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Data presentation form and efficiency in decision making

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Table of content

Abstract

This thesis reviews relevant literature and presents the results of an exploratory experimental study to enhance the understanding of whether - and how - data presentation forms influence decision making effectiveness. 42 MBA students were exposed to decisions regarding the management of a summer restaurant covering a five-month period. This research differs from previous research in this area by examining the effects of the combined use of graphs and tables in decision tasks and the effects of access to decision aids. In addition to measurement of economic performance, level of information processing was measured using an index based on cognitive complexity theory. The results indicate that effective decision-makers need both presentation forms. Graphs give an overview of relationships between variables, while tables increase the understanding of details and provide the basis for further calculations. Also, tabular data seems to be necessary in order to obtain accuracy in complex tasks. The results also show that subjects presented with the tabular or graphic display form only, attempted to complement the presentations using the decision aids. This was particularly true for subjects solving a low-complexity task, and in a high-complexity task, for subjects well acquainted with the spreadsheet program.

Preface

This thesis is written as part of my master degree (Høyere avdeling) at the Norwegian School of Economics and Business Administration (NHH).

I owe my supervisor, Professor Dr. Oecon. Anna Mette Fuglseth, a debt of gratitude for her comments and contributions during my work on this thesis. She has patiently guided me through the work, and made me think differently the times when I have got lost. Sincere thanks!

I am also grateful for the help I have received by Professor Kjell Grønhaug. He has put a lot of effort into commenting on my work during the time I have spent writing on this thesis. Thanks also to the department of strategy and management at NHH, for lending me technical equipment necessary for conducting experiments.

Finally, I want to direct thankfulness to the ones participating in interviews, contributing to complete the data set.

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1 Introduction

This thesis addresses the following research question: Do presentation formats influence decision effectiveness, and if so, how?

The impact of data presentation forms on decision making performance is highly relevant and of great interest in many domains. In the field of information science, for instance, designers of management information systems need to know whether – and how – data presentation forms influence decision making performance in order to make efficient user-interfaces (e.g. Vessey, 1991; Speier, 2006). Likewise, economists need to know how data presentation format might influence decision making processes when communicating financial data (e.g. Beattie and Jones, 1993). Also regarding learning, it is important to know what presentation form is best suited to enhance learning, reduce cognitive load for the learners and enhance understanding of instructions being given (e.g. Marcus, Cooper, Sweller, 1996; Mousavi, Low, Sweller, 1995).

In prior research, different presentation forms have been studied, for instance pictures vs. words, animations vs. text (e.g. Mayer and Anderson, 1991), and tables vs. graphs (e.g. Vessey, 1991). In my work, I will study effects of tables vs. graphs.

Despite numerous studies on graphical presentation and decision effectiveness, there are few empirical studies showing that graphs enhance decision quality (Fuglseth and Grønhaug, 2000). Furthermore, even though there has been extensive research on tables vs. graphs, there are no generally accepted guidelines for what is the optimal way to display data (Meyer, 2000). Instead, there seems to be a common belief that what is the best presentation form depends on the type of task performed (DeSanctis, 1984; Vessey 1991; Vessey and Galletta, 1991). In prior studies, graphs and tables are treated as if they were mutually exclusive. That means, there is an assumption that the best presentation form is *either* a graph *or* a table. In my research, however, I will study the effect of combined use of graphs and tables.

Furthermore, most studies on data presentation forms are based on the assumption that decision makers are unaided (Fuglseth and Grønhaug, 2000). However, in real life managerial decision making, decision makers are usually not unaided. More commonly, decision makers have access to a number of decision aids and additional sources of information. Therefore, consistent with Edwards (1992), I will take this into account, and study whether access to decision aids is of significance for the effectiveness in decision making processes. Hence, an important part of the study will be to evaluate whether or not the decision makers are able to utilize the decision aids in order to increase decision making effectiveness.

Previous research has for the most studied effects of data presentation forms on relatively simple tasks (e.g. Vessey and Galletta, 1991). I want to study the effects of data presentation forms on more realistic decision situations, thus I have based my research on two relatively complex tasks.

I have conducted an exploratory study, aiming at covering the assumptions presented above. My research builds on the work done by Fuglseth and Grønhaug (2000). I have borrowed their results, but also expanded the number of respondents in order to follow up on the tendencies in their results.

The thesis proceeds as follows. In the next section, I review prior research and position my study. Then, I elaborate on the theories underlying my research. In the following section, I present my research model and quasi-experimental design. Finally, I present and discuss the findings. Limitations and future research opportunities are proposed.

2 Literature review

2.1 Presentation format

Numerous studies have been conducted, investigating the relationship between data presentation format and decision quality. The relationship has been studied in a wide range of special fields, e.g. information science, finance and accounting. For instance, Bricker and Nehmer (1994) have found that graphics influence decision speed, but not accuracy, when evaluating financial situations. Further findings also indicated that graphics alone might not be suitable for tasks requiring a high degree of precision and accuracy (Fuglseth and Grønhaug, 2000).

Early studies on data presentation format and decision quality were mostly atheoretical and gave inconsistent results. Some studies concluded that a graphical data presentation format was superior compared to tables, while others concluded with the opposite (see Jarvenpaa & Dickson, 1988; DeSanctis, 1984, for reviews of previous studies).

Even though there has been extensive research on the performance of tables vs. graphs, there are no generally accepted guidelines describing the most optimal way to display data (Meyer, 2000; Vessey and Galletta, 1991). Instead, there seems to be a common belief that what is the best presentation form depends on the type of task performed (DeSanctis, 1984; Vessey, 1991; Vessey and Galletta, 1991).

2.2 Representation – physical and mental

Theories on mental representation are often based on characteristics of physical representations. For instance Paivio (1986) starts out by describing similarities between physical and mental representation. For instance, he claims that they are symbolic (they stand for something else), and they vary in abstractness (e.g., from pictures to linguistic descriptions). He continues by pointing to a clear distinction among physical representations, namely that some physical representations are *picture-like* and others are *language-like*. The features of these two categories of physical representations are quite different, according to Paivio (1986), and have attracted a lot of attention in research on mental representations.

Research in the area has concentrated on the symbolic system available for human cognition, that is, mental representation codes available for humans. Principally, (at least) two approaches exist (see Santa, 1977; Anderson, 1978; Mayer and Anderson, 1991):

1) *Simple-code theories* – All information is represented in *one* common underlying conceptual format.
2) *Multi-code theories* – These theories emphasize the existence of multiple symbolic codes (verbal and spatial), containing different functional properties regarding information storage and –processing.

Based on prior research, it seems reasonable to conclude that the multi-code theories have defeated simple-code theories (Helstrup and Kaufmann, 2000). According to multi-code theories, humans can represent information both as verbal and as spatial structures. However, this does not imply that the human ability of mental representation is reduced to *one* basic representational system consisting of abstract constructs. On the contrary, it seems clear that humans have developed different representational systems (codes) related to different information processing functions (Helstrup and Kaufman, 2000).

An example of a multi-code theory is the Dual-coding theory by Paivio (1971, 1986).

