9.1 shows how this study relates to the DSS studies considered fundamental for this research, and reveals that, compared to the target studies performed by Chu and Spires, and Todd and Benbasat, this study can be considered a replication study with one and two extensions respectively. The dimensions problem, theory, and context are nearly identical for all three studies presented. The differences primarily focus on the details of the method dimension. However, in this context it is important to recognize that two of the four contributions distinguished for this research project specifically aim at this dimension: development of an enhanced DSS environment, and development of an extended set of operators for measuring decision behavior. Given the level of congruency among the three studies presented in table 9.1, we consider it legitimate to use both target studies as references for validating the findings of this study.

A point of interest to be addressed in this context is the difference in methods employed for data acquisition: VPA versus CPT. Whereas Todd & Benbasat primarily used VPA, this study employs a CPT method. To verify whether the data acquired by means of the CPT environment used in this study is in line with the data acquired through VPA in the target study by Todd and Benbasat, detailed data on command usage acquired from this ‘VPA-study’ (Todd & Benbasat, 1999) is compared with data on command usage acquired through the CPT environment used in this research. This ‘comparison-analysis’ will only focus on the commands DROP ROW/COLUMN and CONDITIONAL DROP for two reasons: 1) the functioning of these commands is exactly the same in both studies, and 2) both commands are used under all different DSS-treatment levels. Table 9.2 shows the data on command usage for both experiments. The numbers represent the average times a command was used by a decision maker during the execution of the decision task.

TABLE 9.2: Comparison Average Command Usage VPA-study (Todd & Benbasat (1999)) and CPT Environment Employed in this Study

	Average times a command was used by a decision maker			
Level of compensatory support	*DROP*		*CONDITIONAL DROP*	
	VPA	CPT	VPA	CPT
None	4.9	3.41	1.91	1.95
Low	5.8	Na[29]	.62	Na
Moderate	3.7	2.73	.77	1.65
High	2.4	2.03	.52	.97

An investigation of the data in table 9.2 reveals that the same ‘high-to-low’ pattern of average command usage can be distinguished across all DSS treatments for both data acquisition methods. Added to the fact that the CPT data does not show unexpected numbers, we interpret this finding as an indication for the appropriateness of this study’s CPT environment in capturing

[28] The original study is called “target” study, whereas the new study is the “focal” study.
[29] No ‘low level’ of compensatory support was provided in our study.

decision behavior. However, the most important support for the validity and reliability of the DSS and CPT environment developed in this study is the fact that the findings concerning the influence of automated decision support on decision behavior, reported in this study, are not only consistent with the findings of the target studies by Todd and Benbasat (1999), and Chu and Spires (2000), but also with the other DSS studies of Todd and Benbasat (1991, 1994a, 1994b, 2000) as well as with the DSS study performed by Wang and Chu (2004).

9.2.2 Processing index

To value the validity of the processing index developed as part of this research project, this index will be evaluated in context of the three other dependent variables employed in this study. A first indication for the validity of the processing index as a measure for information processing behavior is the fact that the development of the processing index values across the different treatment combinations is in line, and consistent with the development of the other variables. To support this statement we would like to recall the data presented in figures 8.1a-f, representing the means on the dependent variables for the two treatments. According to this data the processing index develops from -.55 (‘no compensatory support’ condition) to .71 (‘high compensatory support’ condition). Apart from the fact that this development is in line with the direction assumed under Hypothesis 1, a shift from noncompensatory to more compensatory information processing induced by increased levels of automated compensatory decision support, it is also consistent with the development of the other dependent variables as showed in table 9.4.

TABLE 9.4: Development of Dependent Variables for DSS Treatment

Dependent Variable	**From**	**To**
Amount of Information Search	*M*=.90 More *noncompensatory* oriented information processing	*M*=.98 More *compensatory* oriented information processing
Variability of Information Search	*M*=.08 More *noncompensatory* oriented information processing	*M*=.02 More *compensatory* oriented information processing
Search Index	*M*=-.77 More *noncompensatory* oriented information processing	*M*=-.54 Less *noncompensatory* oriented information processing
Processing Index	*M*=-.55 More *noncompensatory* oriented information processing	*M*=.71 More *compensatory* oriented information processing

A quantitative foundation for the relationship among the dependent variables can be found in table 8.3, representing the correlation matrix for the dependent variables. Table 8.3 also reveals a second indication for the validity of the processing index: a significant correlation between the search index and the processing index. The assumption of an association between these two variables is important, since actually the processing index is closely related to the search index. Remember from paragraph 4.2.4 that the search index must primarily be interpreted in a context of information *acquisition* behavior, whereas the processing index must be interpreted in a context of information *processing* behavior. From a logical point of view, information acquisition behavior must be reflected in information processing behavior, in the end, any piece of information processed must be acquired before it can be processed.

From a statistical point of view the significant correlation between the two variables can be regarded as support for this logical view. The existence of an association between how information is 'manually' acquired (search index) and how it is 'automatically' processed (processing index) can be considered as support for the validity of the processing index developed in this research.

9.2.3 CPT: an enhanced model

Given the findings concerning the DSS and CPT environment developed in support of this research, we consider it legitimate to propose that, under conditions of automated decision support, it is possible to extend CPT models with methods and measures that integrate information *processing* behavior. According to our data, CPT tools are not only valuable in capturing data on information *acquisition*, but can also be employed for the purpose of gathering data on *information* processing behavior. This enhancement can have consequences for both DSS research and DSS development. Our extended CPT model makes it possible to broaden the application scope of CPT methods. The enhanced CPT model developed in this study can, under certain conditions, be considered a full substitute for VPA, hereby both exploiting the advantages of VPA as well as tackling its limitations as described in paragraph 4.1.2.

Regarding the development of decision support systems the enhanced CPT model developed in support of this study can contribute to the micro-level analyses. Micro-level analyses that focus on both the impact of individual DSS features on decision behavior as well as on decision effectiveness.

9.3 Limitations

This paragraph will address the most important limitations recognized for this study so far. The limitations elaborated on will be used as input for the development of suggestions for further research.

9.3.1 Mental information processing not fully captured

The design of the DSS employed in this experiment was guided by the functional requirements developed in chapter 4. Similar to Chu and Spires this research fully relies on CPT tools for capturing data on decision behavior. Actually, the DSS and CPT method developed by Chu and Spires (2000) are important drivers for the development of the DSS and CPT environment employed in the experiment reported so far. Despite the fact that an enhanced process tracing model is developed, aimed at integrating data on both information *acquisition* and information *processing* behavior, there is still an area of actual decision behavior that is not fully covered by the DSS environment developed so far.

Consider the 'none' and 'moderate' compensatory support conditions of our experiment. As their names already explain, the DSS functions included in these two treatments provided '*none*' and '*moderate*' support for the execution of compensatory decision strategies respectively. However, a decision maker acting under one of these two conditions can chose to acquire all relevant information and process it mentally. Although, according to the fundamentals of the "effort-accuracy" framework (Payne *et al.*, 1993) this behavior will not be very common, especially when the number of alternatives increases, the DSS environment developed so far will not be able to cover this kind of behavior. Theoretically a decision maker can open all the cells of the decision matrix and mentally calculate a WADD score for each of the alternatives available. This kind of information processing behavior, executed 'between the ears' of a decision maker, will not be captured by our CPT model. An indication for the level of 'mental processing' might be the average time between the execution of two DSS commands. In the end, this time will most likely increase when more information is processed mentally, assuming that a decision maker is doing something meaningful in context of the decision task to be executed. Svenson (1979) also proposes that "..a longer period of attention to an aspect is assumed to be paralleled by a more complex cognitive process than is a shorter fixation" (p.96).

To support an 'average execution time' analysis the average time elapsed between the execution of two DSS commands for each participant was calculated. Table 9.5 presents the group averages for each DSS condition.

TABLE 9.5: Group Averages Average Elapse Time between Execution of DSS Commands

DSS treatment	*M*	*SD*
No Compensatory Support	95,04	108,68
Moderate Compensatory Support	78,15	122,45
High Compensatory Support	51,75	80,15

Although the averages presented in table 9.5 do not differ significantly ($F(2,182)=2.691$, $p=.071$), they decrease as the level of compensatory decision support increases, indicating that less information is processed mentally when additional automated compensatory decision support is provided. Only under the assumption that information is processed in exactly the same way it was acquired, the search index can be used to infer on information processing behavior (Svenson, 1979). When this fit is existent, the CPT tool developed in support of the experiment presented will properly capture information processing behavior. However, when information is mentally processed in a way that deviates from the way it was acquired, this kind of processing will not be captured by this CPT tool. This limitation can be solved by extending the level of detail in automated decision support in a way that is appropriate to support noncompensatory as well as compensatory decision strategies under all experimental DSS conditions. The appropriateness of this solution can be investigated in a DSS experiment offering more detailed decision support. (The details of such a solution will be elaborated on in chapter 11).

9.3.2 Number of alternatives

A second limitation is in the number of alternatives (10) employed in this study. Although this number is in line with prior research on behavioral decision making (Chu & Spires, 2000; Payne *et al.*, 1993; Todd & Benbasat, 1991, 1992, 1994b, 1999, 2000), increasing the number of alternatives will potentially address two issues: increased external validity of research findings, and increased value added of the DSS employed due to increased complexity of the decision task. Both issues will be explained below.

The popularity of interactive media, such as the World Wide Web, created extended possibilities regarding the search for and the number of alternatives to be included in evaluation processes aimed at solving preferential choice problems (Häubl & Trifts, 2000). The reach of web enabled search engines makes it possible to include an almost unlimited number of data sources in the search process, resulting in large numbers of alternatives to be considered in the decision process. For example, a search for MP3-players on a Dutch consumer product review portal, called *www.kieskeurig.nl* (November 16th, 2005), produced a choice menu including exactly 100 brands, whereas the selection of the 'Philips' brand alone delivered an overview of more than 70 unique MP3-players to chose from. Prior research (Wang & Chu, 2004) even proposed: "It is believed that a VLCP *(Very Large Choice Problem)* is not only possible, but will also frequently occur in a modern business environment [italics added]" (p. 104). As such, increasing the number of alternatives will contribute to an increased level of external validity.

The second issue concerning increasing the number of alternatives is closely related to the limitation addressed in the previous sub-paragraph (9.3.1). Increasing the number of alternatives will increase the complexity of the decision task (Payne *et al.*, 1993). The more complex the decision task, the more potential gain in effort reduction can be expected from the use of automated decision aids. One can imagine that under conditions of large numbers of alternatives an aided decision maker will be induced to extend the "limits of its bounded rationality" by means of automated information processing support. Todd and Benbasat[30] (1992), for example, found that aided decision makers compared to unaided decision makers "processed less information themselves and relied on the decision aids to reduce their information processing burden. Such behavior is consistent with effort minimization." (p. 389). By increasing the number of alternatives a decision maker will more or less be "forced" to use the DSS due to limited mental information processing capacity. The "risk" of not capturing information processing behavior can be reduced by increasing the number of alternatives. In the end, the probability that information on a large number of alternatives is processed mentally will most probably be much less than the probability that information on a limited number of alternatives is processed mentally. When a decision maker is induced to use automated decision aids for information processing purposes, the resulting decision process traces stored in the CPT environment will be more complete when it comes to capturing information processing behavior.

9.3.3 Number of measures for capturing information processing behavior

Apart from the search index, which can be considered an 'intermediate' between dedicated information *acquisition* and dedicated information *processing* measures, this study

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[30] Although decision strategy selection was not influenced by the interaction of the DSSxNumber of Alternatives in this 1992 study, this study showed that DSS use was influenced by the number of alternatives (see Todd & Benbasat, 1992, table 7, p.387).

developed only one measure for capturing information processing behavior: the processing index. In particular the DSS research projects of Todd and Benbasat (e.g. (1994a, 1994b, 1999, 2000)) employed a range of measures to capture information processing behavior. For example, in their 1999 paper Todd and Benbasat mention *proportion of independent evaluations*, *the number of elimination statements*, and *proportion of compensatory statements* expressed by the decision makers during the execution of their decision tasks as dependent variables (see chapter 3 for an overview and explanation of the dependent variables employed by Todd & Benbasat). Our research findings so far indicate that it is possible to integrate information processing measures in CPT tools. Based on this finding it does make sense to develop a CPT model that integrates a broader range of measures that aim at capturing information processing behavior.

9.3.4 Additional dimensions of cognitive style

Although the cognitive style construct is acknowledged to be multidimensional (Zmud, 1979), only one dimension of cognitive style is employed in this research project so far. Since there are many individual differences related to decision making behavior (Huber, 1983) integrating more dimensions of cognitive style in DSS research will contribute to insights on the influence of cognitive style on decision behavior.

9.4 Directions for further research

If we consider the conclusions and limitations presented in this chapter as a point of departure for the enhancement of DSS models, CPT methods and DSS research designs, subsequent DSS research should at least:

- develop a DSS and CPT environment that offers sufficient information processing support to cover both compensatory and noncompensatory decision strategies;
- increase the number of alternatives included in the choice set;
- enrich the CPT method by including a wider range of information processing measures, and;
- include additional cognitive style constructs.

We have chosen to address all these issues in a second experiment.

9.5 Summary

This chapter evaluated and interpreted the results of the first experiment in the context of the research question. The findings presented concerning the positive effect of our DSS on the selection of compensatory decision strategies are in line with the findings of prior research. A possible explanation for the lack of an alternative similarity effect might be in the fact that the effort reduction made possible by our DSS already influenced the decision maker to use compensatory strategies, in which case alternative similarity does not play a key role. The lack of a cognitive style effect is explained in the context of the task-technology fit. It is most likely that the DSS fits the decision task to be performed in such a way that little room is left for cognitive style to play an important role. A review of the findings of Experiment 1 in the context of comparable prior DSS research revealed support for the validity of the processing index as a measure for characterizing decision behavior. The findings presented in this chapter can also be considered as support for the notion that CPT tools can be employed to capture both information acquisition and information processing behavior. Based on the findings and limitations of Experiment 1, this chapter developed directions for further research and proposed to address these directions in a follow-up experiment.

CHAPTER 10

ENHANCED CONCEPTUAL FRAMEWORK

10.0 Introduction

This chapter aims at enhancing the concepts included in the research framework developed in support of the experiment reported so far. The research findings and limitations presented in the previous chapter will be used to develop an enhanced conceptual framework for a follow-up experiment. For reasons of clarity this follow-up experiment will be referred to as Experiment 2, whereas the experiment reported so far will be referred to as Experiment 1.

Additional functional requirements for the DSS to be employed in Experiment 2 will be developed first. The second part of this chapter will elaborate on additional measures for capturing information processing behavior, followed by the introduction of an additional dimension of cognitive style. Finally, in the last section of this chapter the research model and hypotheses for Experiment 2 will be presented. For completeness it should be noticed that this chapter builds upon the theoretical framework developed in support of Experiment 1.

10.1 Extending the possibilities for capturing information processing behavior

An important limitation recognized in Experiment 1 is the fact that not all potential information processing behavior is captured under the ‘low’ and ‘moderate’ compensatory decision support conditions. Prior to elaborating on a possible clue for this finding, the notion of potential uncovered information processing behavior will be exemplified first.

Suppose a decision maker acting under conditions of ‘low’ compensatory decision support starts the decision process by revealing the closed cells of the full decision matrix. The cells are opened per column, so the first attribute of the first alternative is opened first, then the first attribute of the second alternative and so on (alternatives are organized as rows in a 10 alternatives by 8 attributes decision matrix). When all cells of the first column (attribute) are opened, the process continues with the second column until all data of the decision matrix is revealed. So far, the dependent variables are as following: 1) *amount of information search* = 1.00 (100% of the potential available information is acquired), 2) *variability of information search* = 0.00 (all information on all alternatives is acquired), 3) *search index* = -1.00 (intra-alternative movements only), and 4) the *processing index* has no value because no automated information processing took place so far. It is interesting to see that the first two variables both assume ‘compensatory’ information processing while the search index aims at ‘noncompensatory’ information processing behavior.

Suppose this decision maker chooses to calculate an additive score for the first two alternatives and mentally sums all attribute values for both of them. This act of compensatory information processing will not be captured and as such not be reflected in the processing index, simply because no decision aids were used. If it was, it would at least enrich the image of the actual decision behavior of the problem solver by making it more complete: three measures indicating ‘compensatory’ decision behavior, versus one measure indicating ‘noncompensatory’ decision behavior.

Assuming that this decision maker acts in accordance with the principles of the 'effort-accuracy' framework, this lack in coverage of actual decision behavior will not occur when automated decision support is provided that aims at replacing the mental information processing needed to perform the calculations. Suppose this decision maker has at its disposal the 'Row Total' decision aid, then the 'effort-accuracy' framework assumes that this decision maker will use this DSS function, because triggering this function will cost less effort (one mouse click) than mentally calculating both row totals, given the required level of accuracy (row totals). After all: effort minimizing decision makers are likely to use automated decision aids only if these aids are as easy or easier to apply than competing processes available (Todd & Benbasat, 1992).

This reasoning implies that potentially all relevant information processing behavior can be captured when appropriate automated information processing support is provided. However, in Experiment 1 automated support for both 'compensatory' and 'noncompensatory' information processing strategies was not provided under all DSS treatment conditions. Actually, the 'low' compensatory support condition offered no compensatory support at all.

Is the answer in solving the 'incomplete information processing coverage' limitation in providing automated decision support for both 'compensatory' and 'noncompensatory' decision strategies under all available DSS treatment conditions? The answer to this question will only be 'yes' when the design of the DSS incorporates both the effort required to *interact* with the DSS as well as the cognitive effort *reduction* provided by the DSS.

Remember from paragraph 3.3 that the notion of effort is not only limited to mental effort, but also includes the effort needed to work with the support tools. When all cognitive operations are replaced by the DSS, and as such loose their value as effort 'differentiator', the effort required to interact with the system offers the opportunity to differentiate between different levels of automated decision support. For example, consider the different levels of automated decision support that can be provided for the *weighted additive* (WADD) decision strategy. Under a 'high' condition the user interface can provide the following decision aids: WEIGHTS, GLOBAL, and ROW TOTAL MATRIX, facilitating the full execution of the WADD decision strategy. In fact, implementation of this strategy would only require three system commands, independent of the number of alternatives included in the decision set.

Consider a 'low' condition, providing a user interface including the following decision aids: WEIGHTS, CALCUALTE, and ROW TOTAL ROW. The difference between the ROW TOTAL MATRIX and ROW TOTAL ROW commands is in their impact. Whereas the ROW TOTAL MATRIX calculates a row total for all alternatives included in the decision matrix at the moment the command is executed, the ROW TOTAL ROW calculates a row total for a single alternative. Under this 'low' condition the execution of the WADD strategy implies the following sequence of commands:

1) WEIGHTS, to enter the attribute weights,
2) CALCUALTE, to calculate the weighted attribute values for an alternative,
3) ROW TOTAL ROW, to calculate the weighted additive score for an alternative.

Steps two and three must be repeated for all alternatives available in the decision matrix. Assuming a decision matrix encompassing 50 alternatives, under the 'low' condition a total of 101 commands (1+(50*2)) is needed to apply the WADD strategy on the full decision matrix, whereas the execution of this strategy under the proposed 'high' condition still requires only three system commands. Although both conditions offer full information processing support for the WADD strategy, the effort required to execute this strategy is different under both conditions.

Most important, however, is to recognize that both conditions offer compensatory decision support, so a decision maker willing to execute a compensatory decision strategy is, according to the fundamentals of the 'effort-accuracy' framework, under both conditions assumed to choose for *automated* information processing instead of *mental* information processing. Therefore we argue that it will be possible to capture noncompensatory as well as compensatory information processing behavior for each level of automated decision support provided, given that both kinds of information processing are supported. As argued, effort differentiation can be realized by means of the functions provided in the user interface that aim at supporting the same decision strategies. Support for a typical decision strategy can be provided in many ways, each requiring different levels of effort expenditure.

Therefore we propose to add the following functional requirement to the system requirements developed and expounded in chapter 4:

The user interface for each of the different DSS treatment levels should include support for noncompensatory as well as compensatory decision strategies, provided that equal strategies require different levels of effort across the DSS treatments distinguished.

10.2 Additional information processing measures

Driven by our findings concerning the possibilities of integrating information processing measures in CPT models, the behavioral decision making and DSS research literature presented in chapters 2 and 3 has been reviewed in search for additional operators reflecting information processing behavior. This review delivered that Biggs *et al.* (1985) developed a set of dependent variables aimed at capturing information processing behavior. A subset of the information processing operators distinguished by Biggs *et al.* is also employed by Todd and Benbasat in their DSS research projects (1991, 1992, 1994a, 1994b, 1999, 2000). Since the research variables employed by Todd and Benbasat were already introduced in paragraph 3.6.2. the focus of the explanation presented below will primarily be on their fitness for use in CPT models.

Independent and dependent evaluations: independent evaluations are instances of information processing behavior in which the value of an attribute for a given alternative is compared to some externally identified value or threshold. Dependent evaluations are instances of information processing behavior in which one or more attribute value(s) for a given alternative is/are compared to one or more attribute value(s) of another alternative included in the decision set. In terms of automated decision aids: the CONDITIONAL DROP command is prototypical for *independent* information processing behavior, because it processes attribute values against a externally identified reference point, whereas execution of a CALCULATE command can be considered an instance of *dependent* information processing, since it offers the opportunity to compare two alternatives against each other.

Establishment of the FIP-link will not only make it possible to investigate whether information was processed *inter*- or *intra*dimensional (processing index), but will also make it possible to determine the proportion of dependent and independent evaluations made during the decision process. We propose a so called evaluation index, representing the proportion of dependent evaluations to the total number of evaluations made. This index can be considered an additional indicator for the kind of decision behavior performed: compensatory or noncompensatory. Independent evaluations are characteristic of noncompensatory decision strategies, whereas dependent evaluations are characteristic of compensatory decision strategies

(Todd & Benbasat, 1994b). Where the processing index is a relative measure providing insight in how *much information* was processed in which way (intra- versus interalternative), the evaluation ratio provides a relative measure showing how *many times* information was processed in a specific way, and can as such contribute to an enhanced image of the information processing behavior of the decision maker. Therefore we propose to integrate the *evaluation index* as an additional measure for information processing behavior.

Elimination statements: explicitly dropping an alternative from the decision matrix prior to a complete evaluation of all data on this alternative, is considered an elimination statement. Eliminating alternatives prior to a full investigation of the available attributes is considered characteristic of noncompensatory information processing (Payne *et al.*, 1993). Although the FIP-link makes it possible to determine the number of alternatives that were dropped before all available information on these alternatives was investigated, we propose to ignore the number of elimination statements and to focus on the number of alternatives available in the so called evoked set. An evoked set, sometimes also called consideration set[31] (Farag *et al.*, 2003; Hauser & Wernfelt, 1990), can be defined as the set of alternatives that are evaluated at the *point* of decision making (Häubl & Trifts, 2000; Lehmann & Pan, 1994; Shocker *et al.*, 1991). Due to the execution of elimination 'statements' the number of alternatives available in the initial decision matrix will be reduced to a limited number available at the moment of choice. Although the constructs 'elimination statements' and 'evoked set' are closely related (the size of the evoked set can only be influenced by elimination statements) we propose to focus on the size of the evoked set only for two reasons. At first, the construct elimination statements is rather 'volatile', because an alternative eliminated early in the decision process can be restored (e.g. by means of a RESET) later in the decision process, and second, alternatives in a consideration set are seriously considered by a decision maker "when making a purchase and/or consumption decision" (Hauser & Wernfelt, 1990, p.393). Assuming that 'seriously considered' is an expression of compensatory decision behaviour, the size of the evoked set can be used as an additional indicator for the type decision behaviour performed. Therefore we propose to integrate *evoked set size* in our CPT model.

Compensatory statements: involve "the aggregation and/or trade-off of two or more attributes for a single alternative" (Todd & Benbasat, 1999, p.372). As their name already suggests, compensatory statements are indicative of (additive) compensatory decision strategies. The FIP-link included in our CPT model makes it possible to determine the number of compensatory evaluations performed by a decision maker. For example, the FIP-link not only allows for determining how many times a typical compensatory 'statement' like ROW TOTAL is triggered, but also which information was processed by its execution. By assigning the automated decision aids provided in the DSS user interface to either one of the categories 'compensatory support' or 'noncompensatory support' it will be possible to calculate a compensatory index. We consider the compensatory ratio, being the proportion of compensatory aids triggered to the total number of decision aids triggered, as an additional measure to characterize information processing behaviour. Therefore we propose to integrate the *compensatory index* in our CPT model.

[31] For a discussion on the empirical definitions of both constructs we refer to Hauser and Wernfeldt (1990) and Shocker *et al.* (1991).

Total statements and total information processed. The total number of statements performed is considered to be indicative of the overall amount of information processed in completing the decision task. Todd and Benbasat (1999) argue that the number of total statements performed "should be higher when additive strategies, such as AC, are being used than when elimination strategies, such as EBA, are employed, since for the latter some alternatives are usually eliminated prior to all information about the alternative being evaluated" (p.372). The total number of statements performed can be considered a measure for the overall amount of information processing, therefore we propose to integrate *total statements* in our CPT-model.

Where the total number of statements performed is considered to be indicative of the overall amount of information processed it is also possible to determine the absolute total amount of information searched. The FIP-link provides the mechanisms to develop an additional measure representing information processing behavior: the absolute total amount of information processed by a decision maker. The dependent variable *amount of information search* is a relative measure for information usage, since it considers whether a specific alternative-attribute combination is used by a decision maker. The measure *total information processed* is an absolute measure, because it takes into consideration any time a specific alternative-attribute combination is accessed. We propose to integrate the measure *total information processed* in our CPT-model.

10.3 Additional cognitive style construct

The construct of field dependency used in Experiment1 refers to patterns of information processing and suggests that individuals have varying levels of cognitive ability to recognize different patterns and constructs (Crossland *et al.*, 2000). Field dependency was used as representation of cognitive *skill*. Vroom's (1964) Expectancy Theory addresses a commonly held proposition that *performance* equates *ability* times *effort*. In context of this performance 'formula' the ability-related aspect of the equation is covered by field dependency, therefore we propose to introduce an effort-related cognitive style factor called *need for cognition*. The concept of need for cognition (NFC) was distinguished conceptually by Cohen *et al.* (1955) and represents the tendency for an individual to engage in and enjoy effortful cognitive endeavors (Cacioppo & Petty, 1982; Cacioppo *et al.*, 1984). Research performed in the field of attitude and attitudes change showed that high NFC individuals tend to be engaged in systematic information processing to a greater extent than low NFC individuals (Chaiken, 1980). A NFC literature review performed by Verplanken *et al.* (1992) delivered the notion "that the basic feature of need for cognition is a general tendency to be engaged in cognitive endeavors and seems to be a motivational factor in information processing" (p.129). In a laboratory experiment Veplanken *et al.* (1992) investigated whether individuals who differ in need for cognition employ different strategies in performing an information acquisition and decision making task, and found support for their hypothesis that high NFC subjects expend more cognitive effort on information search than low NFC subjects.

The NFC construct is also employed in the field of behavioral decision making. Levin *et al.* (2000), for example, employed a "'pull-down menu' extension of Payne, Bettman, and Johnson's (1988) software package for generating measures of information processing" (p.171) to track changes in information usage across successive stages of the decision making process and found high NFC subjects to process information in a more focused manner with greater depth and breath than did low NFC subjects.

In the field of management information systems research the NFC dimension of cognitive style is used by Crossland *et al.*(2000). They investigated how cognitive style factors relate to decision making performance for a spatial task by manipulating problem complexity and the availability of a geographic information system. Concerning decision time their results show a significant interaction effect of NFC with problem complexity, indicating that high NFC subjects took significantly longer to complete the task than low NFC subjects did. A significant main effect of NFC was found on decision quality. Subjects with higher NFC had a significantly higher percent error (measure for decision quality) than did subjects with lower NFC.

Despite the fact that the importance of need for cognition for DSS research was recognized by Todd and Benbasat (2000), research on the influence of this cognitive style factor on decision behavior under conditions of automated decision support is sparse if not lacking. Since prior DSS research provides no footing regarding the influence of NFC on decision behavior we adhere to the findings of research in behavioral decision making presented above and therefore propose to test an additional hypothesis in Experiment 2 assuming that high NFC positively influences the use of compensatory decision strategies. This hypothesis will be presented in the next section.

10.4 Research model and hypotheses Experiment 2

Because the enhancements discussed in the previous sections of this chapter do not assume other constructs and relationships than those already included in the research model developed in chapter six, no research model modifications are needed. Although through an enhanced set of parameters, the same relationships will be tested in Experiment 2. Only one additional hypothesis will be formulated to address the cognitive style dimension NFC.

The hypotheses to be tested in Experiment 2 are as follows:

H1: *The level of compensatory decision support available positively influences the use of compensatory decision strategies.*

H2: *The level of alternative similarity positively influences the use of compensatory decision strategies.*

H3: *The effect of alternative similarity on the use of compensatory decision strategies is positively influenced by the level of compensatory decision support.*

H4: *High analytical cognitive style positively influences the use of compensatory decision strategies.*

H5: *High need for cognition positively influences the use of compensatory decision strategies*.

10.5 Summary

This chapter focused on the enhancement of the following concepts included in the research framework underlying Experiment 1: DSS capabilities, decision behavior, and cognitive style. By addressing the limitations recognized in Experiment 1, an enhanced research framework for a follow-up experiment was developed. Implementation of the enhancements proposed in this chapter implies that: 1) the possibilities for capturing decision behavior will be extended, 2) it will become possible to integrate operators for measuring decision behavior, that were traditionally captured through verbal protocol analysis, in a computerized process tracing model, hereby creating an enriched image of decision behavior through the employment of a single process tracing method, and 3) an additional cognitive style dimension (*need for cognition*) will be integrated in DSS research. Whereas the last two issues will be addressed in chapter 12, the next chapter aims at addressing the first issue by developing an enhanced DSS.

CHAPTER 11

ENHANCED DECISION SUPPORT SYSTEM

11.0 Introduction

The aim of this chapter is to introduce the enhanced DSS that has been developed in support of Experiment 2. The outline of this chapter will be equal to the outline of chapter 5, the chapter explaining the DSS used for Experiment 1. A few details concerning the DSS development process will be explained first. Subsequently, the following major components of the enhanced DSS will be explained: (1) user interface, (2) model subsystem, and (3) data subsystem. The additional functional system requirement developed in the previous chapter will be addressed in the section on the model subsystem, followed by a discussion on the impact of the enhanced DSS on effort expenditure. Finally, it will be checked whether the full set of functional requirements developed in this study is covered by the enhanced DSS introduced in this chapter. It is important to recognize that the elements that remain unchanged compared to the system developed in support of Experiment 1 will not be dealt with here. This chapter will elaborate on the enhancements only.

11.1 System development

The enhanced DSS was developed using the same Oracle development tools and database environment as employed for the development of the DSS used in Experiment 1. The existing development repository and data model provided a headstart for this second development process. The same development team that developed the DSS for Experiment 1, staffed with qualified Oracle professionals, accomplished the design and development of the enhanced DSS. Design and development were executed in August and September 2004. Incremental versions of the software were tested by the author during the course of development. Prior to running the pre-test sessions of Experiment 2, the software was tested by two students. When applicable, software bugs were reported and documented and were all resolved as soon as possible.

11.2 The user interface

A screenshot of the DSS user interface employed in Experiment 2 is presented in figure 11.1. The field ‘available alternatives’ was added to the user interface. The number of rows concurrently presented is 15.

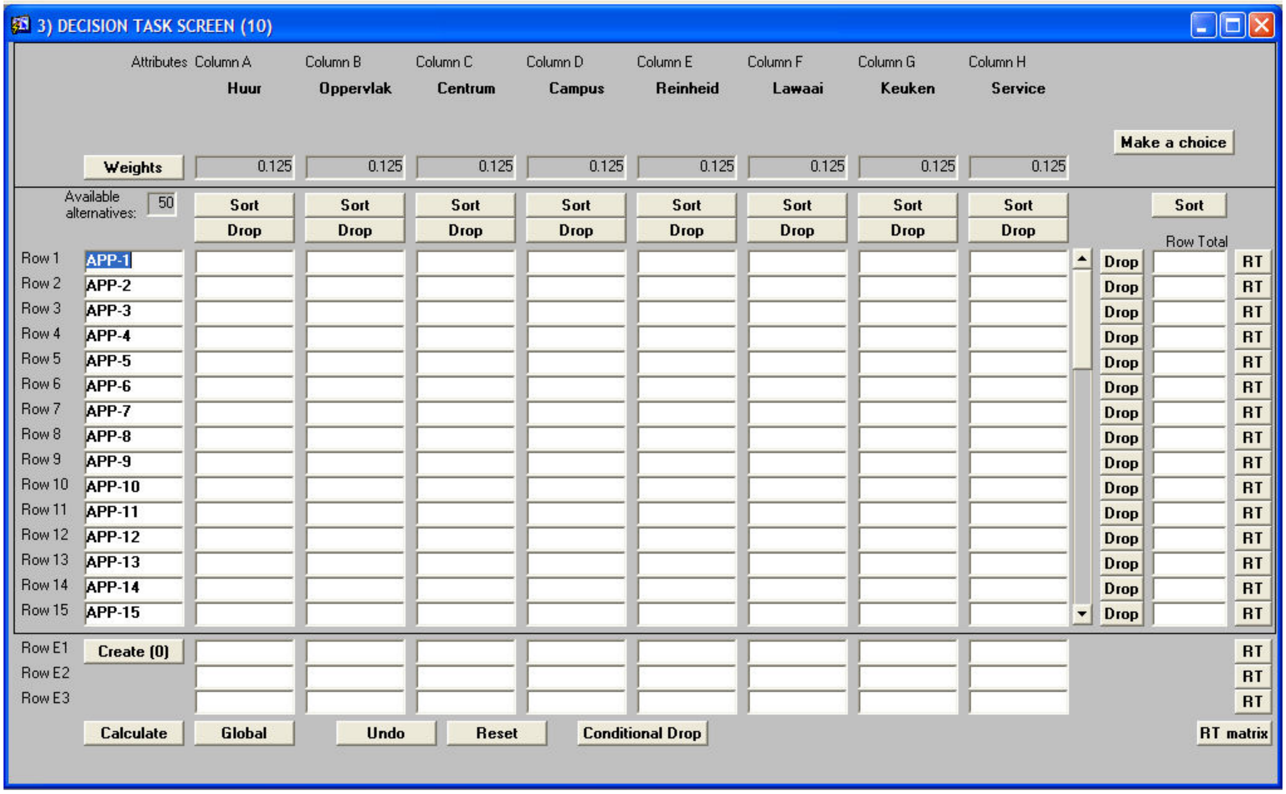

FIGURE 11.1: Screenshot DSS User Interface Experiment 2

11.3 The model subsystem: automated decision aids

Actually the model subsystem for the enhanced DSS can be considered an ‘incremental’ of the model subsystem developed for Experiment 1. When the functional requirement developed in the previous chapter is added to the requirements guiding the development of the Experiment 1 DSS, the total set of functional requirements is as follows:

1. *The experimental DSS should integrate a CPT environment.*
2. *The experimental DSS should provide the decision aids needed to support preferential choice problem solving, at least in such a way that the decision maker is free in its choice which decision strategy to apply.*
3. *The common denominator of the decision aids employed by Todd and Benbasat and Chu and Spires should function as point of departure for the design and development of the automated decision aids to be used in this research project.*
4. *The experimental DSS should provide the mechanisms needed to record the link between a DSS function and the information used, processed and produced by this function.*
5. *The user interface for each of the different DSS treatment levels should include support for ‘noncompensatory’ as well as ‘compensatory’ decision strategies,*

provided that equal strategies require different levels of effort across the DSS treatments distinguished.

The design and development for this second model subsystem will primarily be driven by the last functional requirement (number 5). Since the model subsystem for Experiment 1 offered the appropriate decision aids to support noncompensatory decision strategies under different DSS treatment levels, the focus of the design process for the Experiment 2 model subsystem will be on supporting compensatory decision strategies at different levels of effort expenditure. In this design process the weighted additive (WADD) decision strategy will be used as frame of reference for compensatory decision behavior.

Under conditions of 'high' compensatory decision support, the Experiment 1 DSS supports the WADD strategy most straight-forwardly through the following decision aids: (1) WEIGHTS, (2) GLOBAL, and (3) ROW TOTAL. When these three DSS functions are considered, in particular the GLOBAL and ROW TOTAL command bear the opportunity to be substituted by a set of commands that, when executed together, serve the same objective but require an increased level of effort expenditure.

Actually, the GLOBAL command is the 'automated' version of the execution of a series of CALCULATE commands. For example, the weighted attribute scores for a matrix including ten alternatives can be calculated either by using one GLOBAL command (in this case GLOBAL*WEIGHTS), or by means of the execution of ten individual CALCUALTE commands (in this case CALCULATE: $Row_x = Row_x$ * WEIGHTS). In terms of effort required: the last option requires an increased level of effort expenditure given the same level of accuracy. In order to function as a substitute for the GLOBAL command, the CALCULATE command included in the Experiment 1 model subsystem must be modified, since the results of a CALCULATE under Experiment 1 can only be stored in one of the additional rows created by the CREATE function. Remember that the GLOBAL command 'overwrites' the actual attribute values in the decision matrix. If the working of the CALCULATE command is enhanced in such a way that it can store its results in the decision matrix, hereby 'overwriting' the actual attribute values of an alternative, it can be deployed as a 'single alternative' version of the GLOBAL command.

The ROW TOTAL command supports the calculation of weighted additive scores, however, the scope of this command is the full decision matrix. Execution of the ROW TOTAL command causes a WADD score to be calculated for all alternatives available at the moment of execution. The Experiment 1 model subsystem does not support the calculation of a WADD score for a single alternative. Development of a 'single alternative' ROW TOTAL function can provide a more effortful alternative for the ROW TOTAL function as implemented in the Experiment 1 model subsystem. In terms of effort expenditure: given the working of the 'matrix' ROW TOTAL, the same level of accuracy can be obtained by a 'single alternative' ROW TOTAL, however, at the cost of more effort expenditure.

In context of the two issues addressed above functional requirement number 5 can be implemented by: (1) modifying the working of the CALCULATE command, and (2) the introduction of a new command aimed at calculating a row total for a single alternative. The impact on effort expenditure of the proposed solution will be presented in paragraph 11.5.

The last part of this paragraph will be used to introduce the decision aids included in the Experiment 2 model subsystem. Table 11.1 provides an overview of the decision aids used in both Experiment 1 and Experiment 2.

TABLE 11.1: DSS functions Experiment1 versus Experiment 2

DSS Function	Exp 1	Exp 2	DSS Function	Exp 1	Exp 2
OPEN	√	Mod	CALCULATE	√	Mod
CLOSE	√	√	SORT	√	√
SEQUENCE	√	-	WEIGHTS	√	√
DROP COLUMN/ROW	√	√	GLOBAL	√	√
CONDITIONAL DROP	√	√	MAKE a CHOICE	√	√
ROW TOTAL	√	Mod	UNDO	√	√
ROW TOTAL MATRIX	-	New	RESET	√	√
CREATE	√	√			

√ = function provided; - = function not provided; MOD = function is modified compared to previous model; New = New function.

Since the core of the Experiment 2 model subsystem will be equal to the functions provided in the model subsystem of Experiment 1, only the new decision aids, and the decision aids that are modified will be explained. The explanation of the functions presented below is supported by a website (www.feweb.vu.nl/dssresearch) including multimedia objects that, when triggered, show the working of the DSS functions explained. The descriptions provided below include references to these objects. The website contains objects of all the DSS functions included in the enhanced DSS developed in support of Experiment 2.

OPEN / CLOSE:

The Experiment 1 model subsystem distinguished three different states for an information cue (cell in the decision matrix):

1) Cell closed.
2) Cell opened numeric.
3) Cell opened alphanumeric.

Due to the altered working of the CALCULATE command it will be possible that a cell contains no value. If a cell contains no value the text 'empty[32]' is displayed. This is why a fourth status is added:

4) Cell is empty.

When a cell is 'overwritten' due to the execution of a GLOBAL command, it was no longer possible to change the status of a cell under the Experiment 1 model subsystem. This is altered in the Experiment 2 model subsystem. Even when a cell value is 'overwritten', due to either a CALCULATE or a GLOBAL command, it will be possible to change the status of this cell. However, whereas condition 2 will show the calculated value, because the original attribute value is overwritten, condition 3 shows the original alphanumeric value. This function is provided to offer decision makers the opportunity to switch to the original alphanumeric value in case a reference is needed for the calculated value.

[32] In fact the Dutch word 'leeg' (empty) was displayed.

(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 2-> OPEN/CLOSE)

SEQUENCE:

The SEQUENCE command was not provided in the Experiment 2 model subsystem. This function was eliminated for two reasons: (1) an analysis of the answers to the Experiment 1 debriefing question "The tutorial was clear and obvious to me" (1=fully disagree, 5=fully agree) delivered that the subjects participating in Experiment 1 experienced the tutorial explaining the DSS functions as very clear (M= 3.81, SD =1.91), however, it was frequently remarked that the tutorial was rather elaborate and could be shortened, (2) an analysis of the process traces of Experiment 1 revealed that use of the SEQUENCE command was sparse (approximately 5% of the cell commands). These two observations, combined with the fact that the SEQUENCE command was introduced in this study and has no reference in prior DSS research, led to the decision to eliminate the SEQUENCE command.

CALCULATE

Basically the working of the CALCULATE command employed in the Experiment 2 model subsystem is the same as the CALCULATE command developed for Experiment 1. The only enhancement implemented is the possibility to store the results of a calculation in a row of the decision matrix. For example, the CALCULATE command Alternative 1 = Alternative 1 * Weights, will overwrite the actual attribute values of alternative 1 with the weighted attribute values. The first version of the CALCULATE command could only store its results in the so called additional rows.

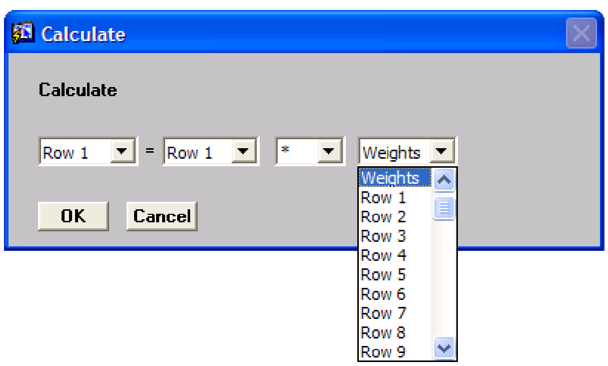

FIGURE 11.2: Screenshot Enhanced CALCUALTE Command

(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 2-> CALCULATE)

ROW TOTAL

Although the name of this command is equal to the ROW TOTAL command employed in the Experiment 1 model subsystem, its working is different. This ROW TOTAL command will limit its impact to a single row. Executing the ROW TOTAL command will calculate the sum of the actual values for the alternative selected. The row total will be shown in the field that is positioned behind the attribute values describing the relevant alternative. Attribute values of the dimensions that are deleted from the decision matrix will not be counted for. A cell does not necessarily have to be opened in order to be counted for in the execution of the ROW TOTAL command. For example, consider a decision matrix in its initial status, so all cells are closed.

After execution of the ROW TOTAL command, the cells will stay closed, but the row total field at the end of the alternative selected will show a row total for the relevant alternative.

Row totals will be presented as long as the values of the decision matrix are in accordance with the row totals calculated. If, for example, a column is deleted from the decision matrix after a row total has been calculated, the row total values will be eliminated because these totals have become inaccurate due to the elimination of a column.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 2-> ROW TOTAL)

MATRIX ROW TOTAL

Since the working of the ROW TOTAL command is altered, a new function must be introduced to calculate all the row totals for the alternatives available in the decision matrix. This new decision aid is called MATRIX ROW TOTAL. Its working is exactly the same as the ROW TOTAL command employed in the Experiment 1 model subsystem. In fact it is the same command, however, to avoid confusion the text MATRIX is added to the name of this decision aid in order to be able to clearly distinguish it from the ROW TOTAL command.
(see also www.feweb.vu.nl/dssresearch DSS User Interface Experiment 2-> MATRIX ROW TOTAL)

11.4 The data subsystem

Implementation of functional requirement number 5 does not influence the data subsystem. All changes needed to fit this requirement can be handled by changing parameter domain values. It will not be necessary to introduce new CPT-model parameters or change the data model of the underlying databases.

11.5 Impact on effort expenditure

To estimate the impact on effort expenditure of the DSS developed in support of Experiment 2 the method explained in chapter 3 will be employed. Since no changes are made in the support of noncompensatory decision strategies the impact analysis will only focus on the effort associated with the implementation of the compensatory WADD strategy.

Consider two different levels of decision support: '*low*' compensatory support and '*high*' compensatory support. The commands available under each of these levels are presented in table 11.2.

TABLE 11.2: Decision Support Commands per Level

LOW Compensatory Support	*HIGH Compensatory Support*
DROP	DROP
CONDITIONAL DROP	CONDITIONAL DROP
WEIGHTS	WEIGHTS
CALCULATE	CALCULATE
ROW TOTAL	GLOBAL
	MATRIX ROW TOTAL

The general purpose commands OPEN, CLOSE, SORT, UNDO and RESET are available under both conditions.

Table 11.3 presents the impact of the different levels of decision support on the effort required to execute the WADD strategy. The exemplary calculations are based on a decision matrix containing ten alternatives, each described by eight attributes. The estimates presented in table 11.3 are valid under the assumption that the DSS functions are used in the appropriate way to support the strategies mentioned.

TABLE 11.3: Impact of Decision Aids on Effort Expenditure.

	Weighted Additive (WADD) Decision Strategy			
Component Formula	Attribute Recall 1*Alt*Att	Tracking 4*(Alt-1)+2	Processing 6*(Alt*Att)	**Total**
Unaided	80	38	480	**598**
LOW WADD support	8	1	0	**9**
HIGH WADD support	8	1	0	**9**
Command Usage				
LOW WADD support	WEIGHTS (CALCUALTE & ROW TOTAL) * 10 SORT ROW TOTAL			**22**
HIGH WADD support	WEIGHTS GLOBAL MATRIX ROW TOTAL SORT ROW TOTAL			**4**

Assuming a predetermined level of accuracy, table 11.3 shows that under the condition of high WADD support there will be no difference in cognitive effort expenditure between both DSS conditions. However, under conditions of ‘*low*’ compensatory support, the implementation of a WADD strategy will ‘cost’ an additional execution of 18 system commands compared to the ‘high’ compensatory support condition.

This impact analysis proves that it will be possible to support the WADD strategy with different kinds of automated decision aids, each requiring different levels of effort expenditure. In terms of functional requirement number 5: the model subsystem developed in support of Experiment 2 includes a set of decision aids that will make it possible to support a single compensatory decision strategy with different combinations of decision aids, each requiring different levels of effort expenditure.

11.6 Coverage of all functional requirements

Since the implementation of the additional functional requirement, developed in context of Experiment 2, does not influence the implementation of the other four functional requirements, developed in the context of Experiment 1, the conclusion is justified that the Experiment 2 DSS covers the full set of functional requirements expanded in this study.

11.7 Summary

This chapter presented the enhanced DSS developed in support of Experiment 2. The functionality of this DSS is explained in the context of the additional functional requirement developed in the previous chapter, as well as in the context of the functional requirements employed to direct the development of the Experiment 1 DSS. The DSS environment developed in this chapter addresses an important limitation of Experiment 1: the Experiment 1 DSS provided insufficient support for "capturing" all mental information processes. The enhanced DSS presented also supports the implementation of the extended set of measures for capturing decision behavior introduced in the previous chapter. The calculation of these measures will be explained in the next chapter on the method for Experiment 2.

CHAPTER 12

METHOD EXPERIMENT 2

12.0 Introduction

To examine the adjusted set of hypotheses, a laboratory experiment was conducted during September and October 2004. The experimental design is a 2x2 between subjects factorial in which alternative similarity (low & high condition) varied across two levels of DSS support (low & high compensatory support). This chapter will describe how the experiment was conducted. Since the design and procedures of this second experiment are nearly identical to those of Experiment 1, the identical parts will only be introduced briefly.

12.1 Decision task

Participants were supposed to perform a multi-alternative, multi-attribute preferential choice task, identical to the task employed in Experiment 1. The objective was to select a one-bedroom apartment.