2.3 Dual code theory

The Dual Coding Theory of memory was initially proposed by Paivio (1971) and later reviewed (Paivio, 1986). The theory describes how humans' storing and processing of information is handled cognitively by two separate, partly independent representational systems: The verbal and the non-verbal (visual) system.

The model contains three major component processes. The first component involves building representational connections between verbally presented information and verbal representation. The second component involves building representational connections between visually presented information. The third component involves building referential connections between elements in the verbal and visual representation.

The Dual Coding Theory has applications in many cognitively related domains such as problem solving, decision making, multimedia learning, language etc (see for example Mayer and Anderson, 1991).

There are numerous studies, testing and supporting this theory, reported in the literature. For instance, Mayer and Anderson (1991) conducted an experimental study where they tested effects of animation (non-verbal), descriptive text (verbal) and combination of the two former presentation forms. Their result showed that presenting verbal and visual explanations together in a coordinated way was found more effective in promoting creative problem solving than giving separate verbal explanations and animated visual explanations.

2.4 Cost–benefit theory

Cost-benefit theory (Beach and Mitchell, 1978; Payne, 1982) has been used as a way of organizing knowledge about decision making and different data presentation formats (Vessey, 1994; Vessey and Galletta, 1991). A considerable amount of research on decision making has studied the underlying processing strategies employed by decision makers in a choice context (see for instance Payne, 1982). Some of these strategies are cognitively more complex than others, requiring the decision maker to consider large amounts of data combined in a complex, typically compensatory fashion. Others are reduced processing strategies, which require a limited information search and simpler evaluation processes (Paquette and Kida, 1988). The latest strategies might however not be as accurate as the first ones.

The cost-benefit theory is based on traditional decision theory (e.g. Simon, 1955), and the recognition that humans information processing capacity is a limited resource (e.g Miller, 1956). As an attempt to overcome this limitation, cost-benefit theory suggests, that decision makers might change information processing strategy in order to minimize the total cost of effort and error in making a decision. A decision maker facing a problem that needs to be solved, carries out the first judgments of the different properties of the problem. Based on these judgments, the decision maker decides what strategy to use. The idea is that, according to Payne (1982), any decision strategy has certain benefits associated with its use and also certain costs. Among the benefits, we find the probability that the strategy will lead to a “correct” decision, the speed of making the decision, and its justifiability. The costs, on the other hand, could include the information acquisition and computational effort involved in using the strategy. The choice of strategy would then involve consideration of both the costs and benefits associated with each possible strategy (Payne, 1982), resulting in a compromise between the desire to make a correct decision and the desire to minimize effort.

In this setting, the term ‘strategy’ denotes a general approach to information processing involving several elementary processes. Examples of such strategies are *holistic* and *analytic* (Tutle and Kershaw, 1998). Holistic strategies involve elementary perceptual processes such as making associations and perceiving relationships in data. Analytic strategies involve verbal processes, such as extracting discrete data values and computations. Perceptual processes are assumed to require less effort than verbal processes, while verbal processes are assumed to give more accurate responses.

Many factors are said to influence the choice of strategy. Vessey (1994) highlights the assumption of presentation format as an important factor. Others (e.g. Payne, 1982; Paquette and Kida, 1988) have found that the level of complexity for a task determines which strategy will be used.

2.5 Task complexity

Research on decision behaviour and strategy selection reveals that decision strategy choice is contingent upon task complexity (Olshavsky, 1979; Payne, 1982) Nevertheless, most research on effects of data presentation format has been carried out using relatively simple tasks (Vessey, 1991), and there has been a call for further research applying more complex tasks (Vessey, 1994; Vessey and Galetta, 1991).

Even though there has been extensive research on task complexity, there is neither a common definition nor an operationalization of task complexity (DeSanctis, 1984; Wood, 1986; Campbell, 1988; Frownfelter-Lohrke, 1998). Different ways of conceptualizing task complexity have however been suggested through dozens of empirical studies (for a review, see Campbell 1988).

Fuglseth and Grønhaug (1995) define task as a piece of work that has to be done within a certain time. A definition of task is an essential premise for approaching task complexity. Research areas interested in the separated effects of task and person need a definition of task complexity that distinguishes between task and effort put into solving the task (Wood, 1986).

In the literature, task complexity has been approached in (at least) two ways, as a) objective task complexity and b) subjective task complexity.

2.5.1 Objective task complexity

The theory of objective task complexity defines task complexity as a function of objective task characteristics (Campbell, 1988). There seems to be a common belief that objective task complexity increases as: 1) the number of information cues that must be processed increases, 2) the number of distinct processes that has to be executed increases, and 3) the number of relations between the different processes increases (Wood, 1986; Campbell 1988).

A more thorough explanation of the three steps might be necessary.

First, a decision maker needs to get information in order to complete a decision task. The more information associated with a task, the more complex the task is – independent of whether or not the information is relevant for the task that is to be to solved.

Second, information gathered needs to be processed in order to solve the task. The more processes necessary to execute, the more complex is the task. The processes can be rather simplistic (as comparing two numeric values) or more complex (involving interpretation and evaluation of information).

Finally, as the number of related (interdependent) processes increase, the task complexity increases. For instance, there is a interdependency between two processes when the output of an initial sub-processes is necessary as input for a subsequent process. Furthermore, it becomes difficult to separate factual information related to the task from the processed information generated in a sub-process (Speier, 2006).

2.5.2 Subjective task complexity

In the case of subjective task complexity, task complexity is depending on the problem solver and the way he/she experiences it. The concept of subjective task complexity has received little attention within any field of research (Braarud, 2001). However, there are some identified factors influencing a decision maker's perceived complexity, and one of them is objective task complexity (Wood 1986; Campbell, 1988). Furthermore, the problem solvers' skills and insight are also mentioned as possible factors affecting subjective complexity.

Most prior research on cognitive fit has been done using simple tasks. Speier (2006), however, claims to gain support for the cognitive fit theory when using complex tasks. However, the complexity of her tasks is questionable. Even though her tasks are more complex then the tasks used by Vessey (1991, 1994), they still they can be classified as rather simple tasks. The so-called complex tasks contains almost no uncertainty, few conflicting interests, and are mainly consisting of choice among predefined alternatives. As an example of a complex symbolic task, Speier (2006) uses a facility location task. In this task respondents were presented with five different cost estimates associated with six warehouse locations. They were then asked to determine which locations to develop and to rank order the locations based on cost. Compared to Wood's (1986) definition, this task involved the examination of 30 information cues and required 18 calculations (Speier, 2006).

2.6 Cognitive fit theory

Vessey (1991) introduces the theory of cognitive fit, which later provides much of the foundation for examining effects of data presentation on decision making in simple tasks. The theory is a special case of the cost-benefit theory, and aims to explain under what circumstances one representation format outperforms the other. Further, the cognitive fit theory describes decision making that primarily involves information acquisition and well-defined evaluation (Vessey, 1994).

The cognitive fit theory acknowledges the notion that different data presentation format can present the same data, yet in fundamentally different ways (Vessey, 1994). For instance, a graphical presentation format emphasizes spatial information, whereas a table emphasizes symbolic information (Vessey, 1991). Graphs are spatial presentation format, i.e. they emphasize relationships in the data. Tables, on the other hand, are symbolic, i.e. they emphasize presentation of numeric and discrete data values. Hence, tables do not present relationship in the data directly.

To achieve the most effective and efficient problem solving, the data presentation format has to match the task being solved (Vessey, 1991). Vessey and Galetta (1991) describe two basic types of tasks, *spatial* tasks and *symbolic* tasks. An example of a spatial task is (Vessey & Galetta, 1991): In which month is the difference between deposits and withdrawals greatest? Solving this task requires comparison of trends, and it is, according to the authors, best accomplished using perceptual processes. An example of a symbolic task is (Vessey & Galetta, 1991): Provide the amount of withdrawals in April. This task requires a specific amount as response and is best accomplished using verbal processes.

According to the theory of cognitive fit, graphs are the appropriate representation form for spatial tasks, whereas tables support symbolic tasks. The argument for this is that when the data presentation format and the task type mach, the decision makers can form a mental representation and use information processes that fit the external presentation of the data.

When the data presentation format does not match the task, similar processes cannot be used both to act on the data and to solve the problem, which will require more cognitive effort. Thus, cognitive fit is supposed to lead to an effective (accurate) and efficient (fast) problem solution (Vessey, 1994).

The cognitive fit theory is successful in explaining results in fairly simple tasks involving data acquisition and also well-defined evaluation, where the processes required to support data acquisition and evaluation are similar (for an overview, see Vessey, 1994; Umanath and Vessey, 1994; Tuttle and Kershaw, 1998; Speier, 2006).

In tasks involving complex evaluations cost-benefit theory suggests that the information processing strategy may occur as a result of trade-off between error and cognitive effort (Vessey, 1994). Complex *spatial* tasks will normally be solved using perceptual processes since this strategy will result in least effort. With a requirement for accuracy, however, decision-makers may be induced to switch from perceptual to analytical processes, which are facilitated by tables. Complex *symbolic* tasks place significant strain on the decision-makers' cognitive resources. As the complexity of a symbolic task increases, decision-makers may prefer - or have to - use perceptual rather than analytical processes due to limited cognitive capacity. In such tasks, therefore, the appropriate data presentation format might not be a table, but a graph, which supports perceptual processes (Vessey, 1994). Evaluating the results of three published graph versus table studies using complex tasks with performance constraints, Vessey (1994) also finds empirical support for such strategy shifts.

2.7 Research contribution

Most studies investigating relationships between data presentation form and decision quality use tasks that can be characterised as either spatial or symbolic (e.g. Vessey, 1991, 1994; Vessey and Galetta, 1991; Frownfelter-Lohrke, 1998; Tutle and Kershaw, 1998; Speier 2006). In addition, they assume a decision processing strategy that is either holistic (using mainly perceptual processes) or analytic. However, real-life managerial decision tasks are often more complex. They can be handled involving a variety of both spatial and symbolic subtasks, and they usually require both perceptual and analytical processes. Therefore, how decision-makers choose to structure complex tasks into subtasks may have significant implications for the accuracy of the outcome and the effort expended (Vessey, 1994).

Furthermore, most studies assume that the decision-makers are unaided. However, real-life managers and analysts use various decision aids, such as electronic databases and spreadsheet models in addition to written information sources (e.g. reports, memos) and persons (e.g. assistants, special advisors). Therefore, I agree with Edwards (1992) stating that researchers should take this aspect into consideration in their research design.

Previous research on data presentation format and decision quality is for the most done by studying the outcome of a decision making process. A focus on outcome does not take into consideration conditions such as luck, misinterpretations of the decision problem and so forth. Therefore, it is necessary to investigate the processes and strategies underlying the decision making process (Vessey, 1994).

This study aims at extending the research by Vessey (1994) in three ways:

- I will examine the effects of combined displays of graphs and tables.
- I will examine the effects of access to decision aids.
- I will emphasise measurement of the level of information processing involved in interpreting data presentation and decision-making as advocated by Vessey (1994) and Kleinmuntz and Schkade (1993).

3 Theoretical framework

The Dual-code theory (Paivio, 1986) is underlying the theory of cognitive fit, proposed by Vessey (1991, 1994). However, Vessey is only partly using the dual-coding theory to understand effects of presentation format in decision making processes, namely that humans have developed a mental representational system consisting of both a verbal and a non-verbal sub-system. Vessey acts as if the two sub-systems are independent of each other, and therefore treat graphs and tables as if they were mutually exclusive. Paivio (1986) on the other hand, stresses the fact that the two sub-systems are inter-dependent and that the verbal and the non-verbal system can complement each other. This supports the idea of combined displays of graphs and tables.

Also, the literature review points at the importance of investigating the mental processes and strategies underlying the decision making process. This can be done using a measure on level of complexity (Schroder et al., 1967).

In the extending of the research by Vessey (1994), I have found the Dual code theory (Paivio, 1986) and the concept level of information processing from the cognitive complexity theory (Schroder et al., 1967) useful. Hence, in the remaining of this chapter, I will elaborate on these theories.

3.1 The Dual-code theory

3.1.1 An overview of the theory

As described in the literature review, the Dual-code theory by Paivio (1986) is a theory of memory and of mental representations, suggesting that humans have both visual and verbal modes of mental representations as well as connections between these modes. The following presentation builds on Paivio (1986).

The non-verbal representation system is specialized for representation and processing of information related to non-verbal objects and events (e.g. mentally representing a crying face). The verbal representational system on the other hand is specialized for handling language (e.g. mentally formulate a sentence).

3.1.2 Differences in structure and functionality

The idea of two separate sub-systems implies a difference between the two systems, regarding structure and functionality. Structurally, they differ in composition, as the representational building blocks differ between the two sub-systems.

In the verbal system, the building blocks are referred to as *imagens,* whereas they in the non-verbal system are referred to as *logogens*. Both imagens and logogens are assumed to vary in size, but the two classes of units differ in the nature of their internal structure in a way that reflects their perceptual-motor origins. Thus, imagens correspond to natural objects, holistic parts of objects, and natural grouping of objects. Imagens are typically part of a synchronously organized hierarchical structure, or a nested collection, which in turn can be part of an even larger structure. Thus, the different imagens can be seen simultaneously in time. Like visual perception, visual imagery has a limited span and different parts of a synchronously available representation may have to be imaged successively or "scanned".

The logogens are different from the imagens regarding internal structure. Smaller units are organized into larger units in a sequential or successive fashion. Hence, a direct dependency among the different imagens exists.

Visual logogens that correspond to print differ in that, up to some limit, they are functionally equivalent to linear spatial structures than can be processed as visual units. Thus, we can imagine letters and short words, maybe even up to three or four words at the time. Such visual word representations presumably do not differ from those that correspond to the representations of non-verbal objects except in the linear arrangement of smaller units into larger ones.