The structure of the choice matrix employed in this experiment was modified. To address the limitation concerning the size of the choice set, established in Experiment 1, the number of alternatives was increased: 50 apartments were included in the decision matrix. This number was chosen for two reasons: (1) a search for single bedroom apartments, using dedicated websites of housing agencies specialized in student accommodations[33], on average delivered approximately 50 alternatives when attribute ranges representative for the values in the decision matrix were entered in their search engines, and (2) we assume 50 alternatives a problem size that goes beyond human tractability.

The attributes employed in the decision matrix were identical to the attributes used in Experiment 1: Rent, Size, Distance to centre, Distance to campus, Cleanliness, Noise, Kitchen and Landlord service attitude.

An overview of the datasets employed in this experiment, including both the numeric and text values used, is included in appendix 6.

No time constraints were imposed and participants were free to use as much or as little information as they wanted.

12.2 Participants and treatment assignment

All participants were graduate and undergraduate business administration students. Participants were enrolled from both an optional class in Decision Support Systems and a mandatory class in Management Information Systems at the Faculty of Economics and Business Administration of the *Vrije Universiteit* Amsterdam. Participants volunteered to participate in return for partial class credit. In total 273 individuals participated.

Assignment to the different treatment combinations took place through random assignment without replacement. The software automatically assigned each participant to a

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[33] www.opkamers.nl , www.kamernet.nl , www.studentenkamers.nl , and www.kamergids.com. All websites were searched in September 2004.

specific treatment during the log on procedure that provided access to the experimental DSS environment.

12.3 Manipulations

The manipulations of the experiment were the level of compensatory decision support and alternative similarity. The operationalization of both manipulations will be explained below.

12.3.1 Level of compensatory decision support

The level of compensatory decision support was manipulated by the availability of automated decision aids included in the decision support system. Two levels of compensatory decision support were distinguished: '*low*', and '*high*'. A detailed overview of the decision aids available under each of the two levels of decision support provided is presented in table 12.1.

TABLE 12.1: Automated Decision Aids Provided Under DSS Treatments

Commands	*Low*	*High*
Open/Close	√	√
Drop Row	√	√
Drop Column	√	√
Conditional Drop	√	√
Sort	√	√
Undo	√	√
Reset	√	√
Create	√	√
Weights	√	√
Calculate	√	√
Row Total	√	√
Global	-	√
Matrix Row Total	-	√
Make a Choice	√	√

12.3.2 Alternative similarity

Alternative similarity was operationalized in exactly the same manner as was done in Experiment 1. The variances in the attribute values for all attributes under the '*similar alternatives*' condition (M_{similar}= 0.71; SD_{similar}= .28) were significantly lower than the average under the '*not similar*' condition ($M_{\text{not similar}}$= 7.82; $SD_{\text{not similar}}$=1.84,), $t(14)$=10.763, $p< .001$. The maximum difference between alternatives on an attribute under the '*similar*' condition was 3 points, whereas this maximum difference under the '*not similar*' condition was 9 points. Under the '*similar*' condition 79% of the pairwise comparisons of all alternatives on an attribute resulted in a difference of 1 point or less, whereas this number was only 30% for the '*not similar*' condition. The attractiveness scores were equal (5.625) for all alternatives under the '*similar*' condition, under the '*not similar*' condition the attractiveness scores varied between 4.88 and 6.63.

The direction of the attribute differences was varied in such a way that none of the alternatives in both datasets dominated the other alternatives.

12.4 Measures

The third independent variable of interest in this study (next to *alternative similarity* and the *level of compensatory decision support*) is *cognitive style*. Measurement of the '*field dependency*' cognitive style construct happened in the same way as explained in chapter 7. The *need for cognition* scale will be explained in this section. However, prior to an elaboration on the operationalization of cognitive style, the method applied to infer on decision strategy selection will be explained first.

12.4.1 Decision strategy

The dependent variables employed to infer on decision strategy selection are:

1. Amount of information search.
2. Variability of information search.
3. Pattern of information search.
4. Processing Index.
5. Evaluation index.
6. Evoked set size.
7. Compensatory index.
8. Total statements.
9. Total information processed.

Since the operationalization of the first four variables does not deviate from the explanation given in chapter 7, these operators will not be elaborated on in this chapter.

Evaluation index: the evaluation index developed in this study represents the ratio of dependent evaluations to the total number of evaluations made by a decision maker, or in formula:

$$Evaluation\ Index = \frac{Number\ of\ \ Dependent\ Evaluations}{Number\ of\ \ Dependent\ Evaluations + Number\ of\ \ Indpendent\ Evaluations}$$

A comparable index is also used by Biggs (1985) and Todd and Benbasat (2000) to infer on decision strategy selection.

The Function-Information-Processing (FIP)-link supports the determination of dependent and independent evaluations. For example, the CONDITIONAL DROP command can be considered exemplary for independent information processing. By means of the FIP-link it is possible to determine how many alternatives 'independently' are evaluated against the external standard specified in the parameters of the CONDITIONAL DROP command. Compensatory information processing is characterized by higher ratios of dependent information processing (Biggs *et al.*, 1985; Todd & Benbasat, 2000).

Evoked set size: The size of the evoked set is determined at the moment a decision maker confirms the MAKE-a-CHOICE command. When a decision maker knows which alternative to choose, its preference can be entered using this command. Actually, confirming the MAKE-a-CHOICE marks the end of the decision process. The number of alternatives available in the decision matrix at this moment is considered to be the evoked set size. The evoked set size is inversely proportional to the *number of alternatives eliminated* before choice episode, a measure employed by Biggs *et al.* (1985) and Todd & Benbasat (2000). For reasons explained in chapter 10 this study employs the mirror image of the number of alternatives eliminated. Proportionally greater evoked set sizes are associated with compensatory information processing.

Compensatory index: represents the ratio of compensatory decision commands to the total number of commands employed, or in formula:

$$Compensatory\ Index = \frac{Compensatory\ Commands}{Compensatory\ Commands + Noncompensatory\ Commands}$$

When the decision aids provided in the DSS user interface are assigned to either one of the following categories: ‘compensatory commands’, or ‘noncompensatory’ commands, the computerized process traces (CPT) stored in the CPT database can be used to calculate the compensatory index. Calculation of this index is comparable to the method employed by Biggs *et al.* (1985) and Todd & Benbasat (2000). Proportionally higher values on this index are associated to compensatory decision behavior.

Total statements and total information processed. Todd and Benbasat (1999) are very explicit in how to calculate command use and propose to sum the number of times the following commands are used: DROP, CONDITIONAL DROP, CALCULATE, CREATE, ROW TOTAL and GLOBAL (p. 369). We have chosen to adopt the same calculation method. The MATRIX ROW TOTAL command, developed in this research, is included in the calculation of the total number of statements performed. Higher levels of total statements used are associated with compensatory decision behavior.

Whereas Todd and Benbasat assume that total statements used is “indicative of the overall amount of information processed in completing the task” (1999, p.372), this study integrates the *actual* total amount of information processed as additional measure. Due to the FIP-link it will be possible to calculate this operator rather precisely. The total amount of information processed is an absolute measure representing cumulative information usage, and is calculated as follows:

$$Total\ Information\ Processed = \sum_{Alt=1}^{N}\sum_{Attr=1}^{A}(total\ number\ of\ references\ made\ to\ cue_{(alternative,attribute)})$$

where N represents the number of alternatives, and A the number of attributes available in the decision set. Compensatory decision strategies are supposed to be associated with increased levels of total information processing (Payne *et al.*, 1993).

Appendix 7 provides a detailed overview showing how the measures explained in this paragraph are influenced by the individual decision aids included in the DSS.

12.4.2 Cognitive style

Need for cognition was measured using the short form of the Need for Cognition scale (Cacioppo *et al.*, 1984). The Dutch translation of this scale, developed by Verplanken (1993) and Verplanken *et al.* (1992), was employed in this study. The scale contains 18 items, which are measured on 7-point Likert scales. Some examples of the items are “I would prefer complex to simple problems”, “The idea of relying on thought to make my way to the top appeals to me”, “The notion of thinking abstractly is appealing to me”, and “Learning new ways to think doesn’t excite me very much.” The full scale is included in appendix 8. After reverse-coding the negatively worded items, the NFC score is calculated as the total of the individual item scores (Pieters *et al.*, 1987).

12.5 Pre-testing

Prior to the execution of the final experiment two pre-test sessions were organized in which in total 32 individuals participated. During these pre-tests the experimental procedures and associated documents were tested. The output of the pre-tests was also used to verify the accuracy and completeness of the data stored in the computerized process tracing environment. The versions of the documents, procedures and DSS software used during both pre-test sessions proved to be appropriate for the experiment, no enhancements were needed.

12.6 Experimental procedures and apparatus

Before explaining the experimental procedures and apparatus it should be mentioned that, unless stated otherwise, the tasks that are also included in Experiment 1 are executed according to the same procedures and details as described in chapter 7.

The experimental sessions were performed in the same DSS laboratory as used for Experiment 1. An image of the lecture room in which the experimental sessions were performed is shown in figure 12.1. In total eight three hour sessions were scheduled in an unbroken time frame of four days. Each subject could choose which session to attend according to the ‘first come, first served’ principle.

FIGURE 12.1: Images of the Setting of the Experiment

12.6.1 Experimental procedures

All sessions were supervised by an instructor who directed the sessions and provided instructions. Preparation, instruction, briefing, document coding and system logon procedures were identical to the procedures implemented in Experiment 1. The general instructions explicitly stated that participants could take as much time as they wanted to fulfill the experimental decisions tasks.

12.6.2 Plenary part and individual part

A session consisted of two parts: 1) a plenary part in which all instructions were given by the instructor, and 2) an individual part in which each participant worked on the experimental tasks in his or her own tempo. During the second, individual part, instructions were given by the software. The tasks to be performed were embedded in the same workflow application as employed in Experiment 1.

12.6.3 Experimental tasks

After the general briefing the participants were asked to read the nondisclosure statement and when agreed upon to sign it. All participants agreed to sign the nondisclosure statement. Next participants were instructed to read the document called ‘general instructions’, a document providing an overview and a brief explanation of all the tasks to be performed during the session. A session of the experiment included the following tasks:

1. Need for cognition questionnaire
2. Hidden Figures Test
3. Tutorial
4. Practice task
5. Decision Task
6. Post experiment survey questionnaire

An online survey tool was used to administer the need for cognition scale. The same 'paper-and-pencil' test as applied in Experiment 1 was used to administer The Hidden Figures Test. After holding both cognitive style tests the instructor provided additional instructions regarding the second part of the session. Next to this instruction participants were asked to log on to the workflow environment using the codes provided. Treatment assignment was executed by a dedicated software procedure that was triggered as part of the logon procedure for the workflow application. After execution of the logon procedure the documents including the DSS tutorials were distributed. The tutorials were modified for the enhancements made in the user interface to suit the requirements of Experiment 2.

Whereas in Experiment 1 a so called 'tutorial test' was part of the experimental tasks, this test was not included in the sessions of Experiment 2. The tutorial test was eliminated in favor of a practice task. The decision to integrate a practice task was driven by the assumption that participants will be more prepared to execute the final decision task when they have the opportunity to practice the commands explained in the tutorial. If not, the possibility exists that participants will execute a few 'training' commands at the beginning of the decision task, which will potentially bias the observations. We assume that this potential bias will be negligible when participants do have the opportunity to practice the commands explained in the tutorial in a dedicated practice task. Introducing a practice problem gives participants the chance to familiarize themselves with the task setting, gain further experience with DSS command use, and become comfortable with the user interface (Todd & Benbasat, 1999). Since the time needed to fulfill the experimental tasks was already extended through inclusion of the NFC scale, we have chosen to substitute the tutorial test for the practice task. Based on the Experiment 1 tutorial test results we knew that the tutorial was appropriate in explaining the DSS functions. The average answer to the post experiment statement "The tutorial was clear and obvious to me" (1=fully disagree, 5=fully agree), was 3.81 (*SD*=1.49) in Experiment 1, and 4.21 (*SD*=.98) in Experiment 2, indicating that the tutorial functioned properly anyway.

The practice task concerned the selection of a holiday by air and was introduced by a four page document explaining the purpose of the task, and the dimensions characterizing the holidays to choose from. The decision set for this practice task included 50 summer holiday options, each described by eight dimensions. The attribute values in the practice task were such that no resemblance with the attribute values in the final decision task existed. The practice task was the same for both DSS treatment groups.

After finishing the practice task, subjects were instructed by the workflow application to begin with the decision task. The decision task was exactly the same as the decision task employed in Experiment 1: the selection of a one-bedroom apartment.

The final task of the experiment concerned answering a post experiment survey questionnaire, administered through an online survey tool (see appendix 9). After the instructor made sure that a participant indeed finished all tasks included in the experiment, all documents were collected and the participant was asked to exit the workflow application. Since all documents were numbered, the instructor was able to verify whether all documents were returned.

When all subjects finished the experiment they were asked to react on the experiment or, if wanted, to ask questions. As long as questions asked were not related to the essentials of the experiment the questions were answered. All sessions were finished within the planned three hours time frame.

12.7 Verification process traces and dependent variables

Completeness of the computerized process traces was verified by comparing the manually registered actions performed by five 'verification subjects' with the actions registered in the CPT environment. No deviations were observed. The *accuracy* of the software routines establishing the dependent variables was verified by comparing the manually calculated values of the dependent variables with the values calculated by the software. To verify whether these procedures worked in accordance with the rules explained in appendix 7 the dependent variables were manually calculated for a sample of 18 subjects (5 'verification' subjects, and 13 subjects drawn from the total participant population). The 13 observations drawn form the total participant population were randomly selected for verification, taking into account that from each treatment group at least two observations were to be selected. The process traces of the 13 verification subjects were used by a university graduate student to manually calculate the dependent variables. Based upon the data of the 18 verification subjects the automated calculation routines were found to be accurate.

12.8 Summary

This chapter explained the details of Experiment 2. The preferential choice problem employed in this second experiment was similar to the problem used in Experiment 1: the selection of a one-bedroom apartment. The choice set included fifty alternatives each described by eight attributes. The DSS treatment was operationalized through *two different levels of compensatory decision support*: low and high. The *alternative similarity* treatment was realized in a way similar to the method employed in Experiment 1. Decision behavior was characterized through an extended set of operators, including the operators employed in Experiment 1: *amount of information search*, *variability of information search*, *search index*, and *processing index*, supplemented with five new information processing operators: *evaluation index*, *evoked set size*, *compensatory index*, *total statements*, and *total information processed*. The two instruments used to differentiate between the cognitive style constructs employed in Experiment 2 were: the *Hidden Figures Test* (field dependence/field independence, similar to Experiment 1), and the *Need for Cognition scale* of Cacioppo *et al.* (1984). The procedures executed to verify the completeness of the computerized process traces as well as the accuracy of the software routines that calculated the operators for characterizing decision behavior revealed that both completeness and accuracy were appropriate.

CHAPTER 13

RESULTS EXPERIMENT 2

13.0 Introduction

This chapter will present summaries of the data collected and the results of the statistical treatments used for Experiment 2. The characteristics of the subject population and the results of the manipulation checks will be presented first, subsequently the findings of the multivariate analyses executed will be shown.

13.1 Characteristics of the participants

Initially 273 participants attended the sessions of the experiment. One observation was excluded from the analyses since an analysis of the computerized process traces delivered that this subject only executed the MAKE-a-CHOICE command, without acquiring any data. In total 272 participants (male: 201/female: 71) successfully fulfilled the experimental tasks. The average age of the participants was 21.3 years (*SD*=2.6), and 54% of the participants reported to have been involved, in some way or another, in the process of selecting an apartment, whereas 36% reported to actually live in an apartment at the time the experiment was executed.

13.2 Randomization

Three univariate analyses of variance were performed to check the functioning of the randomization routine. Age, as well as the scores on both cognitive style tests did not differ significantly over the different treatment groups, we can conclude that the random assignment procedure functioned properly. Both age and the cognitive style scores are evenly dispersed over the groups.

13.3 Manipulation checks

Two questions were included in the post experiment survey to check the alternative similarity manipulation: 1) “To which extent do you consider the apartments in the decision set similar?”, and 2) “The variance in attribute values (e.g. rent, size, etc.) for the different apartments was limited”. The results of a *t*-test for equality of means presented in table 13.1 show that the groups differed significantly on the alternative similarity responses in the correct direction. We conclude that the manipulation was successful.

TABLE 13.1: Statistics Manipulation Checks

			Similar Condition		*Not Similar Condition*	
Question	***t(270)***	***P***	***M***	***SD***	***M***	***SD***
Question 1: To which extent do you consider the apartments in the decision set similar? (1=not similar at all, 5=very similar)						
t-test question 1:	-10,58	.000	3.53	.88	2.50	.71
Question 2:The variance in attribute values (e.g. rent, size, etc.) for the different apartments was limited. (1=fully disagree, 5 fully agree).						
t-test question 2:	-10,71	.000	3.30	1.04	2.17	.65

13.4 Dependent variables

Table 13.2 provides the means and standard deviations for the nine dependent variables: *amount of information search*, *variability of information search*, *search index*, *processing index*, *evaluation index*, *evoked set size*, *compensatory index*, *total statements*, and *total information processed*. The correlation matrix for the dependent variables is presented in table 13.3.

TABLE 13.2: Means and Standard Deviations on the Dependent Variables for the Four Treatment Combinations

		Dependent Variables																		
		Amount of Information Search		*Variability of Information Search*		*Search Index*		*Processing Index*		*Evaluation Index*		*Evoked Set Size*		*Compensatory Index*		*Total Statements*		*Total Information Processed*		
Treatments		***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***	***n***
DSS (level of Compensatory support)	Similarity																			
LOW	No Similarity	.55	.26	.23	.14	-.38	.48	-.09	.59	.20	.30	11.0	15.7	.30	.26	126	100	650	429	68
	Similarity	.55	.19	.26	.14	-.55	.39	-.04	.53	.28	.36	13.1	16.1	.38	.31	118	59	677	399	68
HIGH	No Similarity	.85	.25	.09	.15	-.13	.51	.52	.51	.38	.37	18.7	20.6	.62	.30	272	197	1868	1475	67
	Similarity	.86	.23	.09	.15	-.17	.56	.46	.57	.38	.38	21.2	20.5	.62	.33	288	226	2010	1768	69

TABLE 13.3: Correlation Matrix Dependent Variables

	Correlations among variables								
	Amount of Information Search	Variability of Information Search	Search Index	Processing Index	Evaluation Index	Evoked Set Size	Compensatory Index	Total Statements	Total Information Processed
Amount of Information Search	- -	-.832***	.281***	.675***	.461***	.370***	.670***	.528***	.593***
Variability of Information Search		- -	-.325***	-.534***	-.405***	-.334***	-.547***	-.476***	-.532***
Search Index			- -	.383***	.194**	.253***	.354***	.308***	.341***
Processing Index				- -	.476***	.467***	.907***	.360***	.512***
Evaluation Index					- -	.508***	.689***	.227***	.417***
Evoked Set Size						- -	.610***	.249***	.388***
Compensatory Index							- -	.340***	.550***
Total Statements								- -	.936***
Total Information Processed									- -

** $p < .05$, *** $p < 0.001$

13.5 Test of the hypotheses

A two-way multivariate analysis of variance (MANOVA) was conducted to determine the effect of the alternative similarity and DSS treatments. The cognitive style dimensions *field dependency* and *need for cognition* were treated as covariates. The MANOVA results show that both cognitive style dimensions do not influence the use of compensatory decision strategies. Hypothesis 4, stating: *High analytical cognitive style positively influences the use of compensatory decision strategies* (Wilks' Λ =.940, being not significant $F(9,258)=1.844$, $p=.061$), as well as Hypothesis 5, stating *High need for cognition positively influences the use of compensatory decision strategies* (Wilks' Λ =.964, being not significant $F(9,258)=1.068$, $p=.387$) are not supported by our data. Because the results of this analysis show that the dependent variables are not influenced by cognitive style, the hypotheses are tested under exclusion of the cognitive style covariates. The results of the multivariate and univariate analyses are presented in tables 13.4 and 13.5 respectively. An alpha level of .05 was used for all statistical tests.

Box's M test showed that the variances and covariances among the variables were not the same (Box's M=557.763, $p<.001$). This implies that the analyses should be interpreted with caution.

TABLE 13.4: Multivariate Analysis of Variance of Main and Interaction Effects (without covariates*))

	Multivariate			
	Wilks's Λ	***df***	**F**	***p***
DSS	.625	260	17.342	.000
Alternative Similarity (AS)	.953	260	1.420	.180
DSS*AS	.974	260	.771	.644

*) The analyses with covariates produced the same results.

TABLE 13.5: Univariate Analyses of Variance Main and Interaction Effects (without covariates)

	Univariate									
	Amount of Information Search		***Variability of Information Search***		***Search Index***		***Processing Index***		***Evaluation Index***	
	F	***P***	**F**	***P***	**F**	***P***	**F**	***p***	**F**	***p***
DSS	110.716	.000	99.705	.000	28.250	.000	69.505	.000	11.112	.001
Alternative Similarity (AS)	.017	.897	.998	.319	3.138	.078	.002	.967	1.062	.304
DSS*AS	.061	.806	.507	.477	1.145	.286	.725	.395	.963	.327

	Evoked Set Size		***Compensatory Index***		***Total Statements***		***Total Information Processed***	
	F	***P***	**F**	***P***	**F**	***P***	**F**	***p***
DSS	12.594	.000	58.699	.000	65.688	.000	78.222	.000
Alternative Similarity (AS)	1.034	.310	1.150	.285	.039	.843	.343	.559
DSS*AS	.007	.931	1.369	.243	.381	.537	.159	.690

Hypothesis 1, proposing that the level of compensatory decision support available positively influences the use of compensatory decision strategies, is supported by the data. The univariate analyses presented in table 13.5 show that the influence of the level of compensatory decision support on the dependent variables is significant for each of the dependent variables. The group means for the DSS treatment develop in the right direction.

Hypothesis 2 stated that the level of alternative similarity positively influences the use of compensatory decision strategies. The data did not support this hypothesis.

Hypothesis 3 assumed an interaction effect between the level of compensatory support and alternative similarity that will positively influence the use of compensatory decision strategies. We did not find support for this hypothesis either.

13.6 Effect sizes and power

Table 13.6 presents the effects sizes and observed power for the nine dependent variables under the DSS condition.

TABLE 13.6. Effects Size and Observed Power under DSS Condition

Source	Dependent Variable	Partial Eta Squared η^2	Observed Power*)
Level of Compensatory Support	Amount of Information Search	.292	1.000
	Variability of Information Search	.271	1.000
	Search Index	.095	1.000
	Processing Index	.206	1.000
	Evaluation Index	.040	.913
	Evoked Set Size	.045	.943
	Compensatory index	.180	1.000
	Total Statements	.197	1.000
	Total Information Processed	.226	1.000

*) computed using $\alpha = .05$

Table 13.6 shows that the sample size was sufficient to show the effect sizes reported.

13.7 Summary

The results presented in this chapter show that the manipulations were successful. The findings of Experiment 1 are confirmed by the results of Experiment 2. The multivariate analyses of variance (MANOVA) conducted on the Experiment 2 data revealed that only the hypothesis concerning the assumed positive effect of *automated decision support* on the selection of *compensatory decision strategies* could be confirmed. The data of Experiment 2 did not support the hypotheses concerning the effects of *alternative similarity*, the interaction of *DSS x alternative similarity*, and *cognitive style* on *decision strategy* selection.

CHAPTER 14

CONCLUSIONS and DISCUSSION

14.0 Introduction

Two experiments were conducted in this study. Both experiments aimed at investigating the influence of *decision support systems* (DSS), *alternative similarity* and *cognitive style* on *decision strategy* selection. The DSSs developed in support of this study focused on supporting multi-alternative, multi-attribute preferential choice problem solving.

The DSS employed in Experiment 1 included a synthesis of the automated decision aids developed in the DSS studies that are considered fundamental for this research project. The Experiment 1 DSS environment also integrated a computerized process tracing (CPT) model that allows for capturing both information acquisition and information processing behavior. To capture information processing behavior through CPT, an additional operator, called *processing index*, was introduced in Experiment 1.