3.1.3 Relations between the sub systems

The non-verbal and verbal sub-systems are assumed to be functionally independent in the sense that one system can be active without the other, or both can be active in parallel. Usually, the verbal and the non-verbal system work together, mutually supporting each other. However, in cases where one of the systems drops out, the other can work alone. This implies that the two systems are partially independent.

The representations in the two systems are assumed to be interconnected. However, these interconnections are incomplete or partial in the sense that the connections are only available between certain representations in each system. Thus, a structural connection between those representations exists, optional in the sense that it is sometimes used and sometimes not.

The points of functional contact between systems are between imagens and logogens. Furthermore, the connections are of the type “one-to-many” in both directions. Consequently, if you hear the word chair, you can imagine many types of chairs (e.g. armchair, stool etc).

3.1.4 The manner of operation for each sub system

Kaufmann (1988) characterises the two information processing systems in the following way: A linguistic-propositional (verbal) representational format is strong in the sense that great precision may be achieved in the form of explicit descriptions. It is easily and quickly manipulated and contains the full range of computational operations. In contrast, imagery is more ambiguous and less easily manipulated, and only comprises simple cognitive operations of a perceptual kind, like anticipations and comparisons. This may be useful and even necessary in complex task environments, where computational operations in the sense of rule-governed inferences are difficult or impossible to perform. Therefore, in tasks with high novelty, complexity or ambiguity human beings seem to switch from a linguistic-propositional representation to an imagery-based representation.

3.1.5 Activation of the sub-systems

The activation of verbal and non-verbal representations is a joint function of variables in the stimulus situation and relevant individual difference variables. Empirical observations indicate that the non-verbal system is more likely to be evoked and used with objects of pictures as stimuli than with words as stimuli, and with concrete words rather than with abstract words.

The verbal system is activated when words serve as stimuli, especially ones that are high in their acquired capacity to arouse verbal associations. Activation of the verbal system would also occur when a task demands verbal processing or when instructions are given to carry out a task verbally.

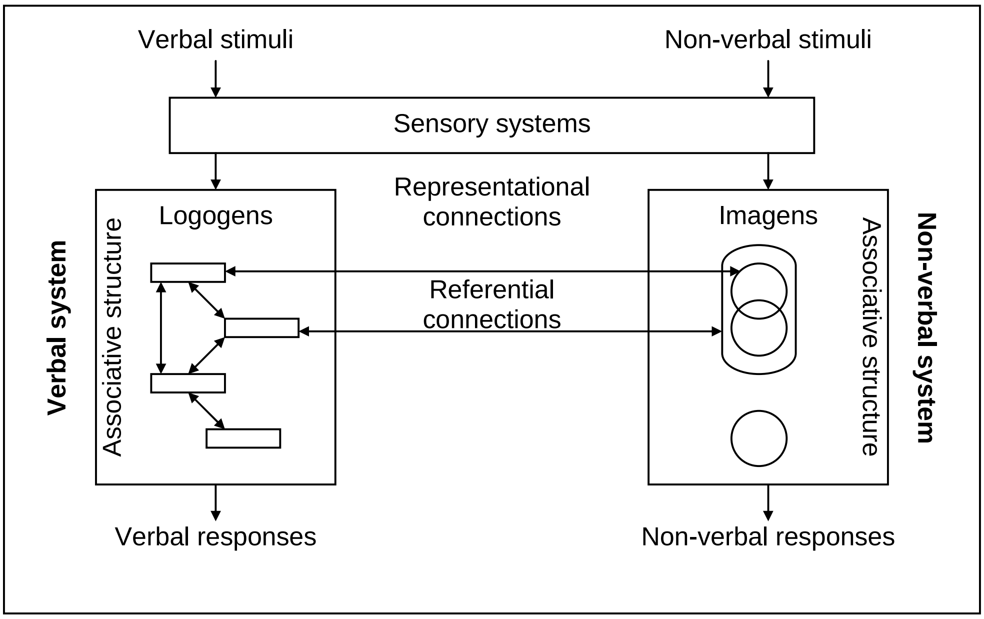


Figure 3.1 – Components of Paivio's Dual-code theory.

Figure 3.1 shows how the theory assumes the two representational systems to be structurally connected to each other, and how they receive information from the external world through an independent sensory system.

3.1.6 Implications of the Dual-code theory

In the studies performed so far, displays of graphs and tables are presented as if they were mutually exclusive. However, the description by Paivio (1986) supports the idea of examining the effects of combined displays of graphs and tables. In relatively simple tasks with limited strain on working memory, I expect that the decision-maker can mentally visualise the relationship between variables from the tabular display and does not need the graphic display. In complex tasks the graphic display may give an overview, but not enough details to reach a high decision quality. Furthermore, the tabular display may not give sufficient overview to handle the details appropriately. Therefore I expect that graphical displays will increase decision makers' general understanding of the relationships between variables in complex tasks, and that additional tables will increase the understanding of details.

3.2 Level of information processing

Decision makers use the information they have available when making their decisions. However, given the same amount of information, different people use different conceptual rules in thinking, deciding and interrelating. Hence, the decision result may wary significantly among different decision makers. This is the starting point for Shcroder et al. (1967) in their development of the concept "Level of information processing". In this section, I will elaborate on this concept, based on a summary by Fuglseth and Grønhaug, (2001, 2003) and by Schroder et al. (1967).

Cognitive complexity theory explains the relationship between the development of human beings' knowledge structures (concepts and relationships between concepts) and their level of information processing. The theory also argues that level of information processing is influenced by the complexity of the task. If the handling of a complex task places a heavy demand on an individual's cognitive capacity, the level of information processing may be reduced (information overload).

A low level of information processing is characterized by the generation of few alternative interpretations of a stimulus. If conflict is introduced, it is supposed to be minimized and resolved quickly, and the result is fast "closure". Individuals able to function at a high level of information processing are supposed to be more sensitive to environmental changes and have an increased perception of uncertainty. They are supposed to be more sensitive to environmental changes and to have an increased perception of uncertainty. They are supposed to take more variables into consideration when evaluating an event and to generate many alternative explanations – and consequences – of the changes. They should also be able to generate broad and varied perspectives of the development of the environment without having perceived actual changes in external conditions.

Schroder et al. (1967) assume a gradual increase in the number of relationships among concepts. Furthermore, they distinguish between four levels of information processing: 1) low, 2) moderately low, 3) moderately high and 4) high. However, this grouping is just a suggestion from the authors – other groupings are believed to be just as appropriate, as many graduations or structural levels could be described along the conceptual-complexity dimension.