Based upon the findings of Experiment 1 an enhanced DSS environment was developed in support of Experiment 2. Compared to the Experiment 1 DSS, this DSS included an improved method for capturing decision behavior. Experiment 2 also employed an extended set of operators for measuring decision behavior. This set encompassed nine operators. Three of these operators (*amount of information search*, *variability of information search* and *search index*) are well established in prior DSS research. Although the *evaluation index*, *compensatory index*, *total statements*, and *total information processed* are common operators in DSS research, they were primarily employed in DSS research that relied on verbal protocol analysis (VPA) for capturing decision behavior. The CPT model developed in support of Experiment 2 allows for the use of these four operators in a CPT environment also. Two operators (*processing index* and *evoked set size*) were newly developed in this research project.

In this chapter the findings of both experiments will be summarized in the context of the research question as well as in the context of the contributions put forward in chapter one of this dissertation. The research question will be answered in the first part of this chapter, and the research contributions will be dealt with in the second part. Thereafter the implications for DSS design will be addressed, and in conclusion, the limitations and directions for further research will be discussed.

14.1 Research question

Central to this dissertation has been the research question: “*What is the influence of automated decision support and cognitive style on decision strategy selection, in particular under varying levels of alternative similarity*?” The results of Experiment 2 are in line with the results of Experiment 1, and therefore this research question will be addressed in the context of the overall findings of both experiments.

The results of both experiments indicate that:

The level of compensatory decision support positively influences the selection of compensatory decision strategies. This effect is neither influenced by alternative similarity, nor by the cognitive style dimensions field dependency and need for cognition.

Each of the individual effects included in the research question will be elaborated on in the following sections.

14.1.1 Effects of automated decision support

Through the design and development of an enhanced DSS environment, this study expanded upon prior DSS research (e.g. (Chu & Spires, 2000; Todd & Benbasat, 1991, 1994b, 1999, 2000)). The user interfaces developed in support of Experiment 1 and Experiment 2 include more detailed decision support functionality, whereas the CPT model developed in support of these experiments extends the possibilities for capturing decision behavior. The findings of both Experiment 1 and Experiment 2, concerning the influence of automated decision support on decision behavior, can be considered strong support for the notion that, under the conditions described, decision strategy selection is positively influenced by automated decision support. Or in context of the effort-accuracy framework: the use of normative decision strategies can be induced through automated decision aids when these aids provide support in such a way that the execution of normative strategies requires less effort than the execution of competing alternative strategies.

Concerning the influence of automated decision aids on decision behavior, the findings of both Experiment 1 and Experiment 2 are consistent with the findings of the DSS research considered fundamental for this study (Chu & Spires, 2000; Todd & Benbasat, 1991, 1994b, 1999, 2000).

The findings of both experiments reported in this study justify the conclusion that:

The enhanced DSS environment developed in support of this research can successfully be employed to support multi-alternative, multi-attribute, preferential choice decision making.

14.1.2 Effects of alternative similarity

The findings of Experiment 2 confirm the lack of an alternative similarity effect found in Experiment 1. The explanation is quite possibly that the DSS has already influenced the decision maker to use normative strategies, in which case alternative similarity does not play a key role. Or put it differently: under conditions of compensatory decision support, an alternative similarity effect, if at all present, is overshadowed by a DSS effect, because effort considerations override the potential alternative similarity effects in determining how to use the decision aids.

14.1.3 Effects of cognitive style

Both cognitive style dimensions included in Experiment 2 were not found to influence decision strategy selection. Just like in Experiment 1, decision behavior appeared to be insensitive to field dependency. The results of Experiment 2 offer support for the conclusion drawn as a result of Experiment 1: the fit between the decision task to be executed and the technology provided in support of this task, leaves no room for cognitive style interaction.

This conclusion was also supported by our findings concerning the cognitive style dimension need for cognition (NFC), since the data of Experiment 2 show that NFC is not related to decision strategy selection. Given the decision task to be executed, the user interface is so clear that its utilization is not influenced by personal traits. For example, high NFC individuals are, compared to low NFC individuals, not in an advantageous or disadvantageous position when it comes to fathoming the working of the user interface, given the decision task to be executed.

Assuming that the lack of cognitive style effects is due to a fit between the DSS employed and the demands of the decision tasks, decision behavior can, ceteris paribus, primarily be explained through the principles of the effort-accuracy framework. This conclusion is in line with findings concerning the lack of an alternative similarity effect.

The findings concerning cognitive style as outlined in this study present a strong case that cognitive style does not influence the selection of decision strategies under the conditions specified.

14.2 Validity of alternative similarity and cognitive style findings

Since research on the influence of cognitive style and alternative similarity on decision behavior under conditions comparable to those employed in this research project is sparse, it is difficult to compare our findings with those of others. Concerning our findings on the effects of alternative similarity and cognitive style reported in Experiment 1, the sample size appeared to be insufficient to indisputably conclude the absence of alternative similarity and cognitive style effects. For this reason the results of Experiment 1 do not justify the conclusion that alternative similarity and cognitive style effects do not exist at all. However, due to consistent findings across two independent experiments it seems fair to conclude that, in all likelihood, alternative similarity and cognitive style simply do not influence decision strategy selection (Keppel, 1991, p.108).

As Experiment 1 and Experiment 2 occurred on two independent occasions, the findings of these experiments can be considered validated support for the notion that both alternative similarity and cognitive style do not influence decision behavior under conditions comparable to those employed in both experiments.

14.3 Decision behavior: an extended set of measures

It is important to recognize that, in Experiment 2, development of the dependent variables across the different DSS treatments is consistent with the findings reported in the fundamental studies underlying the research model presented in this dissertation. The five variables newly introduced in Experiment 2: *evaluation index*, *evoked set size*, *compensatory index*, *total statements*, and *total information processed* as well as the *processing index*, developed in context of Experiment 1, appeared to behave in accordance with Hypothesis 1. The results of Experiment 2 indicate that the Function-Information-Processing (FIP) link makes it possible to capture information *processing* behavior through an extended set of six operators, whereas the established operators for capturing information *acquisition* behavior, *amount of information search* and *variability of information search*, also appear to be adequately registered through the DSS environment developed in this study.

The data in table 13.3 reveals that two pairs of variables are highly correlated: *processing index* and *compensatory index*, and *total statements* and *total information processed*. Whereas it does add value to produce both the *processing index* and *compensatory index* concurrently, as the last delivers which kind of actions contribute most to the way information cues are processed, in contrast, the operators *total statements* and *total information processed* do not have to be included concurrently. In fact, *total statements* was introduced by Todd and Benbasat (1999) as an approximation of the overall amount of information processed in completing a decision task. However, through the FIP-link it is possible to exactly determine the absolute amount of information processed, making the use of approximations to assess the value of this measure redundant. When the total *statements measure* does not add value to the analysis in its own right, it can be considered to omit this operator, and fully rely on the *total information processed* measure to determine the overall amount of information processed in completing a decision task

The findings of both Experiment 1 and 2 justify the conclusion that:

CPT tools can be successfully employed to capture both information acquisition and information processing behavior.

14.4 Contributions reviewed

The contributions realized through this research project can be categorized according to the following three general types of contributions: 1) *synthesis of two previous approaches in DSS research*, 2) *replication*, and 3) *extension*. *Synthesis*, because both the DSS and process tracing models developed in this study in fact synthesize previously established models developed by both Todd and Benbasat, and Chu and Spires. This study has illustrated that it is possible to combine both approaches successfully in one series of DSS experiments (more on this below). *Replication*, since the core of the experimental conditions developed by Chu and Spires, and Todd and Benbasat are also implemented in this study. *Extension* is realized through the development of an enhanced DSS environment and extended measuring instrument, as well as through the introduction of context effects and cognitive style constructs. Table 14.1 shows the relationships between the specific contributions developed in chapter one, and the three general types of contributions explained above.

TABLE 14.1: Categorization of the Contributions

Specific Contributions	Synthesis	Replication	Extension
Development of an extended *DSS environment*.	X	X	X
Development of an enhanced *measuring instrument* to capture decision behavior.	X	X	X
Introduction of *context effects* (alternative similarity) in DSS research.			X
Introduction of *cognitive style* in DSS research on preferential choice decision making			X

According to the categorization presented in table 14.1 each of the contributions developed in chapter one adds to the extension of DSS research, whereas only the first two contributions add to synthesis and replication. Each of the contributions put forward in chapter one will now be addressed in context of our findings below.

14.4.1 Extended DSS environment

The extended DSS model developed in this study brings together two established DSS research lines. The core of our DSS model is a synthesis of the DSS models developed by Todd and Benbastat and that of Chu and Spires. Next to the contribution provided through synthesis, the extended DSS model also provides an extension of DSS research, since the final version of our DSS addresses an important limitation of the DSS models employed in prior studies: incomplete decision process tracing. The DSS model developed in this research project extends the scope of potential decision processes captured by CPT methods, without making concessions to the level of both compensatory and noncompensatory decision support provided.

Our CPT model synthesizes the principles of two process tracing methods common in DSS research: VPA and CPT, whereas the FIP-link, developed in context of this synthesis, is an extension of DSS research, since it allows for extended application of CPT tools. By means of the FIP-link the application scope of CPT tools is significantly broadened. The CPT model developed in this study makes it possible to capture both information acquisition *and* information processing behavior. Prior to the development of the CPT model presented in this study, CPT tools were only appropriate for capturing information acquisition behavior, making the use of VPA a prerequisite whenever data on information processing was required. Implementation of our CPT model implies that the advantages of VPA come available to the DSS research community without inducing the drawbacks associated with its use. The methodology developed in this study allows for testing relationships using process tracing measures aimed at capturing information acquisition as well as information processing behavior.

When it comes to capturing information processing behavior, the CPT model developed in this research project can not only be considered an appropriate alternative for VPA, but also allows for better control in data acquisition. The level of detail in capturing process traces of the CPT environment developed in this study reaches far beyond the level of detail supported by VPA. Since the full status of the decision matrix is recorded prior to any action executed by a decision maker, the CPT database for Experiment 2 included more than 750,000 process traces, associated to 66,662 user actions (e.g. open cell, conditional drop, or sort column). Whereas this study's CPT environment on average registered 244 'statements' per participant, Todd and Benbasat report averages of 69 statements (1994), and 60 statements (2000) registered per protocol observation using VPA.

Our enhanced DSS environment addresses the appeal, made by Todd and Benbasat (1991), for the development of a toolkit of techniques to support micro level DSS research. The research projects of Todd and Benbasat contributed to the development of this toolkit by establishing a method that allows for ex ante[34] analyses of "the impact of individual tools on processing, memory and tracking" (Todd & Benbasat, p. 111). This research contributes to the extension of the micro level toolkit since the DSS environment developed in this study allows for detailed and sophisticated ex post analyses on the impact of specific decision aids on processing,

[34] Ex ante in this context refers to prior to the development and implementation of decision aids. An example of such an analysis is provided in table 11.3.

memory and tracking. The FIP-link, for example, makes it possible to determine exactly which information was processed and how many memory recall and tracking operations were replaced through the execution of a single DSS command for any status of the decision matrix. The FIP-link also makes it possible to isolate specific combinations of decision aids used, and to investigate the effects of these combinations on decision behavior. In terms of Todd and Benbasat: the DSS environment developed in this study "takes us beyond the current studies to determine exactly how and why the individual functions impact decision making processes" (Todd & Benbasat, 1991, p.111). Whereas ex ante analyses assume a status of a decision matrix, ex post analyses consider the actual status of the decision matrix at the moment of execution of a specific DSS function.

Since the FIP-link developed in this study makes it possible to capture information acquisition behavior in different ways, it will also be possible to reconsider the 'classical' way of capturing information acquisition data through the traditional information board method. On answering the debriefing questionnaire participants frequently reported the actions required to open the cells of the decision matrix to be 'burdensome'. The FIP-link covers information acquisition in a very detailed fashion, making the employment of 'cell open' commands for the purpose of capturing information acquisition behavior redundant. In fact, excluding 'cell open' commands will also increase the external validity of the DSS since any command introduced to reveal data is in fact an artifact, not initiated for reasons of decision support, but for reasons of monitoring decision behavior.

A final contribution delivered in this context is replication. By replicating the core elements of prior DSS experiments, the results reported in this study contribute to the validation of their findings.

14.4.2 Enhanced measuring instrument

The measuring instrument developed in this study includes nine operators that have never been tested together in a single DSS experiment before. DSS research was extended by the development of the *processing index*, whereas the remaining set of operators is a synthesis of dependent variables applied in prior DSS and marketing research (*evoked set size*). Synthesis is also realized through the implementation of the 'traditional' VPA-operators: *evaluation index*, *compensatory index*, *total statements* and *total information processed* in a CPT environment. The set of operators developed in this study not only increases the degrees of freedom in measuring decision behavior, but can also be considered a measuring instrument for the purpose of creating an enhanced image of the decision process.

14.4.3 Alternative similarity

According to our findings it is legitimate to conclude that, under conditions of automated decision support, alternative similarity does not influence decision behavior. Therefore further research on the effects of alternative similarity on decision behavior under conditions equal to the experimental and DSS conditions specified in this study should be discouraged.

14.4.4 Cognitive style

The findings of this study indicate that cognitive style does not play a significant role in decision strategy selection under the conditions specified. Although the two cognitive style dimensions employed in this study are no more than a modest subset of all cognitive style dimensions available, we discourage further research on the influence of cognitive style on decision behavior in comparable task-technology settings since our data provides strong support for the notion that the decision aids developed in this study (= technology) fit preferential choice decision making (=task) in such a way that little room is left for cognitive style to influence the decision process.

14.5 Implications for DSS design

Implications of DSS research findings for the design of decision support systems are frequently (e.g. (Todd & Benbasat, 1991, 1992, 1999)) shaped in context of the change agency model for directed and nondirected change developed by Silver (1990). Silver contends that DSSs serve as agents for directed and nondirected individual and organizational change. According to the directed change model a DSS is intended to move the decision maker in a predefined direction, whereas the nondirected model aims at designing DSSs that provide "information-processing capabilities that are potentially valuable for performing the task, and the decision maker decides if and how to make use of these capabilities" (Silver, 1990, p.50). The notion of directed and nondirected change underlies the basics of decisional guidance, which can be defined as how a DSS influences its users as they structure and execute decision making processes (Parikh *et al.*, 2001).

By confirming the results of prior DSS research the findings of this study provide additional evidence that it will be possible to *guide* the users of a DSS towards the implementation of normative decision models through effort reducing DSS functions. In the process of designing DSS user interfaces it is important to evaluate the impact of specific decision aids on effort reduction for problem solving. If DSS designers understand the link between DSS functions and effort reduction it will be possible to design systems that fully employ the possibilities of decisional guidance. Although effort reducing principles are a major concern in the design of DSS user interfaces that aim at effectuating shifts toward normative decision behavior, we do not propose to design user interfaces which only include support for normative strategies at the lowest level of effort expenditure and concur with Stabell who argued "The design should not constrain the user in terms of how the system can be used to support the decision process" (Stabell, 1983, p.251). For example, a DSS including only the functions needed to implement the WADD strategy can guide a decision maker to a choice through a minimal number[35] of actions to be performed. However, an analysis of our process traces revealed that the use of the optimal command sequence associated to the implementation of this normative strategy: WEIGHTS, GLOBAL, MATRIX ROW TOTAL, SORT ROW TOTAL was mainly embedded in command sequences also including commands that are not directly associated to this strategy. Based on the findings of this study we recommend a DSS design process that meticulously balances the provision of effort reducing functions, as driver for directed decision behavior, against "providing support that is process independent and under full

[35] In case of the DSS employed in this study: WEIGHTS, GLOBAL, MATRIX ROW TOTAL, SORT ROW TOTAL.

control of the user" (Sprague & Carlson, 1982, p.95), as driver for nondirected decision behavior.

Regarding the support of decision strategies DSS design does not have to deal with alternative similarity. According to our findings decision tasks including similar alternatives do not require support for other decision strategies then tasks including alternatives that are substantially different. The same conclusion can be drawn concerning cognitive style. The fact that DSS design choices can be made less dependent on personal traits can have considerable consequences for the application reach of DSSs. For example, the dissemination of so called customer decision support systems (CDSS) can more easily be executed when DSS development and design does not have to deal with personal characteristics. A customer decision support system is a system that connects a business to "its existing or potential customers, providing support for some part of the customer decision-making process" (O'Keefe & McEachern, 1998, p. 72). Since CDSS aim at existing or potential customers of a company, the developer of a CDSS does not have a captive user that can function as frame of reference for the CDSS design and development process. The fact that the models developed in this study are less sensitive to personal traits increases their 'universality' and will as such contribute to reduced design complexity, which in turn can potentially lead to increased dissemination of CDSSs. Due to increased possibilities of web-enabled decision support technology companies face a broad range of opportunities in supporting decisions of anonymous, unknown decision makers. This observation calls for more universal solutions.

14.6 Limitations

The results of this study are bound by the nature of the problem solving task, subjects and experimental procedures. This study used well-structured problems from the domain of apartment selection. Actual apartment selection decisions are likely to involve more attributes than those employed in the experimental tasks of this study. As one participant remarked on answering the 'final remarks' question included in the post experiment survey: "The only thing missing were pictures of the available rooms, you've got to have the right feeling about the room you select, such a feeling can not be produced from the pure facts presented…..". Although the technology used to develop the DSS employed in this study allows for the integration of additional dimensions as well as multimedia objects such as pictures, we have chosen to use dimensions that are established in prior research on decision making. As a result some external validity may have been sacrificed.

The decision makers in this study were undergraduate business administration students. The use of student participants as surrogates for actual decision makers is not undisputed (e.g. (Gordon *et al.*, 1986; Greenberg, 1987; Khera & Benson, 1970)). When students are used in laboratory experiments as substitutes, the generalizability of the findings is often questioned (Parikh *et al.*, 2001). Although we are aware of this we do believe that the use of student participants is not likely to impact the generalizability of this study's results. Calder *et al.* (1981) argue that most empirical research studies involve two types of generalizability: effects application and theory application. "The first type of generalizability, which we term *effects application*, maps observed data directly into events beyond the research setting. That is, the specific effects obtained are expected to mirror findings that would be observed if data were collected for other populations and settings in the real world. The second type, which we term *theory application*, uses only scientific theory to explain events beyond the research setting.

…..The distinction lies in whether the researcher's primary goal is to apply the specific effects observed or to apply a more general theoretical understanding" (Calder *et al.*, 1981, p. 197). Whereas effects application is based on the premise that sufficient correspondence exists between the sample and the population to expect the observed effects to repeat in the real world, theory application attempts to apply a more general theoretical understanding to various real world situations (Parikh *et al.*, 2001).

Concerning effect application the generalizibility of the findings reported in this study is not considered to be reduced, because students are familiar with apartment selection, and should therefore not be considered surrogates.

On the other hand, theoretical research may not require the use of representative samples, but should rely instead on distinctly different groups of homogeneous samples, since internal validity of the operationalizations used require greater attention than representativeness of the sample used (Berkowitz & Donnerstein, 1982), in other words: "in research designed for theory-testing, concerns about representative samples may be sacrificed in favor of addressing threats to internal validity" (Greenberg, 1987, p.158). Parikh *et al.* (2001) even argue that relatively close substitution does not have to be inappropriate for theory application, provided that a well-controlled research design provides the information needed to evaluate the adequacy of the theory. Especially concerning the evaluation of the validity of the measuring instruments developed in this study we find that homogeneity outweighs representativeness.

Concerning the experimental procedures a potential limitation can be the use of the automated information boards employed for monitoring information acquisition behavior. Although data presentation through information boards is well established in DSS research, the structured tasks required by information boards may have been a limitation. For multi-alternative, multi-attribute preferential choice problems requiring more unstructured environments, generalization of our findings may be diminished. On the other hand, information boards are known to provide objective evidence of information acquisition behavior (Biggs *et al.*, 1985).

The fact that the decision makers participating in the experiments do not have to live with the consequences of the decision made, and as such were less committed to the decision task, may also influence decision behavior. Lack of involvement, however, did not appear to be a problem because in both experiments the answers to the post survey question: "I experienced the decision task as: very boring (=1); boring (=2); neither boring nor enjoying (=3); enjoying (=4); very enjoying (=5)" indicated that the participants enjoyed the execution of the decision task (Experiment 1: M=4.02, SD=1.21; Experiment 2: M=3.87, SD=.61). In addition, more than 70% of the participants took the effort to answer a non mandatory open ended question, asking for a reaction on the experimental session, included in the post experiment survey. Investigation of the answers given revealed that most students provided answers showing a significant level of involvement, frequently including qualifications explicitly addressing that they enjoyed the experiment and considered it valuable to participate.

14.7 Directions for further research

Individuals are often unable to evaluate all available alternatives in great depth prior to making a choice and tend to use two-stage decision processes consisting of an early stage of editing and a subsequent stage of evaluation (Beach, 1993; Kahneman & Tversky, 1979; Payne, 1982; Tversky & Kahneman, 1981). The editing stage covers a preliminary analysis of all available alternatives and is used for screening (or editing) in order to identify the most promising options. The 'editing' performed in this phase of the decision process often yields a simpler representation of the alternatives available which might simplify subsequent evaluation and choice, performed in the second 'evaluation' phase. Bettman and Park (1980) even argue that a more detailed notion of contingency is needed since "the *elements* of the choice heuristics used at any given time are contingent on the properties of the choice task at that particular time" (p.235). To stay in line with prior DSS research this study did not differentiate for multi stage decision processes. However, the measurement instrument and DSS environment developed in this study make it possible to test hypotheses concerning the influence of automated decision aids, task-related differences, and individual differences on decision strategy selection for any particular moment in the decision process. We propose follow up research that aims at investigating how the aforementioned factors influence decision strategy selection across the decision process, using the process tracing measures developed in this study.

Todd and Benbasat (1994b) explain how decision strategies can be discussed in terms of three different effort components: 1) processing effort, 2) attribute recall effort, and 3) tracking effort (see also § 4.2.3). The models developed in this study allow for an investigation of the relationships between specific decision aids and their impact on effort reduction, specified according to the aforementioned three components. We propose follow-up research investigating these relationships.

According to the Elaboration Likelihood Model (ELM) of persuasion, developed by Petty and Cacioppo (1986), an individual's motivation to engage in issue-relevant information processing (the "elaboration likelihood") is fostered by both situational and individual factors. Through the integration of need for cognition this study addressed an important individual motivational factor, however, the perceived personal relevance of information cues, which is believed to be a very important factor affecting an individual's motivation to process information (Petty *et al.*, 1991), is not addressed in this study. The willingness to engage in information search prior to making a decision is influenced by the importance a decision maker gives to the product or service to be chosen (Moorthy *et al.*, 1997). For example, consumers "tend to engage in more search when purchasing higher priced, more visible, and more complex products- i.e., products that intrinsically create greater perceived risk" (Beatty & Smith, 1987, p. 84). The methodology developed in this study can be employed to investigate the influence of product/service importance on decision strategy selection under conditions of automated decision support. Therefore we propose to replicate this study while extending the research design with repeated within-subjects measurements, using a sequence of decision tasks involving different products or services selected from categories that are associated with different levels of involvement[36].

Since this study primarily focused on decision *process* variables, a natural extension would be the integration of decision *outcome* variables. DSS research would benefit from the development of a set of decision outcome variables for two reasons: (1) correct outcomes are difficult to determine for preferential choice problems (Todd & Benbasat, 1994b), and (2) the use of decision outcome variables in DSS research on preferential choice decision making is scarce. For example, the fundamental DSS studies for this research project developed only one decision outcome variable: relative decision quality (Chu & Spires, 2000). Relative decision quality, an operator comparable to the relative performance measure developed by Johnson and Payne

[36] In the behavioral literature the importance given to a product or service is also referred to as 'involvement'

(1985), is operationalized by Chu and Spires (2000) through decision proximity to the normative WADD strategy, calculated by expressing the WADD score of the chosen alternative as a percentage of the highest ranked alternative. This method requires decision makers to either report attribute weights prior to the decision process, or to register attribute weights during the execution of the decision task. Both modes are supported by the methods developed in this study and can as such be used to extend the DSS research reported in the dissertation. However, this relative decision quality approach does not allow for a change in priorities during execution of the decision process. For example, how will proximity be calculated when a decision maker decides to perform a kind of "what-if" analysis using different combinations of attribute weights? This issue requires additional attention in future research. Another opportunity can be the integration of decision outcome variables employed in other areas of DSS research. Based on a literature review, Sharda *et al.* (1988) produced an overview of measures of decision quality employed in DSS research. A potential performance measure that can also be integrated in DSS research on preferential choice decision making is decision time. Decision making speed is critical for success in today's dynamic business environment. Since our study did not impose time constraints, the research design employed in this study can be extended by integrating decision time as dependent variable.

A final direction for further research is the integration of accountability in the research design. When a decision maker is accountable to someone else, the ability to justify a decision will become a factor of interest. Accountability is identified as a factor that might influence decision strategy selection (Beach & Mitchell, 1978; Payne *et al.*, 1993).

14.8 Summary

This chapter reviewed the findings of this study in the context of the research question put forward for this dissertation: "*What is the influence of automated decision support and cognitive style on decision strategy selection, in particular under varying levels of alternative similarity?*" The findings of both experiments conducted in this research indicate that: *the level of compensatory decision support positively influences the selection of compensatory decision strategies. This effect is neither influenced by alternative similarity, nor by the cognitive style dimensions field dependency and need for cognition*. The enhanced DSS environments developed in support of this study includes a computerized process tracing (CPT) model that allows for capturing both information acquisition and information processing behavior. So far, computerized process tracing has only been applied to capture information acquisition behavior. This CPT model, in conjunction with the DSS user interface developed in support of Experiment 2, addresses important limitations of prior DSS experiments. The computerized process tracing model developed in this study also supports the application of an extended set of operators for measuring decision behavior. This extended set allows for the creation of an enriched image of decision behavior. The final section of this chapter addressed the limitations of this study and proposed directions for further research.

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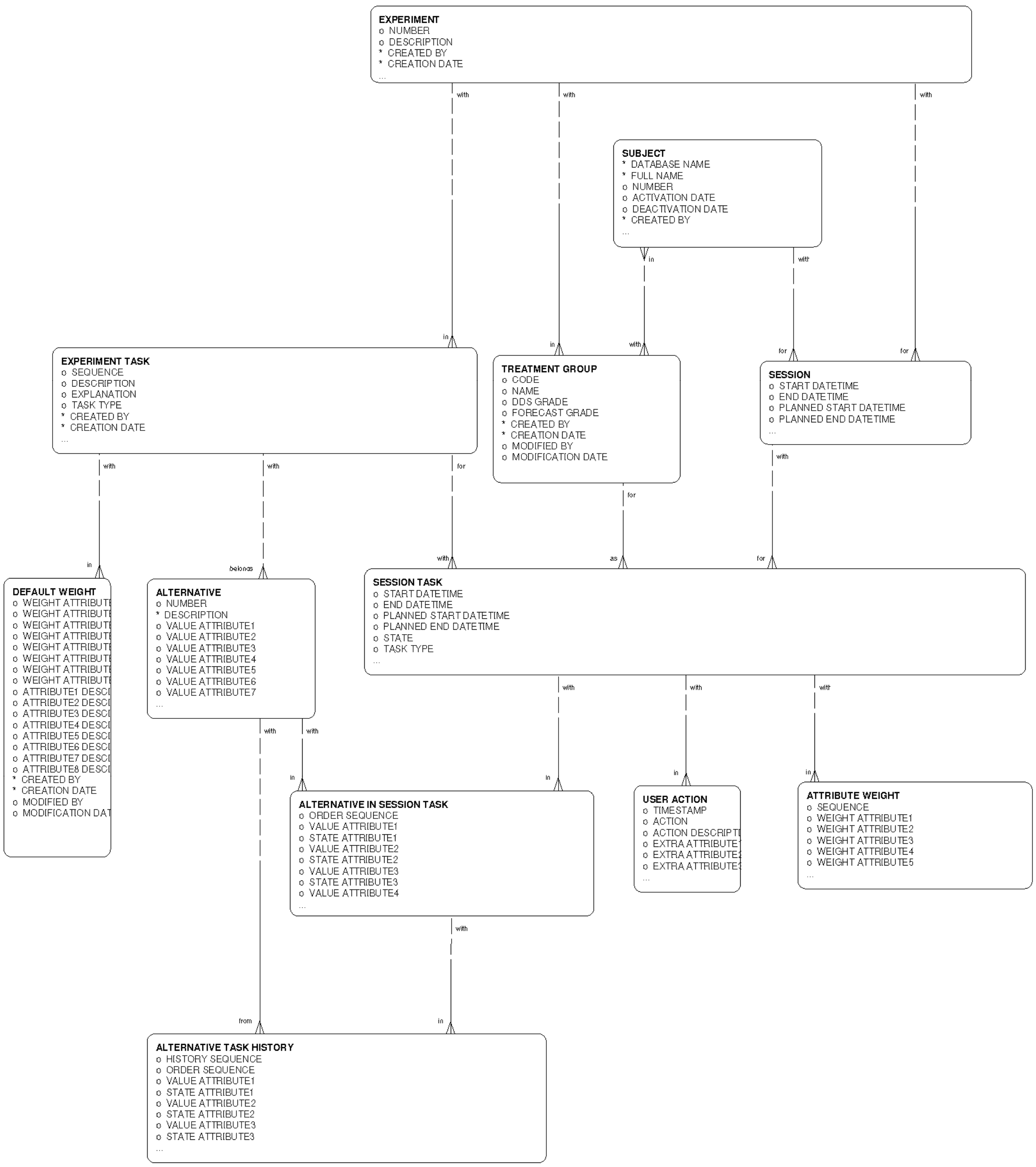
APPENDICES

APPENDIX 1
Data Model Computerized Process Tracing Database



Model version: Final

APPENDIX 2
Choice Sets Experiment 1

The second section of this appendix includes the English version of the Dutch explanation provided to the participants.

Choice Set SIMILAR condition (numeric values)								
	Attributes							
	Rent	***Size***	***Distance City Centre***	***Distance Campus***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord Service Attitude***
Apartment								
App-A	7	5	8	4	7	5	4	5
App-B	8	4	7	6	5	4	7	4
App-C	7	6	6	5	6	4	6	5
App-D	7	6	7	6	7	4	4	4
App-E	6	4	7	6	6	5	7	5
App-F	6	5	7	4	7	6	5	6
App-G	6	5	8	5	7	5	5	4
App-H	8	4	6	5	7	6	6	3
App-I	7	6	7	5	7	4	5	4
App-J	7	5	7	6	6	5	5	4

Choice Set NOT SIMILAR condition (numeric values)								
	Attributes							
	Rent	***Size***	***Distance City Centre***	***Distance Campus***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord Service Attitude***
Apartment								
App-A	7	6	9	4	5	6	6	3
App-B	8	6	4	6	8	8	9	4
App-C	5	7	8	7	8	2	6	4
App-D	4	4	6	8	10	7	6	7
App-E	1	9	10	8	7	5	5	9
App-F	7	3	4	9	9	4	4	5
App-G	9	5	7	10	4	8	5	7
App-H	9	6	6	8	7	8	6	6
App-I	8	3	9	2	6	7	7	5
App-J	9	2	5	5	4	9	6	8

APPENDIX 2
Choice Sets Experiment 1

Onderstaande toelichting op de beslismatrix was opgenomen in de omschrijving van de beslistaak.

Toelichting beslismatrix:
De waarden die de attributen aan kunnen nemen zijn zowel NUMERIEK als ALFANUMERIEK. De numerieke score op een kenmerk wordt uitgedrukt op een schaal die loopt van 1 t/m 10. Voor alle kenmerken geldt dat een score van 1 zeer slecht is en een score van 10 uitmuntend is. Voor iedere numerieke waarde is er tevens een corresponderende alfanumerieke waarde. Een en ander is samengevat in de onderstaande tabel:

	Huur	***Oppervlakte***	***Loopafstand tot centrum***	***Loopafstand tot campus***	***Reinheid***
Stapgrootte	25 euro	2,5 m^2	5 minuten	5 minuten	n.v.t.
Score					
1	450 euro	7,5	45	45	Onacceptabel
2	425 euro	10,0	40	40	Onacceptabel
3	400 euro	12,5	35	35	Zeer Smerig
4	375 euro	15,0	30	30	Smerig
5	350 euro	17,5	25	25	Smoezelig
6	325 euro	20,0	20	20	Redelijk
7	300 euro	22,5	15	15	Schoon
8	275 euro	25,0	10	10	Zeer Schoon
9	250 euro	27,5	5	5	Werkster 1 x per week
10	225 euro	30,0	0	0	Werkster 2 x per week

	Lawaai	***Keuken***	***Service Verhuurder***
Stapgrootte	n.v.t.	n.v.t	n.v.t
Score			
1	Ligt in de aanvliegroute van Schiphol	Zeer Slecht	Onacceptabel
2	Ligt langs een drukke weg	Slecht	Onacceptabel
3	Zeer Rumoerig	Zeer Matig	Noodgevallen
4	Rumoerig	Matig	Contractor <1 kwartaal
5	Normaal Stad	Redelijk	Contractor <1 maand
6	Rustig	Voldoende	Contractor < 1 week
7	Zeer Rustig	Ruim Voldoende	Contractor < 48 uur
8	Stil	Goed	Contractor < 1 dag
9	Zeer Stil	Zeer Goed	24 hrs service contractor
10	Sereen	Uitmuntend	24 hrs service zelf

APPENDIX 2

Choice Sets Experiment 1

Toelichting attributen:

Onacceptabel:
De kwalificatie **'onacceptabel'** heeft te maken met het feit dat er geen appartementen in de beslissingsmatrix zijn opgenomen met een dergelijke score op het betreffende attribuut. Voorbeeld: Een verhuurder die in noodgevallen niet eens reageert wordt als onacceptabel beschouwd.

Reinheid:
De score 9 (werkster 1 X per week) impliceert dat bij de huur een werkster is inbegrepen die 1 keer per week het appartement schoonmaakt.
De score 10 (werkster 2 X per week) impliceert dat bij de huur een werkster is inbegrepen die 2 keer per week het appartement schoonmaakt.

Keuken:
De score 1 (Zeer Slecht) betekent dat er alleen een aanrecht is met een wasbak.
De score 8 (Goed) vertegenwoordigt een moderne inbouwkeuken voorzien van elementaire inbouwapparatuur (dus: veel kastruimte, dubbele spoelbak, fornuis en oven).
De score 9 (Zeer Goed) vertegenwoordigt een moderne inbouwkeuken voorzien van extra inbouwapparatuur (dus: veel kastruimte, dubbele spoelbak, fornuis, oven en magnetron).
De score 10 (Uitmuntend) vertegenwoordigt een moderne inbouwkeuken voorzien van luxe inbouwapparatuur (dus: veel kastruimte, dubbele spoelbak, fornuis, oven, magnetron en afwasmachine).

Service verhuurder:
De twee belangrijkste elementen die bepalend zijn voor de score serviceniveau verhuurder zijn:

1) Tijd waarin de verhuurder garandeert dat een gemeld probleem wordt opgelost, en
2) de vrijheid die men heeft om een keuze te maken wie het probleem oplost. Contractor impliceert dat de verhuurder een bedrijf aanwijst om het probleem op te lossen (score 4-9). De service is uitmuntend als de huurder zelf, 24-uur per dag, een bedrijf mag inhuren om het probleem op te lossen.

Noodgevallen betekent dat de verhuurder alleen problemen oplost in geval van nood, hier geldt echter geen enkele toetsingsgrond wat een noodgeval is en contractueel is de verhuurder nergens toe verplicht.

APPENDIX 2
Choice Sets Experiment 1

ENGLISH VERSION:

The following explanation was included in the description of the decision task.

Attribute values could be viewed in two formats: numeric and text. Numeric values were expressed on a 10-point scale. A numeric value of 1 represents a very bad score, whereas a numeric value of 10 represents an excellent score on the relevant attribute. Each numeric value has a corresponding text value. The relationship between numeric and text values is summarized in the following table.

	Rent	*Size*	*Distance City Centre*	*Distance Campus*	*Cleanliness*
Step Size	25 euros	2,5 m^2	5 minutes	5 minutes	--
Score					
1	450	7,5	45	45	Unacceptable
2	425	10,0	40	40	Unacceptable
3	400	12,5	35	35	Very dirty
4	375	15,0	30	30	Dirty
5	350	17,5	25	25	Dingy
6	325	20,0	20	20	Reasonable
7	300	22,5	15	15	Clean
8	275	25,0	10	10	Very clean
9	250	27,5	5	5	Cleaning lady once a week
10	225	30,0	0	0	Cleaning lady twice a week

	Noise	*Kitchen*	*Landlord Service Attitude*
Step Size	--	--	--
Score			
1	On the Schiphol flight path	Very bad	Unacceptable
2	Near highway	Bad	Unacceptable
3	Very noisy	Very Moderate	Emergency
4	Noisy	Moderate	Contractor <1 quarter
5	Regular city	Reasonable	Contractor <1 month
6	Quiet	Satisfactory	Contractor < 1 week
7	Very quiet	More than satisfactory	Contractor < 48 hours
8	Hushed	Good	Contractor < 1 day
9	Very hushed	Very good	24 hrs contractor
10	Serene	Excellent	24 hrs personal service

APPENDIX 2
Choice Sets Experiment 1

Explanations attribute values:

Unacceptable:
The qualification 'unacceptable' implies that no apartments were included in the choice set with 'unacceptable' scores on the relevant attributes. For example: a landlord that does not even react in case of emergency is considered unacceptable.

Cleanliness:
A score higher than 8 on the cleanliness attribute implies that a cleaning lady is included in the rent (9= once a week, 10=twice a week).

Kitchen:
Very bad (1): only a small kitchen-sink unit is available.
Good (8): implies the presence of a modern built-in kitchen equipped with basic appliances (much cupboard space, double sink, kitchen-range and oven).
Very good (9): implies the presence of a modern built-in kitchen equipped with additional appliances (much cupboard space, double sink, kitchen-range, oven and microwave).
Excellent (10): implies the presence of a modern built-in kitchen equipped with luxurious appliances (much cupboard space, double sink, kitchen-range, oven, microwave, and dishwasher).

Landlord Service Attitude:
The two determinants for establishing a score on this attribute are:

3) Response time guaranteed by the landlord in case of troubles.
4) The extent to which the tenant is allowed to select a contractor to fix the problems.

The qualification 'contractor' implies that the landlord selects a contractor to fix a problem (score 4-9). Service attitude is qualified 'excellent' when a tenant is free to select any contractor itself, 24 hours a day. The qualification 'emergency' implies that the landlord will only fix problems in case of emergency. However the notion 'in case of emergency' is not legally defined and the landlord is not bound by contract to take action.

APPENDIX 3:
Relationship between Decision Aids and Dependent Variables (Experiment 1)

Introduction

This appendix explains how the individual decision aids influence the operators employed to measure decision behavior: *amount of information search*, *variability of information search*, *search index*, and *processing index*. The relationships between the decision aids and these operators are developed in accordance with the methods described by Payne (1976), Payne *et al.* (1993), Chu and Spires (2000), and Biggs *et al.* (1985) (see also § 4.2.4 and § 7.4.1)

Decision Aid(s)	**OPEN**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	The first time an attribute value is accessed it is registered as being “used”.
Variability of Information Search	Yes	Indirect. Each cue that is registered as being “used” is counted for in the calculation of the variability in information accessed per alternative.
Search Index	Yes	Each movement between two cells of the decision matrix is registered. If the n^{th} +1 cell opened by a subject was within the same dimension as the n^{th} cell, but involved a different alternative, then that constituted an instance of an intradimensional (or vertical) move. If the n^{th} +1 cell opened by a subject was within the same alternative as the n^{th} cell, but involved a different dimension, then that constituted an instance of an interdimensional (or horizontal) move. If the n^{th} + 1 cell opened was neither within the same alternative or the same dimension as the n^{th} cell opened, then that was considered to be a *shift* in the pattern of information search.
Processing Index	No	

Decision Aid(s)	**SEQUENCE**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	A cell must already be opened in order to determine its sequence within the attribute range.
Variability of Information Search	No	
Search Index	Yes	Same procedure as applicable to the OPEN command.
Processing Index	No	

APPENDIX 3:
Relationship between Decision Aids and Dependent Variables (Experiment 1)

Decision Aid(s)	**DROP ROW**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	Indirectly (see assumption)
Variability of Information Search	No	Indirectly (see assumption)
Search Index	No	
Processing Index	Yes	The variable *alternative_elements* is increased with the number of opened and not deleted attributes of the alternative selected, at the moment it was dropped.
Assumption: It is assumed that all the available data (cells opened and not deleted) on the alternative selected is processed prior to the elimination of this alternative. (See also: 'upper bound estimates' Todd and Benbasat (1994b, p. 41, footnote 3).		

Decision Aid(s)	**DROP COLUMN**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	Indirectly (see assumption)
Variability of Information Search	No	Indirectly (see assumption)
Search Index	No	
Processing Index	Yes	The variable *attribute_elements* is increased with the number of opened and not deleted attributes of the dimension (column) selected, at the moment it was dropped.
Assumption: It is assumed that all the available data (cells opened and not deleted) in the column selected is processed prior to the elimination of this column.		

Decision Aid(s)	**CONDITIONAL DROP**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	Any attribute value of all available alternatives in the column selected is compared against the threshold value specified.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	The variable *attribute_elements* is increased with the number of not deleted attributes in the column (attribute) selected, at the moment the CONDITIONAL DROP was executed.

Decision Aid(s)	**CALCULATE**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	Any not deleted attribute value of each alternative used in a CALCULATE command is recorded as "used". Because a CALCULATE command will also use the attribute values of cells that are not explicitly opened (cue is "hidden") it will also mark the attribute values which are hidden as "used".
Variability of Information Search	Yes	

APPENDIX 3:
Relationship between Decision Aids and Dependent Variables (Experiment 1)

Decision Aid(s)	**CALCULATE**	
Dependent Variables	***Influenced***	***Remarks***
Search Index	No	
Processing Index	Yes	The variable *alternative_elements* will be increased with the total number of attribute values processed due to the execution of a CALCULATE command. Cells do not have to be "opened". In case two rows are used in a CALCULATE command the variable *attribute_elements* is increased with the number of columns (attributes) available at the moment the command was performed. Each available column "causes" an intradimensional comparison of the relevant attribute values of the two rows specified. Cells do not have to be "opened".
General remarks: Any calculate command performed on TWO rows is an instance of both intradimensional and interdimensional information processing behavior. For example: In the process of determining the difference between two alternatives it is necessary to subtract one alternative from the other (intra) and to compare the results of the individual subtractions over the dimensions (inter).		

Decision Aid(s)	**ROW TOTAL**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	Each not deleted attribute value will be recorded as "used" after the execution of a ROW TOTAL command. Attribute values of cells that are "not opened" are also considered in the ROW TOTAL command.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	Information is processed per alternative so the variable *alternative_elements* is increased with the total number of not deleted attribute values available in the decision matrix at the moment the ROW TOTAL command was executed. Cells do not have to be "opened".

Decision Aid(s)	**GLOBAL**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	Each not deleted attribute value will be recorded as "used" after the execution of a GLOBAL command. Attribute values of cells that are "not opened" are also considered in the GLOBAL command.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	The nature of the GLOBAL command is 'alternative driven' so the variable *alternative_elements* is increased with the total number of not deleted attribute values available in the decision matrix at the moment the GLOBAL command was executed. Cells do not have to be "opened".

APPENDIX 3:
Relationship between Decision Aids and Dependent Variables (Experiment 1)

Decision Aid(s)	**SORT (column)**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	Attribute values must be revealed (='opened') in order to be processed due to the SORT command. The order of the alternatives containing "closed" cells within the dimension (column) specified will not be changed.
Variability of Information Search	No	
Search Index	No	
Processing Index	Yes	A SORT command processes all not deleted and "opened" attribute values within the column (attribute) specified, so the variable *attribute_elements* will be increased with the number of opened cells in the column specified.

Decision Aid(s)	**SORT (row total column)**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	Information usage was already counted for as a result of the ROW TOTAL command.
Variability of Information Search	No	
Search Index	No	
Processing Index	Yes	Whereas the SORT COLUMN command is typically "attribute driven" in its consequences, the SORT ROW TOTAL command is assumed to be "alternative driven". In fact a row total is the accumulation of all data available on an alternative, so a SORT performed on the row totals column can be considered as a reordering of the decision matrix in which all available data on the alternatives not deleted is considered. The variable *alternative_elements* is increased with the number of alternatives available at the moment the SORT ROW TOTAL was performed.
Remarks: Execution of a ROW TOTAL command is a prerequisite for the execution of a SORT on the row totals column.		

The **UNDO**, **RESET**, **CREATE**, **WEIGHTS** and **MAKE a CHOICE** commands do not directly influence the dependent variables.

APPENDIX 4
Relevant Post Experiment Survey Questions (Experiment 1)

The post experiment survey (debriefing) questions were asked in Dutch. The English version of the survey is included in the second part of this appendix.

Dutch version:

Vraag 1:
Wat is uw leeftijd?
Vraag 2:
Wat is uw geslacht? (Man/Vrouw)
Vraag 3:
Woont u op kamers? (Ja/Nee)
Vraag 4:
Heeft u wel eens een kamer geselecteerd? (Ja/Nee)
(Of bent u wel eens actief betrokken geweest bij de keuze van een kamer?)

Vraag 5:
In hoeverre bent u het eens met de volgende stelling?

De tutorial was helder en duidelijk.

Volledig mee oneens	Mee oneens	Noch mee eens Noch mee oneens	Mee eens	Volledig mee eens

Vraag 6:
De volgende vraag heeft betrekking op de beslistaak (selectie van een kamer).

In welke mate vond u de kamers waaruit je kon kiezen op elkaar lijken:

Leken totaal niet op elkaar	Leken niet op elkaar	Neutraal	Leken op elkaar	Leken heel erg op elkaar

Vraag 7:
De volgende stelling heeft betrekking op de beslistaak (selectie van een kamer).

Het selecteren van een kamer uit de gegeven alternatieven vond ik:

Zeer moeilijk	Moeilijk	Noch Moeilijk Noch Eenvoudig	Eenvoudig	Zeer Eenvoudig

Vraag 8:
De volgende stelling heeft betrekking op de beslistaak (selectie van een kamer).

Het selecteren van een kamer uit de gegeven alternatieven vond ik:

Zeer Vervelend	Vervelend	Noch Vervelend Noch Leuk	Leuk	Zeer Leuk

Vraag 9:
Indien u opmerkingen heeft over het totale experiment dan stellen wij het bijzonder op prijs als u deze onderstaand verwoordt.

APPENDIX 4
Relevant Post Experiment Survey Questions (Experiment 1)

English version of the post experiment survey questions:

Question 1:
What is your age?

Question 2:
What is your gender? (Male/Female)

Question 3:
Do you live in rooms? (Yes/No)

Question 4:
Did you ever select an apartment? (Yes/No)
(Or: Have you ever been actively involved in the selection of an apartment?)

Question 5:
The tutorial was clear and obvious to me:

Fully disagree	Disagree	Neutral	Agree	Fully agree

Question 6:
To which extent do you consider the apartments in the decision set similar?

Not similar at all	Not Similar	Neutral	Similar	Very similar

Question 7:
I consider the selection of an apartment from the decision set given:

Very difficult	Difficult	Neutral	Easy	Very easy

Question 8:
I consider the selection of an apartment from the decision set given:

Very boring	Boring	Neutral	Enjoying	Very enjoying

Question 9:
If you have any remarks concerning this experiment, please enter them below.