4 Research model

Based on the discussion above, I will use the following research model:

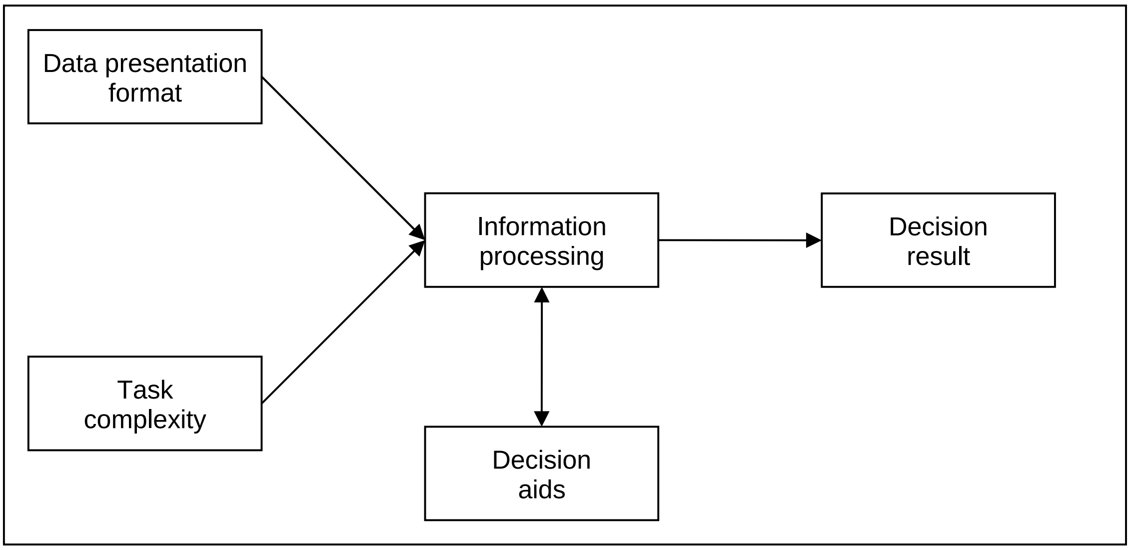


Figure 4.1– Research model

As shown in the model, the independent variables are data presentation format and task complexity. The dependent variable is decision result (measured as total contribution) with information processing including use of decision aids as mediating variables. I have controlled for differences in educational background.

4.1 Data presentation format

I will study the assumption that data presentation format influence on decision making performance. Furthermore, I will study effects of using graph, table or combined use of table and graph.

4.2 Task complexity

In their study, Fuglseth and Grønhaug (2000) have used two relatively identical decision problems, having different complexity as the difference between the two. They examined the influence of data presentation format, both in simple and more complex decision situations. The data presentation format used in the task was graphs, table and a combination of the two. Based on this, they ended up with the following categories to investigate:

		Data presentation format		
		Table	*Graph*	*Table and graph*
Task complexity	*Low*	I	II	III
	High	IV	V	VI

Table 4.1 – Categories to investigate

Findings from Fuglseth and Grønhaug (2000) indicate that decision makers need both graphs and tables when solving decision tasks. Tables are considered important to provide details and basis for further calculations, while graphs are believed to give an overview of relationships between variables. Their findings indicate this tendency quite clear for the simple decision task. Furthermore, many of the respondents presented with tables only, made additional graphs in order to complete the task. Similar, great many of the respondents presented with graphs had to develop tables to be able to perform calculations.

This study is part of a follow-up study, based on the work by Fuglseth and Grønhaug (2000). I will supplement their data set with more results, and I will test the assumption that one might need both representation forms also when solving complex tasks. Hence, I will investigate the same categories as them (Table 4.1).

4.3 Decision aids

Previous studies on the effect of data presentation format on decision making is for the most based on the assumption that decision makers are unaided (Fuglseth & Grønhaug, 2000). This is however rarely the case. Therefore I will take decision aids into account, and study how access to decision aids influence decision making effectiveness.

4.4 Information processing

The research model allows the decision maker's information processing to be influenced by both data presentation format, task complexity and the access to decision aids. The result of the information process is given by the decision result.

An exploratory study is conducted in order to investigate the ideas addressed in the research model.

5 Research design

I have used the same research design as Fuglseth and Grønhaug (2000), and I have therefore borrowed their research model and other research resources. This includes spreadsheet models and task descriptions. (Se appendix 1, 3 and 4)

5.1 Respondents

The respondents in this study were 42 Master students from the Norwegian School of Economics and Business Administration. All the respondents were in their final year when the experiment was conducted.

After five years with an economic education, the respondents are expected to have the relevant background for handling the problem they were presented for. Results for 27 of the respondents are borrowed from Fuglseth and Grønhaug's (2000) equivalent study, whereas I have collected the results for the additional 15 respondents.

The respondents were expected to have sufficient knowledge of the spreadsheet program MS Excel which was used as user interface in the task they should solve during the experiment. All the respondents should have attended an introductory course in data processing, where use of a spreadsheet in an economical setting is an essential part.

There were no time limits placed on the experimental sessions.

5.2 Setting

The task setting was the management of a summer restaurant for a period of four months (June – September), and the respondents were told that the objective of the task was to manage the restaurant with the objective of maximizing contribution.

A demand function was constructed for the relationship between the price of a meal and the number of meals demanded in order to generate income. Costs for ingredients and staff had to be deduced in order to calculate contribution. The demand function was designed to create some amount of uncertainty, so that the demand would not necessarily be the same each week, even though the price was held constant. The number of dinners sold (and with that, gross margin and variable costs) was limited by actual demand and by capacity limitations regarding waiters and assistants. If the respondents did not hire enough waiters/assistants, it would not be possible to cover the whole demand for a given week.

The respondents entered the values of the decision variables into a computerized system, which then calculated and displayed the values of the result variables. The decision variables in the model were: Price per meal, number of kitchen assistants on duty each week and number of waiters on duty each week. The user interface of the system is a spreadsheet, which is expected to be familiar for the respondents (see appendix 3).

Figure 5.1 shows the user interface on one of the models used in the experimental setting.