APPENDIX 5
User Action Report Process Tracing Database

Subject:	T999						
Time	**Action**	**EA-1*)**	**EA-2**	**EA-3**	**EA-4**	**EA-5**	**Alternative**
13:30:34	CO	1	1				106
13:30:34	CO	1	2				106
13:30:35	CO	1	3				106
13:30:36	CO	1	4				106
13:30:36	CO	1	5				106
13:30:37	CO	1	6				106
13:30:38	CO	1	7				106
13:30:38	CO	1	8				106
13:30:39	CO	2	1				107
13:30:40	CO	2	2				107
13:30:40	CO	2	3				107
13:30:41	CO	2	4				107
13:30:41	CO	2	5				107
13:30:42	CO	2	6				107
13:30:43	CO	2	7				107
13:30:43	CO	2	8				107
13:30:44	CO	3	1				108
13:30:45	CO	3	2				108
13:30:46	CO	3	3				108
13:30:46	CO	3	4				108
13:30:48	CO	3	5				108
13:30:48	CO	3	6				108
13:30:49	CO	3	7				108
13:30:50	CO	3	8				108
13:30:51	CO	4	1				109
13:30:51	CO	4	2				109
13:30:52	CO	4	3				109
13:30:52	CO	4	4				109
13:30:53	CO	4	5				109
13:30:54	CO	4	6				109
13:30:55	CO	4	7				109
13:30:56	CO	4	8				109
13:32:28	ROW TOTAL ROW	1					101
13:32:31	ROW TOTAL ROW	2					102
13:32:43	ROW TOTAL ROW	10					110
13:32:55	ROW TOTAL ROW	11					111
13:33:33	SORT COLUMN	10	A				
13:34:19	DROP ROW	4					111
13:35:04	SORT COLUMN	8	A				
13:36:20	CO2	1	1				105
13:36:22	CCL	1	1				105
13:37:15	DROP COLUMN	1					
13:37:27	CREATE ROW	1					
13:41:26	CALCULATE	-20	1	*	-10		

APPENDIX 5
User Action Report Process Tracing Database

Subject:	**T999**						
Time	**Action**	**EA-1*)**	**EA-2**	**EA-3**	**EA-4**	**EA-5**	**Alternative**
13:43:42	CREATE WEIGHT	.1;.1;.1;.1;.1;.1;.1;.3					
13:44:07	GLOBAL	*	-10				
13:44:20	ROW TOTAL MT						
13:45:22	COND DROP	7	<=	.4			
13:45:50	RESET						
13:46:13	DROP ROW	1					101
13:46:32	DROP ROW	1					102
13:47:07	GLOBAL	*	-10				
13:47:21	ROW TOTAL MT						
13:47:34	SORT COLUMN	10	A				
13:48:21	CHOICE ROW	15					

*) EA= Additional Attribute. These additional attributes are used to store command parameters, e.g. attribute weights.

APPENDIX 6
Choice Sets Experiment 2

The second section of this appendix includes the English version of the Dutch explanation provided to the participants.

Choice Set SIMILAR condition (numeric values)								
	Attributes							
	Rent	***Size***	***Distance City Centre***	***Distance Campus***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord Service Attitude***
Apartment								
App-1	6	6	8	5	6	4	4	6
App-2	6	5	6	6	6	5	6	5
App-3	8	4	6	6	7	5	5	4
App-4	7	4	8	5	5	6	4	6
App-5	6	5	8	6	6	5	6	3
App-6	7	4	8	5	6	5	7	3
App-7	8	4	7	4	5	4	7	6
App-8	6	6	7	4	7	4	7	4
App-9	6	6	7	6	6	4	7	3
App-10	8	4	6	4	7	4	7	5
App-11	8	4	6	5	6	5	6	5
App-12	7	5	8	4	7	5	4	5
App-13	6	5	6	4	7	6	5	6
App-14	7	4	7	4	6	6	5	6
App-15	7	5	8	5	7	4	5	4
App-16	8	5	6	4	7	5	7	3
App-17	6	6	6	6	5	6	5	5
App-18	8	5	7	4	5	6	7	3
App-19	6	5	6	5	6	5	7	5
App-20	7	5	7	5	6	4	7	4
App-21	8	4	6	6	6	6	6	3
App-22	6	6	7	4	7	5	7	3
App-23	6	6	7	4	6	4	7	5
App-24	7	4	7	6	6	5	7	3
App-25	6	5	8	6	6	4	4	6
App-26	7	5	7	5	7	4	4	6
App-27	8	4	6	6	6	6	5	4
App-28	6	6	7	4	6	6	5	5
App-29	8	5	7	4	5	4	6	6
App-30	8	5	6	4	6	4	7	5
App-31	6	5	8	6	6	4	6	4
App-32	8	4	6	5	7	6	6	3
App-33	6	6	7	6	5	5	4	6
App-34	6	5	7	5	6	4	6	6
App-35	8	4	6	4	5	5	7	6
App-36	8	5	7	6	5	4	6	4
App-37	7	5	7	6	7	5	4	4
App-38	7	5	7	5	6	6	5	4
App-39	6	5	8	5	7	5	5	4

APPENDIX 6
Choice Sets Experiment 2

Choice Set SIMILAR condition (numeric values)								
	Attributes							
	Rent	***Size***	***Distance City Centre***	***Distance Campus***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord Service Attitude***
Apartment								
App-40	7	5	7	6	7	5	5	3
App-41	6	6	7	5	7	6	4	4
App-42	7	5	8	4	6	5	5	5
App-43	8	5	7	5	7	5	4	4
App-44	7	4	7	5	5	6	6	5
App-45	7	5	7	6	6	5	5	4
App-46	7	4	7	4	7	5	7	4
App-47	7	4	7	5	7	6	6	3
App-48	7	5	7	5	6	5	6	4
App-49	8	4	6	4	7	6	7	3
App-50	7	5	6	5	6	5	6	5

Choice Set NOT SIMILAR condition (numeric values)								
	Attributes							
	Rent	***Size***	***Distance City Centre***	***Distance Campus***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord Service Attitude***
Apartment								
App-1	1	10	3	2	5	10	6	3
App-2	5	5	9	10	8	2	5	9
App-3	2	10	7	6	9	2	1	3
App-4	4	3	3	9	4	10	3	10
App-5	7	3	4	6	10	2	3	7
App-6	3	7	3	10	3	4	4	10
App-7	10	5	10	4	9	4	1	4
App-8	2	8	1	9	9	9	1	9
App-9	4	6	10	1	9	2	3	6
App-10	8	4	10	1	7	7	3	7
App-11	9	5	8	3	5	9	3	3
App-12	6	3	9	2	4	1	10	5
App-13	9	1	10	2	6	9	4	5
App-14	1	8	10	2	7	8	6	10
App-15	2	4	10	8	3	6	5	9
App-16	8	1	8	1	9	6	7	5
App-17	2	6	5	4	10	9	3	7
App-18	1	10	4	6	9	4	3	3
App-19	4	1	9	9	7	5	10	4
App-20	8	5	4	9	7	9	1	8
App-21	6	2	7	9	7	2	5	4
App-22	7	9	2	8	4	2	4	3
App-23	10	1	8	9	3	9	4	4
App-24	5	2	2	10	3	10	2	7
App-25	2	9	5	3	4	7	7	5

APPENDIX 6
Choice Sets Experiment 2

Choice Set NOT SIMILAR condition (numeric values)								
	Attributes							
	Rent	***Size***	***Distance City Centre***	***Distance Campus***	***Cleanliness***	***Noise***	***Kitchen***	***Landlord Service Attitude***
Apartment								
App-26	6	7	8	7	3	3	10	6
App-27	7	2	7	2	6	9	4	8
App-28	4	7	3	4	6	9	8	9
App-29	5	8	2	7	4	3	5	10
App-30	5	6	10	10	5	1	1	9
App-31	10	2	6	3	7	8	3	5
App-32	6	4	5	6	9	8	9	3
App-33	4	4	3	2	5	7	6	9
App-34	8	1	2	8	8	10	6	9
App-35	3	6	1	4	5	10	4	9
App-36	9	1	3	9	4	10	4	10
App-37	9	4	1	10	4	9	10	4
App-38	6	4	10	7	4	10	6	4
App-39	10	1	9	10	3	3	1	7
App-40	1	3	3	7	7	4	10	5
App-41	7	4	3	6	5	4	5	7
App-42	7	6	1	8	9	10	4	3
App-43	3	8	5	9	8	9	3	7
App-44	3	4	10	8	5	8	5	9
App-45	8	3	1	8	5	10	9	3
App-46	10	3	10	6	5	1	6	3
App-47	1	7	8	10	5	3	8	4
App-48	5	1	8	10	8	3	7	4
App-49	3	10	4	3	5	5	4	6
App-50	9	2	7	6	10	7	7	4

Onderstaande toelichting op de beslismatrix was opgenomen in de omschrijving van de beslistaak.

Toelichting beslismatrix:
De waarden die de attributen aan kunnen nemen zijn zowel NUMERIEK als ALFANUMERIEK. De numerieke score op een kenmerk wordt uitgedrukt op een schaal die loopt van 1 t/m 10. Voor alle kenmerken geldt dat een score van 1 waardeloos, en een score van 10 uitmuntend is. Voor iedere numerieke waarde is er tevens een corresponderende alfanumerieke waarde. Een en ander is samengevat in de onderstaande tabel:

APPENDIX 6
Choice Sets Experiment 2

		Huur	*Oppervlakte*	*Loopafstand tot centrum*	*Loopafstand tot campus*
	Stapgrootte	25 euro	2,5 m^2	5 minuten	5 minuten
Score					
1		450 euro	7,5 m^2	45 min.	45 min.
2		425 euro	10,0 m^2	40 min.	40 min.
3		400 euro	12,5 m^2	35 min.	35 min.
4		375 euro	15,0 m^2	30 min.	30 min.
5		350 euro	17,5 m^2	25 min.	25 min.
6		325 euro	20,0 m^2	20 min.	20 min.
7		300 euro	22,5 m^2	15 min.	15 min.
8		275 euro	25,0 m^2	10 min.	10 min.
9		250 euro	27,5 m^2	5 min.	5 min.
10		225 euro	30,0 m^2	0 min.	0 min.

		Reinheid	*Lawaai*	*Keuken*	*Service Verhuurder*
Score					
1		Onacceptabel	Ligt in de aanvliegroute van Schiphol	Geen	Waardeloos
2		Onacceptabel	Ligt langs een drukke weg	Zeer Slecht	Zeer Slecht
3		Zeer Smerig	Zeer Rumoerig	Slecht	Slecht
4		Smerig	Rumoerig	Onvoldoende	Onvoldoende
5		Smoezelig	Normaal Stad	Matig	Matig
6		Acceptabel	Rustig	Voldoende	Voldoende
7		Schoon	Zeer Rustig	Ruim Voldoende	Ruim Voldoende
8		Zeer Schoon	Stil	Goed	Goed
9		Werkster 1 x per week	Zeer Stil	Zeer Goed	Zeer Goed
10		Werkster 2 x per week	Sereen	Uitmuntend	Uitmuntend

Toelichting attributen:

Onacceptabel:
De kwalificatie **'onacceptabel'** heeft te maken met het feit dat er geen appartementen in de beslissingsmatrix zijn opgenomen met een dergelijke score op het betreffende attribuut. Voorbeeld: Appartementen die op het attribuut reinheid minder dan Zeer Smerig scoren worden als onacceptabel beschouwd.

Reinheid:
De score 9 (werkster 1 X per week) impliceert dat bij de huur een werkster is inbegrepen die 1 keer per week het appartement schoonmaakt.
De score 10 (werkster 2 X per week) impliceert dat bij de huur een werkster is inbegrepen die 2 keer per week het appartement schoonmaakt.

Keuken:
De score voor de *keuken* is vastgesteld door een onafhankelijke commissie die is gespecialiseerd in het evalueren van huurwoningen. Uiteraard zijn voor alle beschikbare 1-persoons kamers dezelfde criteria gehanteerd.

Service verhuurder:
De score voor *service* is vastgesteld door een onafhankelijke commissie die is gespecialiseerd in het evalueren van huurwoningen. Evaluatiecriteria waren onder andere: de snelheid van reageren bij problemen, en de vrijheid die de huurder heeft om zelf ondernemingen in te schakelen voor het oplossen van problemen zonder extra financiële consequenties voor de huurder.

APPENDIX 6
Choice Sets Experiment 2

English version:

The following explanation was included in the description of the decision task.

Attribute values could be viewed in two formats: numeric and text. Numeric values were expressed on a 10-point scale. A numeric value of 1 represents a very bad score, whereas a numeric value of 10 represents an excellent score on the relevant attribute. Each numeric value has a corresponding text value. The relationship between numeric and text values is summarized in the following table.

	Rent	*Size*	*Distance City Centre*	*Distance Campus*
Step Size	25 euros	2,5 m^2	5 minutes	5 minutes
Score				
1	450	7,5	45	45
2	425	10,0	40	40
3	400	12,5	35	35
4	375	15,0	30	30
5	350	17,5	25	25
6	325	20,0	20	20
7	300	22,5	15	15
8	275	25,0	10	10
9	250	27,5	5	5
10	225	30,0	0	0

	Cleanliness	*Noise*	*Kitchen*	*Landlord Service Attitude*
Step Size	--	--	--	--
Score				
1	Unacceptable	On the Schiphol flight path	No kitchen	Worthless
2	Unacceptable	Near highway	Very Bad	Very Bad
3	Very dirty	Very noisy	Bad	Bad
4	Dirty	Noisy	Unsatisfactory	Unsatisfactory
5	Dingy	Regular city	Moderate	Moderate
6	Reasonable	Quiet	Satisfactory	Satisfactory
7	Clean	Very quiet	More than satisfactory	More than satisfactory
8	Very clean	Hushed	Good	Good
9	Cleaning lady once a week	Very hushed	Very good	Very good
10	Cleaning lady twice a week	Serene	Excellent	Excellent

APPENDIX 6
Choice Sets Experiment 2

Explanations attribute values:

Unacceptable:
The qualification ‘unacceptable’ implies that no apartments were included in the choice set with ‘unacceptable’ scores on the relevant attributes. For example: a landlord that does not even react in case of emergency is considered unacceptable.

Cleanliness:
A score higher than 8 on the cleanliness attribute implies that a cleaning lady is included in the rent (9= once a week, 10=twice a week).

Kitchen:
The score for kitchen was determined by an independent committee specialized in the evaluation of rented apartments. The same evaluation criteria were applied for all apartments.

Landlord Service Attitude:
The score for landlord service attitude was determined by an independent committee specialized in the evaluation of rented apartments. Important evaluation criteria were: landlord’s response time in case of troubles, and the extent to which a tenant is free to select a contractor to fix the problems without additional financial consequences.

APPENDIX 7:
Relationship between Decision Aids and Dependent Variables (Experiment 2)

Introduction
Concerning the explanation of calculation methods for the dependent variables this appendix will only address the issues that were changed in Experiment 2 compared to Experiment 1 (see Appendix 3). Actually, two modifications are relevant:

1) the introduction of five new operators for measuring decision behavior: 1) *evaluation index*, *evoked set size*, *compensatory index*, *total statements*, *and total information processed*, and
2) the introduction of new DSS commands.

In Experiment 2 no changes were implemented in the calculation method for the dependent variables that were also employed in Experiment 1 (*amount of information search*, *variability of information search*, *search index*, and *processing index*). Accordingly this appendix will only elaborate on these four operators for the commands that are newly introduced (or modified) in Experiment 2. Additionally, the calculation method for the newly introduced operators will be explained for all the functions included in the DSS user interface of Experiment 2. Table A7 shows an overview of the commands included in the DSS user interfaces of both experiments reported in this study.

TABLE A7: DSS functions Experiment1 versus Experiment 2

DSS Function	Exp 1	Exp 2	DSS Function	Exp 1	Exp 2
OPEN	√	Mod	CALCULATE	√	Mod
CLOSE	√	√	SORT	√	√
SEQUENCE	√	-	WEIGHTS	√	√
DROP COLUMN/ROW	√	√	GLOBAL	√	√
CONDITIONAL DROP	√	√	MAKE a CHOICE	√	√
ROW TOTAL	√	Mod	UNDO	√	√
ROW TOTAL MATRIX	-	New	RESET	√	√
CREATE	√	√			

√ = function provided; - = function not provided; MOD = function is modified compared to previous model; New = New function.

The **UNDO**, **RESET**, and **MAKE a CHOICE** commands will not be elaborated on in this appendix because these commands do not directly influence the dependent variables employed in Experiment 2.

Evoked Set Size:
This operator is not directly influenced by individual DSS functions. Evoked set size is calculated as the number of alternatives that are still available in the decision matrix at the moment of execution of the MAKE a CHOICE command (end of the decision process).
Total Statements:
To calculate this operator, the method described by Todd and Benbasat (1999) was adopted and modified for the specific commands developed in this research project (MATRIX ROW TOTAL and WEIGHTS).

The relationships between the decision aids and the other three newly introduced operators in Experiment 2 (*evaluation index*, *compensatory index*, *and total information processed*) are developed in accordance with the methods described by Todd and Benbasat (see also § 3.6.2 and § 12.4.1)

APPENDIX 7:
Relationship between Decision Aids and Dependent Variables (Experiment 2)

Decision Aid(s)	**OPEN**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	See appendix 3.
Variability of Information Search	Yes	
Search Index	Yes	
Processing Index	No	
Evaluation Index	No	
Compensatory Index	No	
Total Statements	No	
Total Information Used	Yes	Any time an attribute value is accessed it is registered as being “used”

Decision Aid(s)	**DROP ROW**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	See appendix 3.
Variability of Information Search	No	
Search Index	No	
Processing Index	Yes	
Evaluation Index	No	Because DROP ROW might as well be part of an INDEPENDENT evaluation process, as well as part of a DEPENDENT evaluation process, we assume that the DROP ROW does not influence the number of (IN)DEPENDENT evaluations. (In the end, the DROP ROW is indirectly accounted for in the operator Evoked Set Size)
Compensatory Index	Yes	Compensatory statement.
Total Statements	Yes	
Total Information Used	Yes	See assumption.
Assumption: It is assumed that all the available data (cells opened and not deleted) on the alternative selected is processed prior to the elimination of this alternative. (See also: ‘upper bound estimates‘ (Todd & Benbasat, 1994b, p.41, footnote 3).		

Decision Aid(s)	**DROP COLUMN**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	See appendix 3.
Variability of Information Search	No	
Search Index	No	
Processing Index	Yes	
Evaluation Index	No	
Compensatory Index	Yes	The DROP COLUMN is a typical noncompensatory statement.
Total Statements	Yes	
Total Information Used	Yes	See assumption.
Assumption: It is assumed that all the available data (cells opened and not deleted) in the column selected is processed prior to the elimination of this column.		

APPENDIX 7:
Relationship between Decision Aids and Dependent Variables (Experiment 2)

Decision Aid(s)	**CONDITIONAL DROP**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	See appendix 3.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	
Evaluation Index	Yes	Independent evaluations. Number of alternatives (cells of not deleted rows) available in the column specified. The cells do NOT have to be opened, because all available alternatives will be evaluated.
Compensatory Index	Yes	The number of alternatives eliminated due to execution of the CONDITIONAL DROP command. In fact this command is the automated implementation of a series of DROP ROW commands.
Total Statements	Yes	
Total Information Used	Yes	The number of alternatives available at the time the CONDITIONAL DROP command was executed.

Decision Aid(s)	**CALCULATE**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	See appendix 3.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	
Evaluation Index	Yes	A CALCULATE-command is the most explicit instance of a dependent evaluation. Two alternatives might be compared to each other.
Compensatory Index	Yes	The number of rows (alternatives as well as additional rows) used in the CALCULATE-command.
Total Statements	Yes	
Total Information Used	Yes	All available data on each alternative included in the CALCULATE command.
General remarks: Any CALCULATE command performed on *two* rows is an instance of both intradimensional and interdimensional information processing behavior. For example: in the process of determining the difference between two alternatives it is necessary to subtract one alternative from the other (intra) and to compare the results of the individual subtractions over the dimensions (inter).		

Decision Aid(s)	**MATRIX ROW TOTAL**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	See appendix 3 (ROW TOTAL).
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	
Evaluation Index	No	
Compensatory Index	Yes	Compensatory statement(s). The number of alternatives available in the decision matrix at the time the MATRIX ROW TOTAL command was executed. Additional rows included. If this command was counted for as 1 compensatory statement, its effect

APPENDIX 7:
Relationship between Decision Aids and Dependent Variables (Experiment 2)

Decision Aid(s)	MATRIX ROW TOTAL	
		would have been similar to the ROW TOTAL command. In fact, its effect should be different. This command should be considered as a series of individual ROW TOTALS.
Total Statements	Yes	
Total Information Used	Yes	Each not deleted attribute value will be recorded as "used" after the execution of a MATRIX ROW TOTAL command. Attribute values of cells that are "not opened" are also considered in the MATRIX ROW TOTAL command.
General remarks: The MATRIX ROW TOTAL command can be considered a substitute for a series of single ROW TOTAL commands.		

Decision Aid(s)	ROW TOTAL	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	Each not deleted attribute value will be recorded as "used" after the execution of a ROW TOTAL command. Attribute values of cells that are "not opened" are also considered in the ROW TOTAL command.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	Information is processed per alternative so the variable *alternative_elements* is increased with the number of attribute values available in the row selected, at the moment the ROW TOTAL command was executed. Cells do not have to be "opened".
Evaluation Index	No	
Compensatory Index	Yes	Compensatory Statement.
Total Statements	Yes	
Total Information Used	Yes	Each not deleted attribute value will be recorded as "used" after the execution of a ROW TOTAL command. Attribute values of cells that are "not opened" are also considered in the ROW TOTAL command.

Decision Aid(s)	GLOBAL	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	Yes	See appendix 3.
Variability of Information Search	Yes	
Search Index	No	
Processing Index	Yes	
Evaluation Index	No	
Compensatory Index	Yes	The number of alternatives available in the decision matrix at the time the GLOBAL-command was executed.
Total Statements	Yes	The number of alternatives available in the decision matrix at the time the GLOBAL-command was

APPENDIX 7:
Relationship between Decision Aids and Dependent Variables (Experiment 2)

Decision Aid(s)	**GLOBAL**	
		executed.
Total Information Used	Yes	Each not deleted attribute value will be recorded as “used” after the execution of a GLOBAL command. Attribute values of cells that are “not opened” are also considered in the GLOBAL command.
General remarks: The execution of a GLOBAL command can be considered a substitute for the execution of a series of single CALCULATE-commands.		

Decision Aid(s)	**SORT (column)**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	See appendix 3.
Variability of Information Search	No	
Search Index	No	
Processing Index	Yes	
Evaluation Index	No	Dependent evaluations. Number of cells opened and not deleted in the column specified. (Cells that are not “opened” are not processed in the SORT command).
Compensatory Index	Yes	Noncompensatory statement.
Total Statements	No	
Total Information Used	Yes	Attribute values must be revealed (=’opened’) in order to be processed due to the SORT command. Each “opened” cell will be counted for.

Decision Aid(s)	**SORT (row total column)**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	See appendix 3.
Variability of Information Search	No	
Search Index	No	
Processing Index	Yes	
Evaluation Index	No	Dependent evaluations. Number of alternatives for which a row total was calculated at the moment the SORT ROW TOTAL was performed.
Compensatory Index	Yes	Compensatory Statement. Because all data concerning an alternative is ‘accumulated’ in the alternative’s row total (compensatory) a sort of the row totals should be considered as a compensatory statement. In fact, all relevant information is used.
Total Statements	No	
Total Information Used	No	
Remarks: Execution of a ROW TOTAL/MATRIX ROW TOTAL command is a prerequisite for the execution of a SORT on the row totals column.		

APPENDIX 7:
Relationship between Decision Aids and Dependent Variables (Experiment 2)

Decision Aid(s)	**CREATE**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	
Variability of Information Search	No	
Search Index	No	
Processing Index	No	
Evaluation Index	No	
Compensatory Index	No	
Total Statements	Yes	
Total Information Used	No	

Decision Aid(s)	**WEIGHTS**	
Dependent Variables	***Influenced***	***Remarks***
Amount of Information Search	No	
Variability of Information Search	No	
Search Index	No	
Processing Index	No	
Evaluation Index	No	
Compensatory Index	Yes	Compensatory Statement.
Total Statements	Yes	
Total Information Used	No	

APPENDIX 8
Need for Cognition Scale

The Dutch version of the need for cognition scale was used in the experiment. The English version is included in the second section of this appendix.

Nederlandstalige versie van de ‘need for cognition scale’ ontwikkeld door Pieters, Verplanken en Modde (1987) en Verplanken (1993).