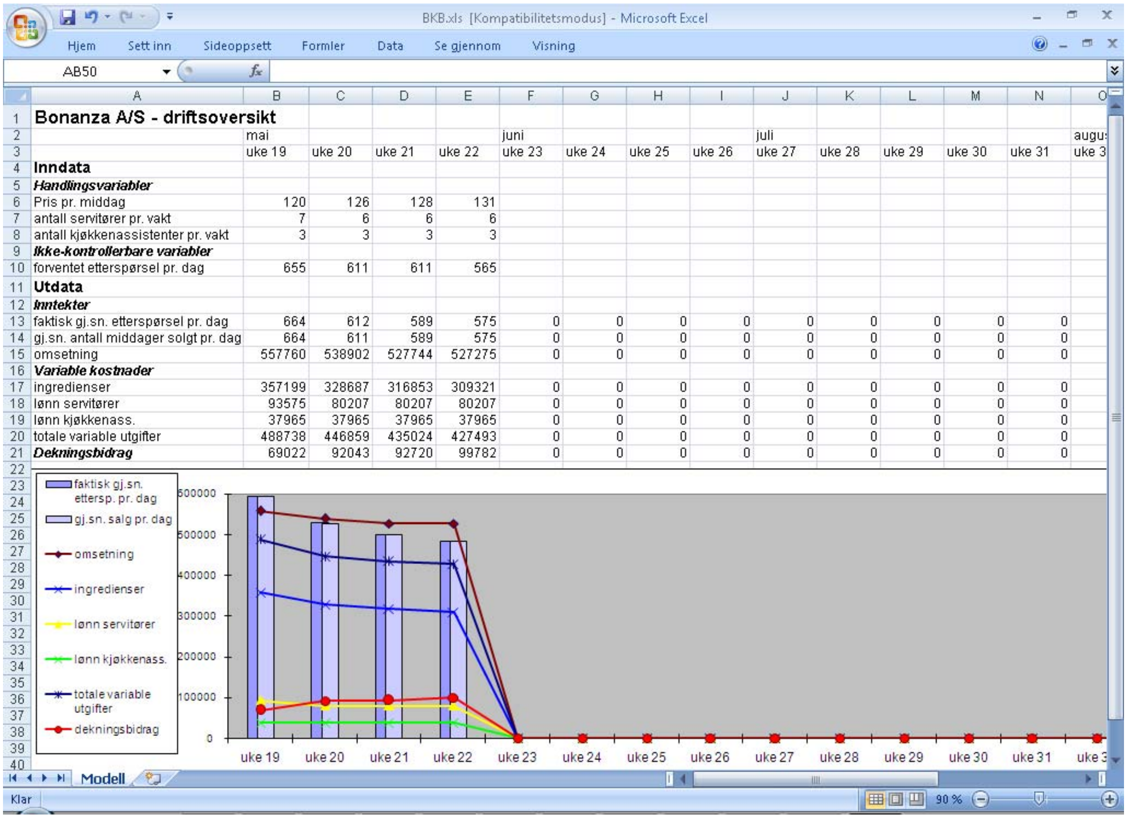
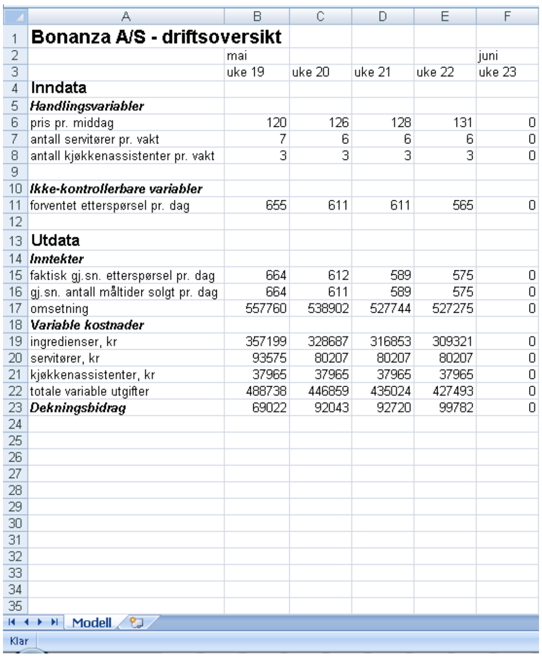


Figure 5.1 – User interface for the models used in the experiments

5.3 Data presentation

The spreadsheet model was designed in three versions, showing the results of the decision variables as graphs, tables or as a combination of graphs and tables. Three versions of the model have been used. In the model versions, there is a clear distinction between input data and output data. The decision variables (input data which were entered into the model) were presented equally in all three versions of the spreadsheet model.

Output data present the results of the decisions the respondents make regarding input data. The values of the output data are the same (given the same input data), but the presentation of them vary in the three versions.



	A	B	C	D	E	F
1	**Bonanza A/S - driftsoversikt**					
2		mai				juni
3		uke 19	uke 20	uke 21	uke 22	uke 23
4	**Inndata**					
5	***Handlingsvariabler***					
6	pris pr. middag	120	126	128	131	0
7	antall servitører pr. vakt	7	6	6	6	0
8	antall kjøkkenassistenter pr. vakt	3	3	3	3	0
9						
10	***Ikke-kontrollerbare variabler***					
11	forventet etterspørsel pr. dag	655	611	611	565	0
12						
13	**Utdata**					
14	***Inntekter***					
15	faktisk gj.sn. etterspørsel pr. dag	664	612	589	575	0
16	gj.sn. antall måltider solgt pr. dag	664	611	589	575	0
17	omsetning	557760	538902	527744	527275	0
18	***Variable kostnader***					
19	ingredienser, kr	357199	328687	316853	309321	0
20	servitører, kr	93575	80207	80207	80207	0
21	kjøkkenassistenter, kr	37965	37965	37965	37965	0
22	totale variable utgifter	488738	446859	435024	427493	0
23	***Dekningsbidrag***	69022	92043	92720	99782	0

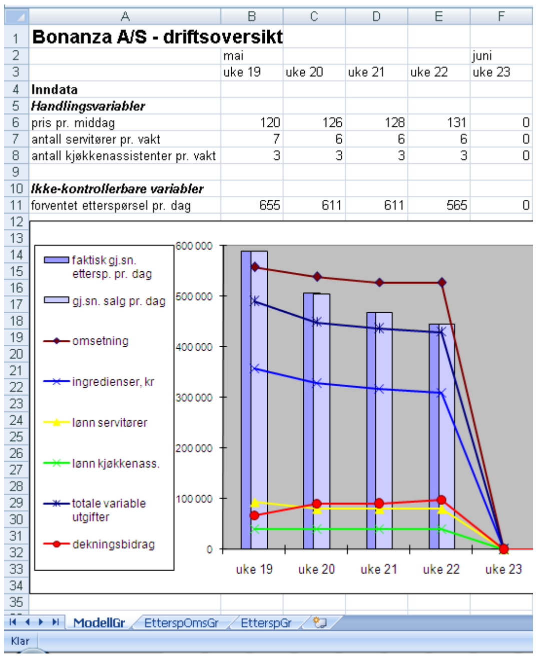


Figure 5.2a – Tabular presentation of output data

Figure 5.2b – Graphical presentation of output data

The historical data were also given in different presentation forms (graphical, tabular or as a combination of the graphs and tables). See appendix 4.

5.4 Measurement

The decision result was measured as total contribution for the period the restaurant was run. Decision result was measured as the total contribution. However, the complex and the less complex task did not have the same optimal solution, hence the decision results were not comparable. Therefore, an index was created in order to make the decision results comparable. The index value is calculated by dividing total contribution by maximum contribution.

Level of information processing was measured based on the four level of information processing presented in the theory of cognitive complexity (Schroder et al., 1967, see section 3.2). By applying such a measure, I hope to obtain a better understanding of the differences in decision-making quality.

A seven point scale was developed from the description of the four levels of information processing in the theory, and by adaptation of a general manual for scoring structural properties from verbal responses. Levels 1, 3, 5 and 7 are the main levels, with rather clear rules for scoring, whereas levels 2, 4, and 6 are used when the participant's responses indicate a development in information processing during problem solving, for example from level 3 to 5, but where level 5 is not clearly attained. The respondents' verbal responses were scored as follows:

- A value of 1 is used when the respondent does not use any critical judgments, but exclusively make use of a "trial and error"-strategy. This information processing level can be characterized as a "black and white" way of thinking (e.g. "if it is not this.. it has to be that..", even though there are given no explanation why this is so), exhibiting a certainty that the chosen alternative is the best. When experiencing unexpected/bad results, the respondents uncritically try with new values for the input data without further effort of problem understanding.

- Level 2 is used when the respondent indicates that there might be some causal relationships in the data, even though he/she does not pursue this thought any further.

- Level 3 is used when the respondents introduce expectations of causal relationships. At this level, however, the respondent considers only one causal relationship at a time, characterized by “either or” conditions (e.g. “If I increase the price, I expect the result to be better than in the previous week”).

- Level 4 is used when the respondents indicate understanding of causal relationships between more than two variables at a time.

- Level 5 is used when the response indicates comprehensive understanding and evaluation of causal relationships between the variables. Now, they can tell that demand will increase by reducing the price, and also what effect this will have regarding determining the number of kitchen assistants and waiters on duty.

- Level 6 has been used for respondents who certainly earn the level of 5, but also try to deduce functional dependencies between variables as numeric quantities.

- Level 7 is used to mark that the respondent deduces functional dependencies between variables. These functions are then used to calculate the “correct” answer to the decision problem. Compared to the level 5, the respondent can not only say that demand will increase by reducing the price with one unit, but also tell how much the demand will increase.

5.5 Data collecting procedures

The respondents were given a task description which gave them an introduction to the summer restaurant Bonanza AS. The respondents were given a task description containing all the information necessary to run the restaurant, for instance what the restaurant could offer their customers, the costs involved in managing the restaurant, how the demand was divided, access to labor, and an introduction to how the former manager had run the restaurant (input- and output data for four weeks in the month of May).

After having read the task description, the respondents got an explanation of the task they were about to solve, and they were given historical numbers concerning the management of the restaurant (price, demand, sales). The historical data was presented as graphical, tabular or as a combination of the two former, depending on what data presentation format was chosen for them.

The spreadsheet model was explained for the students, e.g. decision variables and result variables, and how to use the information system. The students had to use the system that was presented for them, and they had the opportunity to carry out additional calculations in the spreadsheet model, open new spreadsheets for calculations, or make their own graphs. In addition, they could use pencil, paper and a calculator.

The method of data collection was tape-recording of the participants "thinking" aloud while they were interpreting the data displays and making decisions. The results of using the spreadsheet system including additional spreadsheets for calculations or graphs were saved. The results from using paper and calculator were also saved. The tape recording and the use of information system and decision aids were coordinated by the registration of the week number and comments on the use of decision aids on the tapes.

Since I have used data from Fuglseth and Grønhaug (2000), I coordinated my observational routines before conducting the interviews. For instance, discussions have been mad of how "helpful" the observer should be during the interviews etc.

The interviews are transcribed (see appendix 2) and analyzed. The analysis is presented in the next chapter.

6 Analysis

6.1 Results

Parts of the results from the study are presented in Table 6.1 below. The data have been analyzed in SPSS15.0.

No.	Task type	Pres. Form	Elective data	Computation	Graph	Level of info. Proc.	Index	Group Average
1	L	b	d	3		5	0,9993	
2	L	b		2		4	0,9698	
3	L	b		3		5	0,9998	
4	L	b		0		3	0,9965	0,9914
5	L	g	d	3		4	0,9300	
6	L	g	d	3		7	0,9954	
7	L	g	d	3	2	4	0,9587	
8	L	g		0		3	0,9864	0,9676
9	L	t	d	2		4	0,9788	
10	L	t		2	2	5	0,9775	
11	L	t		1	2	5	0,9801	
12	L	t		3	2	5	0,9967	0,9832
13	H	b	d	1		4	0,9105	
14	H	b	d	2		5	0,9026	
15	H	b	d	1		4	0,9743	
16	H	b	d	3		7	0,9878	
17	H	b		1		4	0,7640	
18	H	b		0		3	0,8083	
19	H	b		0		5	0,9240	
20	H	b		0		3	0,8284	
21	H	b		0		4	0,8724	0,8858
22	H	g	d	0		3	0,9028	
23	H	g	d	1		3	0,5131	
24	H	g	d	2	2	3	0,7828	
25	H	g	d	2	1	3	0,8128	
26	H	g	d	3		7	0,9358	
27	H	g	d	0		3	0,8530	
28	H	g		0		3	0,9331	
29	H	g		0		2	0,7838	
30	H	g		0		3	0,8061	
31	H	g		0		3	0,8896	
32	H	g		0		2	0,8274	0,8218
33	H	t	d	3	2	5	0,9843	
34	H	t	d	3	3	7	0,9663	
35	H	t	d	1		3	0,7747	
36	H	t	d	3		5	0,9844	
37	H	t	d	2		6	0,9184	
38	H	t	d	2		4	0,9163	
39	H	t		0		2	0,5918	
40	H	t		1		3	0,8394	
41	H	t		0		1	0,6917	
42	H	t		1		5	0,8782	0,8546
	L = low H = high	b = both g = graph t = table	d = data	1 = simple 2 = compr. 3 = margi/el.	1 = line 2 = XY 3 = XY, compr.	1=low 7=high		

Table 6.6.1 - Results

6.2 Explanation of the data table

In the following, the content of the different columns in Table 6.1 are explained:

- *No.* – States the number of the respondents. There are a total of 42 respondents included in the data.

- *Task type* – Denotes the complexity of the decision problem given to the respondents. H=high complexity, L=low complexity.
- *Pres. Form* – Denotes the data presentation format used for each respondent. b= table and graph, g=graph only, t=table only. Appendix 3 shows an extract of the different model alternatives.
- *Elective data* – Denotes whether or not the respondents have an elective course in data processing. d=elective course in data processing.
- *Computation* – If the respondents performed calculations, either in a spreadsheet, on paper or by means of a calculator, this is denoted in the column labeled Computation. The scope of the calculation is classified on a scale from 1 to 3.
    - The value 1 indicates that the respondent has carried out rather simple calculations (e.g. summing two numbers).
    - The value 2 has been used if the respondents made comprehensive use of computations in their work to find an optimal solution. As an example, the respondent might have put up a table of different prices, and then having calculated the contribution margin for these prices.
    - The value 3 has been used to indicate that the respondent performed rather advanced calculations. Here, the respondents have made marginal analyses regarding the number of kitchen assistants and the number of waiters necessary at different demand alternatives. Furthermore, the respondent might have performed marginal analyses in order to see how the gross margin is affected by a one unit increase in the price.
- *Graph* – If the respondents have prepared their own graphs, this is marked in the column labeled Graph. The degree of details in the graph is graded on a scale from 1 to 3 as follows:
    - The value 1 is used for rather simple line graphs, without detailed information.

- The value 2 is used in cases where the respondent have made an XY-graph, where values for X and Y are plotted, and a line is drawn between the plots.

- The value 3 is used for rather detailed XY-graphs. Here, the respondents have composed scales for the X- and Y-axis, and used the graph to extract values for stated points.

- *Level of info. Proc.* – Level of information processing was measured using a seven point scale, based on the four levels of information processing (Schroder et al., 1967) presented in section 3.2, and section 5.4.