1. Als ik moet kiezen heb ik liever een ingewikkeld dan een simpel probleem.
2. Ik ben graag verantwoordelijk voor een situatie waarin veel nagedacht moet worden.
3. Nadenken is <u>niet</u> mijn idee van plezier hebben. (*)
4. Ik doe liever iets waarbij weinig nagedacht hoeft te worden dan iets waarbij mijn denkvermogen zeker op de proef wordt gesteld. (*)
5. Ik houd niet van situaties waarin ik diep moet nadenken. (*)
6. Iets langdurig en precies afwegen geeft mij voldoening.
7. Ik denk alleen zoveel als nodig is. (*)
8. Ik denk liever over kleine dagelijkse dingen dan over lange-termijn zaken na. (*)
9. Ik houd van taken waarbij weinig nagedacht hoeft te worden als ik ze eenmaal geleerd heb. (*)
10. Het idee om op mijn verstand te vertrouwen vind ik aantrekkelijk.
11. Ik geniet echt van een taak waarbij men met nieuwe oplossingen voor problemen moet komen.
12. Nieuwe manieren leren om te denken trekt me <u>niet</u> bijzonder aan. (*)
13. Ik vind het prettig als mijn leven gevuld is met puzzels die ik moet oplossen.
14. Het idee om abstract te denken vind ik aantrekkelijk.
15. Ik heb liever een taak die intellectueel, moeilijk en belangrijk is, dan een taak die enigszins belangrijk is, maar waarbij je niet veel hoeft na te denken.
16. Als ik een taak heb voltooid die veel mentale inspanning heeft gevergd ben ik meer opgelucht dan voldaan. (*)
17. Ik vind het voldoende wanneer iets blijkt te werken: hoe of waarom het precies werkt interesseert me niet. (*)
18. Gewoonlijk maak ik zelfs uitgebreid afwegingen over zaken die niet persoonlijk op mijzelf betrekking hebben.

Antwoorden werden gegeven op een 7-punts Likert schaal:

zeer mee oneens 1 2 3 4 5 6 7 zeer mee eens

(*) Deze items zijn tegengesteld gecodeerd.

APPENDIX 8
Need for Cognition Scale

Need for Cognition Scale
(Cacioppo, Petty, and Feng Kao, 1984)

1. I would prefer complex to simple problems.
2. I like to have the responsibility of handling a situation that requires a lot of thinking.
3. Thinking is not my idea of fun.(*)
4. I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.(*)
5. I try to anticipate and avoid situations where there is likely chance I will have to think in depth about something.(*)
6. I find satisfaction in deliberating hard and for long hours.
7. I only think as hard as I have to.(*)
8. I prefer to think about small, daily projects to long-term ones.(*)
9. I like tasks that require little thought once I have learned them.(*)
10. The idea of relying on thought to make my way to the top appeals to me.
11. I really enjoy a task that involves coming up with new solutions to problems.
12. Learning new ways to think doesn't excite me very much.(*)
13. I prefer my life to be filled with puzzles that I must solve.
14. The notion of thinking abstractly is appealing to me.
15. I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.
16. I feel relief rather than satisfaction after completing a task that required a lot of mental effort.(*)
17. It's enough for me that something gets the job done; I don't care how or why it works.(*)
18. I usually end up deliberating about issues even when they do not affect me personally.

Answers were given on a seven-point Likert-type scale:

Totally Disagree	1	2	3	4	5	6	7	Totally Agree

(*) Reverse scoring is used on this item.

APPENDIX 9
Relevant Post Experiment Survey Questions (Experiment 2)

The post experiment survey (debriefing) questions were asked in Dutch. The English version of the survey is included in the second part of this appendix.

Dutch version:

Vraag 1:
Wat is uw leeftijd?
Vraag 2:
Wat is uw geslacht? (Man/Vrouw)
Vraag 3:
In het kader van welk vak neemt u deel aan dit experiment?

Business Intelligence/BOS **Information Systems** **Beide vakken**

Vraag 4:
Woont u op kamers? (Ja/Nee)

Vraag 5:
Heeft u wel eens een kamer geselecteerd? (Ja/Nee)
(Of bent u wel eens actief betrokken geweest bij de keuze van een kamer?)

Vraag 6:
In hoeverre bent u het eens met de volgende stelling?

De tutorial was helder en duidelijk.

Volledig mee oneens	Oneens	Neutraal	Eens	Volledig mee eens

Vraag 7:
De volgende vraag heeft betrekking op de laatste taak (DECISION TASK), betreffende de selectie van een 1-persoons kamer.

In welke mate vond u de kamers waaruit u kon kiezen op elkaar lijken:

Leken totaal niet op elkaar	Leken niet op elkaar	Neutraal	Leken op elkaar	Leken zeer veel op elkaar

Vraag 8:
De volgende vraag heeft betrekking op de laatste taak (DECISION TASK), betreffende de selectie van een 1-persoons kamer.

Het bepalen van een keuze uit de gegeven verzameling kamers vond ik:

Zeer moeilijk	Moeilijk	Neutraal	Eenvoudig	Zeer eenvoudig

Vraag 9:
De volgende vraag heeft betrekking op de laatste taak (DECISION TASK), betreffende de selectie van een 1-persoons kamer.

Het selecteren van een kamer uit de gegeven alternatieven vond ik:

Zeer vervelend	Vervelend	Neutraal	Leuk	Zeer leuk

APPENDIX 9
Relevant Post Experiment Survey Questions (Experiment 2)

Vraag 10:
De volgende stelling heeft betrekking op de laatste taak (DECISION TASK), betreffende de selectie van een 1-persoons kamer.

De variatie in waarden van de verschillende kenmerken (huur, oppervlakte, etc.) was beperkt.

Volledig mee oneens	Oneens	Neutraal	Eens	Volledig mee eens

Vraag 11:
Indien u opmerkingen heeft over het totale experiment dan stellen wij het bijzonder op prijs als u deze onderstaand verwoordt.

English version of the post experiment survey questions:

Question 1:
What is your age?
Question 2:
What is your gender? (Male/Female)
Question 3:
For which class did you enroll for this experiment?
Business Intelligence Management Information Systems Both
Question 4:
Do you live in rooms? (Yes/No)
Question 5:
Did you ever select an apartment? (Yes/No)
(Or: Have you ever been actively involved in the selection of an apartment?)

Question 6:
The tutorial was clear and obvious to me:

Fully disagree	Disagree	Neutral	Agree	Fully agree

Question 7:
To which extent do you consider the apartments in the decision set similar?

Not similar at all	Not similar	Neutral	Similar	Very similar

Question 8:
I consider the selection of an apartment from the decision set given:

Very difficult	Difficult	Neutral	Easy	Very easy

Question 9:
I consider the selection of an apartment from the decision set given:

Very boring	Boring	Neutral	Enjoying	Very enjoying

Question 10:
The variance in attribute values (e.g. rent, size, etc.) for the different apartments was limited:

Fully disagree	Disagree	Neutral	Agree	Fully agree

Question 11:
If you have any remarks concerning this experiment, please enter them below.

DUTCH SUMMARY

NEDERLANDSTALIGE SAMENVATTING

van

De Invloed van Beslissingsondersteunende Systemen, Context Effecten en Cognitieve Stijl op de Keuze van een Beslissingsstrategie

Introductie

Het adagium van de wereldberoemde autofabrikant Henry Ford (1863-1947): "*ik kan auto's in iedere kleur leveren, zolang het maar zwart is*" toont hoe de wereld sindsdien is veranderd: een nieuwe Mini Cooper is er in vijftigduizend verschillende uitvoeringen. Het keurslijf van een beperkte keuze, één van de fundamenten onder het succes van Henry Ford, past anno 2006 niet meer in de visie van marktgeoriënteerde organisaties. Integendeel, toenemende keuzevrijheid lijkt voor ondernemingen het toverwoord te zijn. Recent marktonderzoek (Marketresponse, 2005) heeft zelfs aangetoond dat moderne consumenten het aantal keuzemogelijkheden eerder te groot dan te klein vinden en wel in het bijzonder als het gaat om meer complexe producten die een vergelijking op meerdere kenmerken vereisen. De moderne consument leidt zelfs aan keuzestress! Om nu te voorkomen dat consumenten door de spreekwoordelijke bomen het bos niet meer zien ontwikkelen steeds meer organisaties geautomatiseerde hulpmiddelen ter ondersteuning van besluitvormingsprocessen. De Nederlandse overheid bijvoorbeeld, bood in 2006, naar aanleiding van de introductie van een nieuw zorgverzekeringstelsel, middels de website www.kiesbeter.nl, een beslissingsondersteunend systeem, dat haar burgers kon helpen bij het kiezen van een nieuwe ziektekostenverzekering.

Besluitvormingsprocessen kunnen alleen op de gewenste manier worden ondersteund als beslissingsgedrag wordt begrepen. In het begrijpen van beslissingsgedrag staat de volgende vraag centraal: Hoe *beslissen* mensen om te *beslissen* (Payne *et al*., 1993)? Om deze vraag te kunnen beantwoorden is het belangrijk te weten welke strategieën mensen gebruiken om tot een beslissing te komen. Besluitvormers kunnen namelijk gebruikmaken van een scala aan beslissingsstrategieën, variërend van vuistregels voor bijvoorbeeld de keuze van een nieuwe auto, tot en met geavanceerde algoritmes voor het bepalen van een nieuwe locatie voor een te bouwen distributiecentrum. Tevens geldt dat de kwaliteit van een beslissing mede wordt beïnvloed door de toegepaste beslissingsstrategie. In de literatuur wordt *beslissingsstrategie* gedefinieerd als de methode die door mensen wordt gebruikt om gegevens te verzamelen en te combineren ten einde een beslissing te kunnen nemen (Jarvenpaa, 1989). Beslissingsstrategieën staan centraal in dit onderzoek.

Er zijn verschillende factoren die van invloed zijn op de keuze van een beslissingsstrategie. Dit onderzoek richt zich specifiek op de invloed van de volgende factoren: *kenmerken van de beslissingstaak*, *kenmerken van de besluitvormer* en *kenmerken van een beslissingsondersteunend*[37] *systeem*.

Kenmerken van een beslissingstaak kunnen worden onderverdeeld in twee categorieën: *taak effecten* en *context effecten*. Taak effecten betreft een groep factoren die zijn gerelateerd aan

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[37] De termen 'beslissingsondersteunende systemen' en 'decision support systems (DSS)' hebben in dit onderzoek dezelfde betekenis en zullen in deze samenvatting door elkaar worden gebruikt.

de structurele kenmerken van een beslissingstaak, zoals: het aantal alternatieven in een keuzeset, het aantal kenmerken waarmee de alternatieven worden beschreven, tijdsdruk en de manier waarop informatie wordt gepresenteerd. Context effecten betreft een groep factoren die zijn gerelateerd aan de specifieke waarden van de alternatieven die zijn opgenomen in de keuzeset. Voorbeelden van context effecten zijn: mate waarin beschikbare alternatieven op elkaar lijken (‘*alternative similarity*[38]’), mate waarin een keuzeset kwalitatief goede alternatieven omvat en de manier waarop een probleem is verwoord.

Als het gaat om de kenmerken van een besluitvormer speelt het construct cognitieve stijl een belangrijke rol. Cognitieve stijl kan worden gedefinieerd als de manier waarop individuen informatie en data, die relevant zijn voor het oplossen van een beslissingsprobleem, verzamelen, formuleren, analyseren en interpreteren.

Onderzoek heeft aangetoond (bijvoorbeeld: (Chu & Spires, 2000; Todd & Benbasat, 1999, 2000)) dat ook het gebruik van decision support systemen (DSS) van invloed kan zijn op de keuze van een beslissingsstrategie.

Om beslissingsgedrag te kunnen analyseren is het van belang dat de processen die ten grondslag liggen aan een beslissing worden vastgelegd. DSS onderzoek maakt voornamelijk gebruik van twee methoden voor het vastleggen van beslissingsprocessen: *verbale protocol analyse* (VPA), en ‘*computerized process tracing*’ (CPT) (Cook, 1993). VPA is een methodiek waarbij data wordt geanalyseerd die is verkregen door de besluitvormer hardop te laten denken gedurende de uitvoering van een beslissingstaak. Bij CPT hoeft de besluitvormer niet hardop te denken, maar worden software en databases gebruikt om op zeer gedetailleerd niveau vast te leggen welke functies van een beslissingsondersteunend systeem door de besluitvormer zijn gebruikt tijdens het uitvoeren van de beslissingstaak. Verbale protocollen worden voornamelijk gebruikt om vast te stellen *hoe* informatie is verwerkt (‘*information processing*’), terwijl ‘computerized process tracing’ voornamelijk wordt gebruikt om vast te stellen *welke* informatie is verzameld (‘*information acquisition*’). ‘*Information acquisition*’ en ‘*information processing*’ worden beschouwd als de twee determinanten van beslissingsgedrag (Svenson, 1979).

Het doel van dit onderzoek is om vast te stellen wat de invloed is van verschillende niveaus van geautomatiseerde beslissingsondersteuning, eigenschappen van de beslissingstaak en eigenschappen van de besluitvormer op beslissingsgedrag. De volgende onderzoeksvraag staat centraal in deze dissertatie:

Wat is de invloed van geautomatiseerde beslissingsondersteuning en cognitieve stijl op de keuze van een beslissingsstrategie en wel specifiek onder omstandigheden waarin het niveau van ‘alternative similarity’ varieert?

Door middel van dit onderzoek proberen wij de volgende contributies te leveren:

1) *Ontwikkeling van een ‘enhanced DSS environment’*. Deze contributie richt zich op twee aspecten: a) het ontwikkelen van een DSS gebruikersinterface die het mogelijk maakt om analyses van beslissingsgedrag te verbeteren en b) het ontwerp en de ontwikkeling van een CPT-omgeving die zowel gedetailleerde analyses van beslissingsgedrag mogelijk maakt, als *beide* determinanten van beslissingsgedrag (‘information acquisition’ en ‘information processing’) vastlegt.

[38] Indien geen logische vertaling van een Engelse term voorhanden is, of indien het vertalen van een Engelse term niet bijdraagt aan duidelijkheid, dan wordt de voorkeur gegeven aan de oorspronkelijke term.

2) *Ontwikkeling van een uitgebreid instrument ten behoeve van het meten van beslissingsgedrag.* Ieder van de eerder genoemde methoden om beslissingsgedrag vast te leggen (VPA en CPT) kent specifieke variabelen om beslissingsgedrag te meten. Deze studie richt zich onder andere op de uitbreiding van bestaande instrumenten om beslissingsgedrag te meten door te onderzoeken of het mogelijk is om variabelen uit beide methoden te combineren.
3) *De introductie van context effecten ('alternative similarity') in DSS onderzoek.*
4) *De introductie van cognitieve stijl in DSS onderzoek gericht op 'preferential choice decision making'.*

De beslissingstaak die centraal staat in dit onderzoek is een zogenaamd '*preferential choice*' beslissingsprobleem. Bij dit type probleem wordt de besluitvormer geacht een keuze te maken uit een verzameling alternatieven die alle zijn beschreven op basis van een vast aantal kenmerken. In figuur 1 is een voorbeeld keuzeset voor een 'preferential choice' probleem weergegeven.

FIGUUR 1: Keuzeset 'preferential choice' beslissingsprobleem (3 alternatieven)

	Huur	*Oppervlak*	*Keuken*	*Badkamer*	*Geluid*	*Service*
Appartement A	7	6	9	4	5	6
Appartement B	8	6	4	6	8	8
Appartement C	5	7	8	7	8	2

Het onderzoek is gericht op individueel beslissingsgedrag van besluitvormers die handelen onder condities van zekerheid. De causale relaties tussen beslissingsondersteunde systemen, cognitieve stijl en 'alternative similarity' zijn in dit onderzoek empirisch getoetst in twee afzonderlijke laboratorium experimenten.

Behavioral Decision Making

Onderzoek naar de effectiviteit van geautomatiseerde beslissingsondersteunde systemen maakt gebruik van concepten, methoden en theorieën, die afkomstig zijn uit de cognitieve psychologie in het algemeen en '*behavioral decision making research*' in het bijzonder. In hoofdstuk 2 van deze dissertatie zijn de relevante concepten, methoden en theorieën uit dit onderzoeksgebied geïntroduceerd en toegelicht.

Beslissingsstrategieën zijn essentieel voor het analyseren en verklaren van beslissingsgedrag. Svenson (1979) onderscheidt dertien verschillende beslissingsstrategieën die kunnen worden gebruikt voor het oplossen van 'preferential choice' problemen. De twee beslissingsstrategieën die in vrijwel ieder DSS onderzoek worden beschouwd als kenmerkend voor verschillende typen beslissingsgedrag zijn: de '*weighted-additive*' (WADD) strategie en de '*elimination by aspects*' (EBA) strategie.

In de WADD-strategie worden per alternatief alle attributen, ook wel kenmerken genoemd, geëvalueerd, op basis van gewogen attribuutwaarden. De besluitvormer kent, op basis van het belang dat aan verschillende attributen wordt gehecht, gewichten toe aan alle beschikbare attributen. Bijvoorbeeld bij de keuze van een auto 0,8 aan het attribuut 'prijs' en 0,2 aan het attribuut 'kleur'. Door deze gewichten te vermenigvuldigen met de corresponderende attribuutwaarden worden, per alternatief, gewogen attribuutwaarden berekend. Vervolgens wordt een totaalscore per alternatief berekend door de gewogen attribuutwaarden per alternatief te totaliseren. Het alternatief met de hoogste totaalscore geniet de voorkeur van de besluitvormer.

Voorbeeld: alternatief A_1 heeft vier attributen met de volgende waarden: $A_1(4,4,9,4)$. Aan de attributen worden respectievelijk de volgende gewichten toegekend: 0,25, 0,3, 0,2, en 0,25. De totaalscore voor alternatief A_1 bedraagt: $4x0,25 + 4x0,3 + 9x0,2 + 4x0,25 = 5$.

Een besluitvormer die de EBA-strategie toepast bepaalt eerst welk attribuut het meest belangrijk is (bijvoorbeeld prijs) en definieert voor dit attribuut een zogenaamde drempelwaarde (bijvoorbeeld: de prijs mag maximaal 50 euro zijn). Van ieder beschikbaar alternatief wordt vervolgens onderzocht of de relevante attribuutwaarde (prijs) aan de drempel (is 50 euro of minder) voldoet. Ieder alternatief waarvan de attribuutwaarde niet aan de drempel voldoet (bijvoorbeeld omdat de prijs meer dan 50 euro bedraagt) wordt uit de keuzeset verwijderd. Indien er na het eerste attribuut meerdere alternatieven overblijven, dan wordt de procedure herhaald voor het attribuut dat volgt in mate van belangrijkheid voor de besluitvormer. Dit proces wordt net zo lang herhaald tot er één alternatief over blijft.

Op basis van de mate waarin beslissingsstrategieën voorzien in de mogelijkheid om de attributen van een alternatief tegen elkaar af te wegen kunnen ze worden onderverdeeld in twee elementaire typen strategieën: ‘*compensatory*’ versus ‘*noncompensatory*’ (Payne *et al.*, 1993). ‘Compensatory’ beslissingsstrategieën bieden de mogelijkheid om “slechte” waarden op attributen te compenseren met “goede” waarden op één of meerdere andere attributen. ‘Noncompensatory’ beslissingsstrategieën voorzien niet in deze mogelijkheid. In de totaalscore per alternatief die wordt berekend in geval een WADD-strategie wordt toegepast, is per definitie een afweging tussen de verschillende attributen opgenomen. ‘Compensatory’ beslissingsstrategieën worden ook wel ‘*alternative-based*’ strategieën genoemd omdat de evaluatie op alternatiefniveau plaatsvindt. ‘Noncompensatory’ beslissingsstrategieën worden daarentegen ook wel ‘*attribute-based*’ strategieën genoemd, omdat de evaluatie per attribuut, over de alternatieven heen, plaatsvindt. De EBA-strategie wordt als exemplarisch voor ‘noncompensatory’ beslissingsstrategieën beschouwd, en de WADD-strategie als exemplarisch voor ‘compensatory’ beslissingsstrategieën. ‘Compensatory’ beslissingsstrategieën leiden over het algemeen tot betere beslissingen dan ‘noncompensatory’ beslissingsstrategieën, omdat bij toepassing ervan alle relevante informatie in het beslissingsproces wordt meegenomen en ze tevens de mogelijkheid bieden om door middel van gewichten persoonlijke voorkeuren mee te nemen in de besluitvorming . De WADD-strategie wordt ook wel beschouwd als de “norm” voor het oplossen van ‘preferential choice’ problemen.

De keuze voor een bepaalde beslissingsstrategie wordt sterk bepaald door een proces waarin ‘*effort*’ en ‘*accuracy*’ tegen elkaar worden afgewogen. Onder ‘effort’, ook wel ‘*perceived costs*’ genoemd, worden de inspanningen verstaan die gemoeid zijn met de implementatie van een bepaalde beslissingsstrategie. Hierbij kan gedacht worden aan mentale inspanningen, bijvoorbeeld hoofdrekenwerk, maar ook aan het aantal handelingen dat nodig is om een strategie met behulp van een DSS uit te voeren. Onder ‘*accuracy*’, ook wel ‘*perceived decision quality*’ genoemd, wordt de nauwkeurigheid van een beslissingsstrategie verstaan. In zowel ‘behavioral decision making research’ als in DSS onderzoek wordt verondersteld dat een besluitvormer ernaar streeft om de kans te maximaliseren dat de meest nauwkeurige beslissing wordt genomen (Payne *et al.*, 1993). Verschillende beslissingsstrategieën kennen verschillende niveaus van ‘effort’ en ‘accuracy’. Gegeven een bepaalde beslissingstaak, proberen individuen die strategie te selecteren die een hoog niveau aan ‘accuracy’ oplevert tegen een acceptabel niveau aan ‘effort’. Het selecteren van een beslissingsstrategie is een proces waarin ‘effort’ en ‘accuracy’ tegen elkaar worden afgewogen. Immers, de keuze voor implementatie van de WADD-strategie, die een hoog niveau van ‘accuracy’ kent, impliceert tevens dat de nodige inspanning of ‘effort’ geleverd moet worden om de strategie uit te voeren. Zo kan het zijn dat een besluitvormer wel een WADD-strategie wenst toe te passen, maar dat het vanwege cognitieve beperkingen vrijwel onmogelijk is om voor alle beschikbare alternatieven een totaalscore te berekenen. In een dergelijk geval is het niet ondenkbaar dat de besluitvormer “terugvalt” op het toepassen van een EBA-strategie. Onderzoek van Payne, Bettman en Johnson (1993) heeft aangetoond dat de afweging tussen ‘effort’ en ‘accuracy’ resulteert in een compromis tussen de wens om ‘effort’ te minimaliseren enerzijds en de wens om een goede beslissing te nemen anderzijds, waarbij dient te worden opgemerkt dat ‘effort’ een zeer belangrijke rol speelt in deze afweging.

Om beslissingsgedrag te kunnen karakteriseren onderscheiden Payne *e.a.* (1993) de volgende drie dimensies: 1) de *hoeveelheid informatie die in het beslissingsproces wordt gebruikt*, 2) *selectiviteit* in het verzamelen en verwerken van informatie en 3) de *volgorde* waarin informatie wordt verzameld. ‘Compensatory’ beslissingsstrategieën bijvoorbeeld, onderscheiden zich van ‘noncompensatory’ beslissingsstrategieën, omdat ze: relatief meer informatie gebruiken, over de beschikbare alternatieven dezelfde hoeveelheid informatie verzamelen en verwerken, en omdat in ‘compensatory’ beslissingsstrategieën informatie relatief gezien meer per alternatief dan per attribuut wordt verzameld.

DSS Research

De volgende twee DSS onderzoekslijnen worden als fundamenteel beschouwd voor dit onderzoek: 1) het DSS onderzoek dat is uitgevoerd door Peter Todd en Izak Benbasat (1991, 1992, 1994a, 1994b, 1999, 2000), en 2) het DSS onderzoek van Pai-Cheng Chu en Eric E. Spires (2000). In hoofdstuk 3 van deze dissertatie worden genoemde onderzoekslijnen in detail beschreven. Voor beide onderzoekslijnen worden de volgende vragen beantwoord:

1) Hoe wordt beslissingsgedrag door een DSS beïnvloed?
2) Hoe wordt beslissingsgedrag vastgelegd?
3) Hoe wordt beslissingsgedrag gemeten?
4) Hoe luiden de belangrijkste onderzoeksresultaten?

Onderzoekslijn 1: Todd en Benbasat.

De uitgangspunten van het ’*effort-accuracy framework*’ zijn essentieel voor het DSS onderzoek van Todd en Benbasat. Todd en Benbasat beargumenteren dat wanneer door middel van een DSS de benodigde ‘effort’ voor het implementeren van meer ‘accurate’ beslissingsstrategieën (i.c. de WADD-strategie) gelijk of minder wordt aan de ‘effort’ die nodig is voor de implementatie van minder ‘accurate’ strategieën (i.c. de EBA-strategie), een rationele besluitvormer zal kiezen voor de implementatie van de meer ‘accurate’ beslissingsstrategie.

De vertaling van beslissingsstrategieën in zogenaamde elementaire informatieprocessen (EIPs) (Newell & Simon, 1972) is door Todd en Benbasat gebruikt om te bepalen welke functionaliteit in het DSS opgenomen dient te worden om beslissingsgedrag te kunnen beïnvloeden. Deze vertaling maakt het namelijk mogelijk om vast te stellen welke cognitieve ‘efforts’ door middel van specifieke functies door het DSS overgenomen kunnen worden en hoe het gebruik van deze functies kan resulteren in een reductie van ‘effort’.

In hun DSS onderzoek maakten Todd en Benbasat gebruik van verbale protocollen om gegevens over beslissingsgedrag vast te leggen en te analyseren, en werden de volgende variabelen gebruikt om beslissingsgedrag te meten: '*independent evaluations*', zijnde beweringen waarin een attribuutwaarde wordt vergeleken met een extern bepaald criterium (bijvoorbeeld een drempelwaarde); '*dependent evaluations*', zijnde beweringen waarin paarsgewijs twee alternatieven worden vergeleken op basis van een specifiek attribuut; '*elimination statements*', zijnde beweringen waarin expliciet wordt aangegeven dat een alternatief wordt geëlimineerd uit de keuzeset; '*compensatory statements*', zijnde beweringen waarin een afweging wordt gemaakt tussen twee of meer kenmerken van eenzelfde alternatief; en '*total statements*', zijnde het totaal aantal beweringen wat is gedaan door een besluitvormer gedurende het uitvoeren van de beslissingstaak.

De resultaten van het DSS onderzoek van Todd en Benebasat tonen aan dat beslissingsgedrag kan worden beïnvloed door middel van een DSS en ondersteunen de hypothese dat het bieden van 'compensatory decision support' leidt tot 'compensatory' beslissingsgedrag.

Onderzoekslijn 2: Chu en Spires.

Ook Chu en Spires maken gebruik van de uitgangspunten van het 'effort-accuracy framework' om beslissingsgedrag te kunnen verklaren. Chu en Spires richten zich in hun DSS onderzoek niet alleen op de rol van 'effort' (beslissingsproces) in het verklaren van beslissingsgedrag, maar integreren ook expliciet veronderstellingen over de rol die '*decision quality*' (= uitkomst van het beslissingsproces) hierin speelt. Net als Todd en Benbasat maken Chu en Spires gebruik van EIPs om de invloed van hun DSS op beslissingsgedrag te verklaren. Ook de functies die Chu en Spires in hun DSS opnemen zijn erop gericht om beslissingsgedrag te beïnvloeden door middel van 'effort' reductie.

Het DSS onderzoek van Chu en Spires is voor ons onderzoek met name relevant omdat zij gebruikmaken van 'computerized process tracing' als methode om beslissingsgedrag vast te leggen. Chu en Spires gebruiken drie variabelen om beslissingsgedrag te meten: '*information acquisition*', zijnde het percentage van de totaal beschikbare hoeveelheid informatie die in het beslissingsproces wordt gebruikt; '*variability in the amount of information accessed per alternative*', zijnde de standaarddeviatie van het percentage informatie dat per alternatief is geraadpleegd, en '*search index*', zijnde een index die aangeeft in welke volgorde de informatie voornamelijk is verzameld (per alternatief, of per attribuut). Deze drie variabelen zijn alle drie door Payne (1976) ontwikkeld in de context van 'behavioral decision making research'.

Ook de resultaten van het DSS onderzoek van Chu en Spires tonen aan dat een DSS beslissingsgedrag kan beïnvloeden op een manier die consistent is met de veronderstellingen van het 'effort-accuracy framework'.

De Experimentele DSS Omgeving

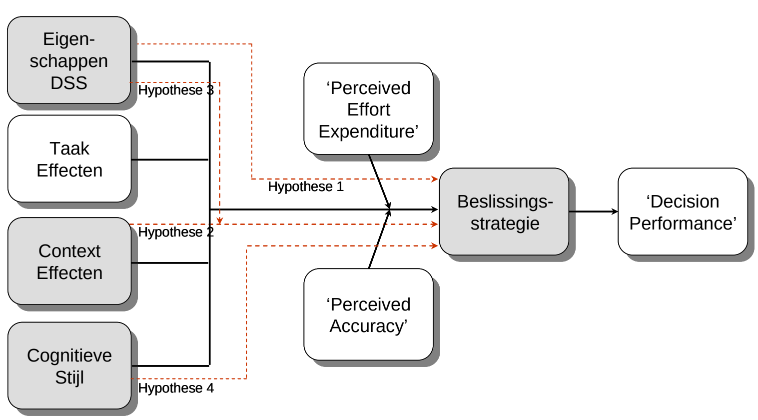
Omdat de ontwikkeling van een 'enhanced DSS environment' is benoemd als één van de contributies van ons onderzoek worden in hoofdstuk 4 de functionele vereisten ontwikkeld die gelden als kader voor de ontwikkeling van de DSS omgevingen die zijn gebruikt in beide experimenten van dit onderzoek. Vertrekpunt voor de ontwikkeling van deze functionele specificaties is een analyse van de concepten, methoden en systemen die zijn toegepast in de twee DSS onderzoekslijnen die ten grondslag liggen aan dit onderzoek. De volgende functionele vereisten zijn in hoofdstuk 4 ontwikkeld:

1) *Het experimentele DSS dient een CPT-omgeving te omvatten*. Op basis van een analyse van de voor- en nadelen van VPA en CPT wordt in hoofdstuk 4 de keuze voor CPT beargumenteerd.

2) *Het experimentele DSS dient te voorzien in geautomatiseerde hulpmiddelen die nodig zijn voor het oplossen van 'preferential choice' problemen en wel zodanig dat een besluitvormer vrij is in de keuze van toe te passen beslissingsstrategie.* In beginsel dient het experimentele DSS een veelheid aan beslissingsstrategieën te ondersteunen en dient de opzet van het DSS zo te zijn dat de besluitvormer niet gericht in de richting van implementatie van een specifieke strategie wordt begeleid.
3) *De grootste gemeenschappelijke deler van de beslissingsondersteunende functies die door Todd en Benbasat, en Chu en Spires zijn gebruikt in hun DSS experimenten, dient te functioneren als vertrekpunt voor het ontwerp en de ontwikkeling van de geautomatiseerde beslissingsondersteunende functies die worden toegepast in het DSS voor deze studie.*
4) *Het experimentele DSS dient te voorzien in de mechanismen om de relatie tussen een DSS functie en de informatie, die wordt gebruikt, verwerkt en geproduceerd, door deze functie, vast te leggen*. Implementatie van dit vereiste maakt het mogelijk om een belangrijk voordeel van VPA, namelijk het verkrijgen van inzicht in *hoe* informatie wordt verwerkt, te realiseren middels CPT, zonder ook de nadelen van VPA te hoeven adresseren. Het vastleggen van de relatie tussen een DSS functie en de informatie, die wordt gebruikt, verwerkt en geproduceerd, door de betreffende functie in een CPT-model, impliceert dat de toepassing van CPT-modellen zich niet hoeft te beperken tot het verzamelen van data over 'information acquisition behavior' (*wat*), maar kan worden uitgebreid met de mogelijkheid om ook data te verzamelen over 'information processing behavior' (*hoe*). Deze relatie wordt in ons onderzoek aangeduid als de 'FIP-link': Functie-Informatie-Processing-Link. Implementatie van deze FIP-link biedt de mogelijkheid om nieuwe variabelen voor het kenmerken van beslissingsgedrag te ontwikkelen (zie tevens Experiment I).

Naast deze functionele specificaties geldt als belangrijke randvoorwaarde voor de ontwikkeling van het experimentele DSS dat het de interpretatie van onderzoeksresultaten in de context van eerder DSS onderzoek mogelijk moet maken.

Onderzoeksmodel en Hypothesen



Figuur 2: Onderzoeksmodel

Figuur 2 toont het onderzoeksmodel voor het eerste experiment. De grijs gemarkeerde constructen en de relaties tussen deze constructen zijn door ons onderzocht.

Een belangrijk context effect dat in de 'behavioral decision making' literatuur wordt onderscheiden is de mate waarin alternatieven in een keuzeset op elkaar lijken, ook wel '*alternative similarity*' genoemd. Ondanks het feit dat 'behavioral decision making research' heeft aangetoond dat 'alternative similarity' van invloed kan zijn op de selectie van beslissingsstrategieën (o.a. (Biggs *et al.*, 1985)), is ons geen relevant DSS onderzoek bekend, waarin de invloed van dit context effect op beslissingsgedrag wordt onderzocht. In beginsel geldt hetzelfde voor DSS onderzoek naar de invloed van cognitieve stijl op de selectie van beslissingsstrategieën. De cognitieve stijl dimensie die in Experiment 1 werd getoetst is '*analytische vaardigheden'* van de besluitvormer.

In Experiment 1 zijn de volgende vier hypothesen getoetst:

H1: *Het beschikbare niveau van 'compensatory' beslissingsondersteuning is van positieve invloed op het gebruik van 'compensatory' beslissingsstrategieën*.
H2: *Het niveau van 'alternative similarity' is van positieve invloed op het gebruik van 'compensatory' beslissingsstrategieën.*
H3: *Het effect van 'alternative similarity' op het gebruik van 'compensatory' beslissingsstrategieën wordt positief beïnvloed door het niveau van 'compensatory' beslissingsondersteuning.*
H4: *Een hoge mate van analytische cognitieve stijl is van positieve invloed op het gebruik van 'compensatory' beslissingsstrategieën.*

Experiment 1

Het ontwerp voor Experiment 1 is een zogenaamd 2x3 '*between subjects*' factorieel ontwerp met 'alternative similarity' (twee niveaus: laag & hoog) en 'level of compensatory support' (drie niveaus: geen, beperkt en veel) als factoren. Deelnemers aan het experiment waren 186 studenten die ten tijde van het experiment studeerden aan de *Vrije Universiteit* Amsterdam. De beslissingstaak die moest worden uitgevoerd was de selectie van een studentenkamer. De keuzeset waaruit een kamer geselecteerd moest worden bestond uit tien kamers die alle waren beschreven op basis van acht kenmerken (huur, oppervlak, afstand centrum, afstand universiteit, omgevingsgeluid, reinheid, keuken, en houding van de huisbaas). Beslissingsgedrag werd gemeten met behulp van de volgende vier variabelen: 1) '*information acquisition*', 2) '*variability in the amount of information accessed per alternative*', 3) '*search index*', en 4) '*processing index*'. De vierde variabele, '*processing index*', is in dit onderzoek ontwikkeld en kan worden berekend op basis van de gegevens die door middel van de FIP-link worden vastgelegd. De cognitieve stijl dimensie 'analytische vaardigheden' is gemeten met behulp van Witkin's 'Embedded Figures Test'. In de analyse is cognitieve stijl meegenomen als covariaat. De MANOVA's uitgevoerd met de data van Experiment 1 toonden alleen significante resultaten voor de invloed van het DSS op beslissingsgedrag. Alleen Hypothese 1 wordt op basis van de data van Experiment 1 ondersteund. Belangrijke conclusies van dit experiment zijn: 1) het ontwikkelde CPT-model kan worden gebruikt voor zowel het vastleggen van 'information acquisition' als het vastleggen van 'information processing' beslissingsgedrag en 2) de door ons ontwikkelde 'processing index' kan worden gebruikt als variabele voor het meten van beslissingsgedrag. Ten aanzien van Experiment 1 gelden de volgende beperkingen: 1) onder twee van drie gebruikte experimentele DSS condities ('geen' en 'beperkt'), geldt in situaties waarin een besluitvormer de informatie op een andere manier verwerkt dan het informatie acquisitiepatroon (‘search index’) veronderstelt, dat de functionaliteit van de DSS omgeving niet toereikend is om het volledige beslissingsproces vast te leggen, 2) het aantal alternatieven dat is opgenomen in de keuzeset is beperkt, 3) er is slechts één variabele gebruikt om ‘information processing’ beslissingsgedrag te meten, terwijl DSS onderzoek dat gebruikmaakt van VPA meerdere variabelen voor het meten van ‘information processing’ beslissingsgedrag onderscheidt en 4) er is slechts één cognitieve stijl dimensie gebruikt terwijl cognitieve stijl een multidimensionaal construct is. Al deze beperkingen zijn overgenomen als aanbevelingen voor vervolgonderzoek en zijn in het vervolgexperiment (Experiment 2) geadresseerd.

Enhanced Conceptual Framework en Decision Support System

Een belangrijke beperking van Experiment 1 is dat de gebruikte DSS omgeving onder de experimentele DSS condities ‘geen’ en ‘beperkt’ onvoldoende functionaliteit omvat om alle relevante beslissingsprocessen vast te kunnen leggen. Onder deze experimentele condities zou een besluitvormer er in theorie voor kunnen kiezen om alle beschikbare informatie mentaal middels een ‘compensatory’ beslissingsstrategie te verwerken, dus zonder gebruik van het DSS. In een dergelijke situatie wordt niet het volledige beslissingsproces “gevangen” in ‘computerized process traces’. Deze beperking kan worden opgelost door onder alle experimentele DSS condities ondersteuning te bieden voor zowel ‘noncompensatory’ als ‘compensatory’ beslissingsstrategieën, waarbij het niveau van ondersteuning wordt bepaald door de ‘effort’ die nodig is om met behulp van de geboden functionaliteit een beslissingsstrategie te implementeren. Immers, de uitgangspunten van het ‘effort-accuracy framework’ veronderstellen dat, gegeven het gewenste niveau van ‘accuracy’, een besluitvormer die strategie zal kiezen die het minste ‘effort’ vereist om het gewenste niveau van ‘accuracy’ te bereiken. Indien bijvoorbeeld onder iedere experimentele DSS conditie functionaliteiten wordt geboden die ‘compensatory’ beslissingsstrategieën ondersteunen, dan zal een rationele besluitvormer die een ‘compensatory’ strategie wenst te implementeren er te allen tijde voor kiezen om hier gebruik van te maken, omdat het laten uitvoeren van berekeningen door het DSS minder ‘effort’ zal kosten dan het mentaal verwerken van de beschikbare gegevens. Gebruikmaken van het DSS om een beslissingsstrategie te implementeren impliceert dat beslissingsgedrag wordt vastgelegd middels ‘computerized process traces’. De genoemde beperking kan dus worden opgelost door implementatie van een aanvullende functionele vereiste: *de gebruikersinterface voor ieder van de beschikbare experimentele DSS condities dient zowel functionaliteit voor het ondersteunen van ‘noncompensatory’ als van ‘compensatory’ beslissingsstrategieën te bieden, waarbij de ‘effort’ die is gerelateerd aan de implementatie van eenzelfde beslissingsstrategie verschillend is voor ieder van de onderscheiden experimentele DSS condities*.

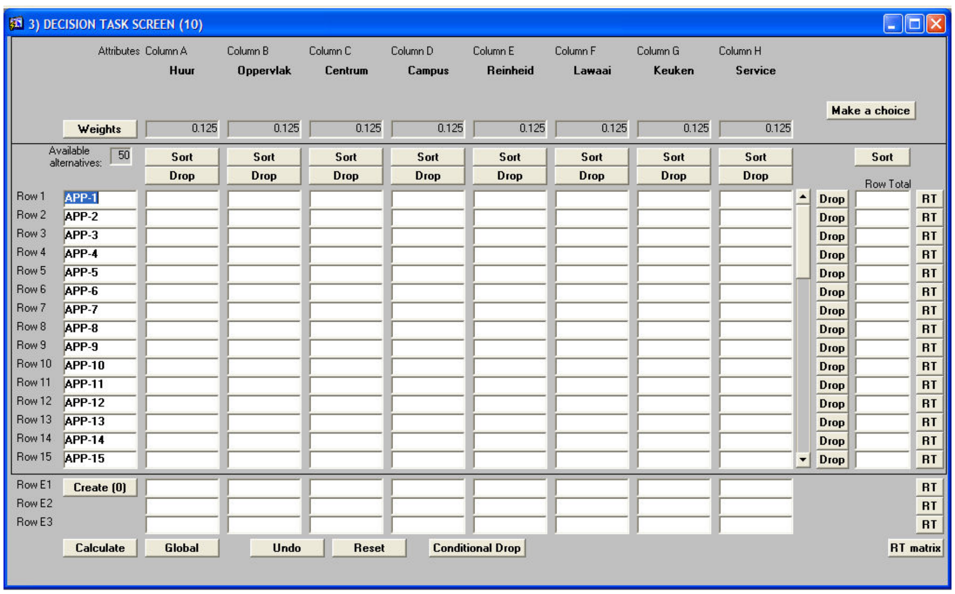
Voor het meten van ‘information processing’ gedrag is in Experiment 1 alleen de variabele ‘processing index’ toegepast, terwijl DSS onderzoek (Todd & Benbasat, 1999, 2000) dat gebruikmaakt van verbale protocol analyse (VPA) meerdere variabelen onderscheidt die kunnen worden gebruikt voor het meten van ‘information processing’ beslissingsgedrag. Ten behoeve van Experiment 2 is door ons een CPT-model ontwikkeld waarin, naast de variabelen die zijn toegepast in Experiment 1, tevens de volgende ‘information processing’ variabelen zijn geïntegreerd: ‘*evaluation index*’, ‘*evoked set size*’, ‘*compensatory index*’, ‘*total statements*’ en ‘*total information processed*’. Genoemde variabelen zijn, voor zover ons bekend, in eerder DSS onderzoek alleen toegepast in studies die gebruikmaken van VPA.

In Experiment 2 is tevens een tweede cognitieve stijl dimensie geïntroduceerd: '*need for cognition* (NFC)'. NFC wordt gedefinieerd als de tendens van een individu om cognitieve inspanningen te verrichten en daarin plezier te hebben (Cacioppo & Petty, 1982).

Omdat geen van bovengenoemde wijzigingen in het conceptueel kader andere constructen, of andere relaties tussen constructen, veronderstelt dan de constructen en relaties die reeds in het onderzoeksmodel voor Experiment 1 zijn opgenomen, hoeft het onderzoeksmodel niet te worden aangepast en zullen in Experiment 2 dezelfde hypothesen worden getoetst als in Experiment 1. Wel is een aanvullende hypothese geformuleerd betreffende de invloed van de extra cognitieve stijl dimensie 'need for cognition':

H5: *Een hoge mate van 'need for cognition' is van positieve invloed op het gebruik van 'compensatory' beslissingsstrategieën.*

De DSS omgeving die in Experiment 2 is gebruikt, is ontwikkeld op basis van dezelfde vier functionele vereisten die golden voor Experiment 1, aangevuld met de vijfde vereiste die is ontwikkeld naar aanleiding van de conclusies van Experiment 1. De gebruikersinterface van de DSS omgeving die in Experiment 2 is gebruikt ziet er als volgt uit:



Figuur 3: DSS Gebuikersinterface Experiment 2

Experiment 2

Het ontwerp voor Experiment 2 is een 2x2 '*between subjects*' factorieel ontwerp met 'alternative similarity' (twee niveaus: laag & hoog) en 'level of compensatory support' (twee niveaus: laag & hoog) als factoren. Deelnemers aan Experiment waren 273 studenten die ten tijde van het experiment studeerden aan de *Vrije Universiteit* Amsterdam. Ook in Experiment 2 was de beslissingstaak de selectie van een studentenkamer. De keuzeset waaruit een kamer geselecteerd moest worden bestond in Experiment 2 uit 50 kamers, die alle waren beschreven op basis van dezelfde acht kenmerken zoals gebruikt in het eerste experiment. Beslissingsgedrag werd gemeten met behulp van de variabelen die ook in Experiment 1 zijn gebruikt, aangevuld met: '*evaluation index*', '*evoked set size*', '*compensatory index*', '*total statements*' en '*total information processed*'. De cognitieve stijl dimensie '*need for cognition*' werd gemeten met behulp van de verkorte NFC-schaal van Cacioppo *e.a.* (1984). In de analyses zijn beide cognitieve stijl dimensies meegenomen als covariaten. De MANOVA's uitgevoerd met de data van Experiment 2 toonden alleen significante resultaten voor de invloed van het DSS op beslissingsgedrag. Op basis van de data wordt ook in Experiment 2 alleen Hypothese 1 ondersteund.

Conclusies en Discussie

Indien de resultaten van ons onderzoek worden geïnterpreteerd in de context van de voor dit onderzoek geformuleerde probleemstelling, dan blijkt onder de beschreven omstandigheden alleen een DSS van invloed te zijn op beslissingsgedrag. De resultaten van beide in dit onderzoek uitgevoerde experimenten duiden op een significante invloed van decision support systemen op beslissingsgedrag en wel zodanig dat het mogelijk is om het gebruik van '*compensatory*' beslissingsstrategieën op positieve wijze te beïnvloeden door middel van specifieke beslissingsondersteunde functies. Deze bevinding is in overeenstemming met de resultaten van eerder DSS onderzoek. In geen van beide experimenten bleek '*alternative similarity*' van invloed te zijn op de keuze van een beslissingsstrategie. Een mogelijke verklaring voor deze bevinding kan zijn dat de invloed van 'alternative similarity', voor zover aanwezig, volledig wordt overheerst door de kracht van het geconstateerde DSS effect. Ook beide in dit onderzoek gebruikte cognitieve stijl dimensies bleken niet significant van invloed te zijn op het gebruik van beslissingsstrategieën. Een mogelijke oorzaak voor deze constatering kan zijn dat de gebruikte technologie zo goed past bij de uit te voeren beslissingstaak, dat er weinig ruimte overblijft voor cognitieve stijl om deze relatie te beïnvloeden. Naast de introductie van context effecten en twee cognitieve stijl dimensies in DSS onderzoek voor 'preferential choice decision making' zijn twee andere belangrijke contributies van dit onderzoek: 1) de ontwikkeling van een '*computerized process tracing*' model dat kan worden gebruikt voor *zowel* het vastleggen van '*information acquisition*' als van '*information processing*' beslissingsgedrag en 2) de ontwikkeling van een uitgebreide verzameling variabelen die kan worden gebruikt om beslissingsgedrag te meten middels CPT. Een beperking van het onderzoek is de gekozen structuur van de beslissingstaak. De deelnemers aan de experimenten konden de aangeboden kamers alleen beoordelen op basis van een vaste verzameling criteria. Een andere beperking van ons onderzoek is dat de gebruikte '*information board*' methode de generaliseerbaarheid van onze bevindingen naar meer ongestructureerde beslistaken zou kunnen beperken. Het onderscheiden van verschillende fasen in het beslissingsproces en het analyseren van beslissingsgedrag per onderscheiden fase, een analyse van beslissingsgedrag gedifferentieerd naar verschillende 'effort' componenten, het selecteren van producten of diensten die een verschillend niveau van betrokkenheid impliceren en de integratie van 'decision outcome' variabelen zijn enkele van de aanbevelingen voor vervolgonderzoek die worden geïntroduceerd.

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A Dutch market research company recently reported that consumers are suffering from so called 'choice stress' (Dutch: 'keuzestress'). Although, "freedom of choice" appears to be the magic word for modern businesses when it comes to responding to the needs of the market. For example, a well known computer manufacturer offers consumers the opportunity to buy personal computers through its website. The configuration tool integrated in this website requires consumers to select options from each of the 25 different features. This means that if only the options available on the features 'processor' (11) and 'hard disk' (7) are evaluated, a consumer has to decide on 77 different models, this number will increase almost exponentially when the personal computer is not limited to a single brand. This is just one example, however, if we consider the vast amount of choices available to a modern consumer, ranging from mobile phones to summer vacations, it is not surprising that consumers become stressed. In order to deal with this phenomenon an increasing number of organizations recognize the opportunities of automated decision aids to support, or even more important, to improve decision making. The points of departure for an investigation into the improvement of decision making include: 1) the decision processes underlying decision behavior, and 2) the factors that influence these decision processes. Research on behavioral decision making employs the notion of decision strategies to qualify decision processes. A decision strategy may de defined as the method whereby a decision maker acquires and processes information to reach a decision. This study departs from the findings of behavioral decision making and decision support systems (DSS) research. The hypotheses developed and examined in this study investigated the influence of the following factors: decision support systems, characteristics of the decision problem ('context effects'), and characteristics of the decision maker ('cognitive style'), on decision strategy selection. Two laboratory experiments were conducted. Beyond an investigation of the influence of the aforementioned factors on decision behavior, this study contributed to DSS research through the development of a new model for capturing decision behavior through computerized process tracing, as well as through the development of an extended set of operators to measure decision behavior.

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