  When going through transcriptions of the interviews, notes were taken regarding what cognitive processes were used by the respondents in their information processing. This has been used when deciding upon level of information processing. I have distinguished between analytical (verbal) and perceptual (spatial) processes.

  The following criteria where used as indications when deciding what types of processes the respondents used:

  Perceptual processes:

  - The respondent is in need of graphs, and complements the decision data with graphs if necessary.

  - The respondent is quiet for long periods of time (silence). The respondents were asked to think aloud. However, it is hard to give a verbal presentation of the content of perceptual processes.

  - The respondent makes graphical/spatial evaluations. This can include such as analyzing trends in the different line graphs, e.g. “The demand curve is declining – I should probably use a lower price…”

  - Simple comparisons (larger/less than, the graph points up/down). E.g. “I increased the price from 126 to 128. This resulted in an increase in contribution… The costs appear to be the same… well, that's ok, I haven't changed them."

    - Effort and error, followed by comparisons/judgements.

  Analytical processes:

    - The respondent makes calculations. Calculations, both in spreadsheet, in paper and articulated calculations. E.g. "Ehh.. a price of 144 gives a demand of 478. This gives sale of 144*478.., that is 68 832. A demand of 478 and one kitchen assistant per 200…. 478/200 is roughly 2,5.."

    - Calculations in spreadsheet and on paper. Use of a calculator.

    - Calculations in the respondent's head. The respondent's articulation of thought shows that a mental, numerical calculation takes place.

    - Relatively detailed calculations.

- *Index* – The decision results shown as an index, comparable for the low and high complexity task.

- *Group average* – This column shows the average contribution for each presentation form, sorted by sub-groups.

6.3 A first look at the data

Table 6.1 shows part of the obtained data. The table shows a clear difference in decision results between the low and the high complexity task. The average value of the contribution index for the low complexity task is 0,981 whereas the average value for the high complexity task is 0.852 ($p < 0.0001$). This result is as expected, as it should be easier to reach the optimal solution for the low complexity task, as opposed to the high complexity task, and therefore confirms that we have been able to differentiate regarding complexity in the quasi-experiment.

6.4 Economic understanding – adjusting the data set

A closer inspection of the results in Table 6.1 reveals that some of the respondents, no. 23 (index= 0,5131) and no. 39 (index=0,5918), perform considerably worse than the rest. This is an interesting phenomenon that needs further investigation.

The task presumes that the respondents have adequate economic skills, both in order to understand problem and in order to solve it. However, analyzing the transcripts of respondent no. 23 and no. 39 clearly reveals that this is not the case for them. They lack the adequate economic understanding necessary to solve the decision problem, and this in turn lead to very poor result (e.g. one of these two respondents maximized sales instead of contribution).

As already stated, economic knowledge is a premise for understanding the task they are asked to solve in the quasi-experiment, and it is in no way related to data presentation format. Including them in the data set would therefore bias the study, and a correction seems fair. Thus, it is reasonable to remove the results from these two respondents (no. 23 and 39) when performing further analyses. Table 6.2 presents the results without respondent no. 23 and no. 39.

No.	Task type	Pres. Form	Elective data	Computation	Graph	Level of info. Proc.	Index	Group Average
1	L	b	d	3		5	0,9993	
2	L	b		2		4	0,9698	
3	L	b		3		5	0,9998	
4	L	b		0		3	0,9965	0,9914
5	L	g	d	3		4	0,9300	
6	L	g	d	3		7	0,9954	
7	L	g	d	3	2	4	0,9587	
8	L	g		0		3	0,9864	0,9676
9	L	t	d	2		4	0,9788	
10	L	t		2	2	5	0,9775	
11	L	t		1	2	5	0,9801	
12	L	t		3	2	5	0,9967	0,9832
13	H	b	d	1		4	0,9105	
14	H	b	d	2		5	0,9026	
15	H	b	d	1		4	0,9743	
16	H	b	d	3		7	0,9878	
17	H	b		1		4	0,7640	
18	H	b		0		3	0,8083	
19	H	b		0		5	0,9240	
20	H	b		0		3	0,8284	
21	H	b		0		4	0,8724	0,8858
22	H	g	d	0		3	0,9028	
24	H	g	d	2	2	3	0,7828	
25	H	g	d	2	1	3	0,8128	
26	H	g	d	3		7	0,9358	
27	H	g	d	0		3	0,8530	
28	H	g		0		3	0,9331	
29	H	g		0		2	0,7838	
30	H	g		0		3	0,8061	
31	H	g		0		3	0,8896	
32	H	g		0		2	0,8274	0,8527
33	H	t	d	3	2	5	0,9843	
34	H	t	d	3	3	7	0,9663	
35	H	t	d	1		3	0,7747	
36	H	t	d	3		5	0,9844	
37	H	t	d	2		6	0,9184	
38	H	t	d	2		4	0,9163	
40	H	t		1		3	0,8394	
41	H	t		0		1	0,6917	
42	H	t		1		5	0,8782	0,8838
	L = low H = high	b = both g = graph t = table	d = data	1 = simple 2 = compr. 3 = margi/el.	1 = line 2 = XY 3 = XY, compr.	1=low 7=high		

Table 6.2 – Results adjusted for economic knowledge

6.5 The importance of data presentation format

Inspection of the table 6.2 reveals that respondents presented with both graphs and tables perform better than respondents in the other categories. This tendency seems to be the same for both the high and the low complexity task. Table 6.3 shows the average values of the contribution index for different presentation formats in high and low complexity tasks.

		Presentation format		
		Table	*Graph*	*Table and Graph*
Task complexity	*Low*	**0,9832** N=4, st.dev.=0,090	**0,9676** N=4, st.dev.=0,030	**0,9914** N=4, st.dev.=0,014
	High	**0,8838** N=9, st.dev.=0,100	**0,8527** N=10, st.dev.=0,059	**0,8858** N=9, st.dev.=0,075

Table 6.3 - Average values of the contribution indext for different presentation formats in high- and low-complexity tasks

These findings support the assumption that decision makers need both spatial and verbal representation formats (see section 3.1), even though the results are more evident for the low complexity group compared to the high complexity group. Particularly the table format seems to be important as respondents presented with tables (table or table and graph together) achieve a higher contribution compared to the ones presented with graphs only. This tendency is present, both in low and high complexity task, but still more striking for the high complexity task.

Table 6.2 also reveals that some respondents (Nos. 6, 7, 10, 11, 12, 26, 33, and 34) have made adjustments to the presentation form they originally received. Three respondents presented with graphs only (Nos. 6, 7 and 26) prepared their own data tables in a spreadsheet based on the graphical presentation format they were given. This was necessary for them in order to be able to perform the calculations they needed to make. Further, five of the 14 respondents presented with tables only, made graphs themselves (Nos. 10, 11, 12, 33 and 34) in order to visualize the data they received as tables. This indicates that the respondents needed both graphs and tables in order to solve the decision task properly.

Common for all the respondents adjusting their originally presentation format is that they actually gained access to both presentation forms in their decision making process. Even though their self made additional presentation format did not include as many details as the spreadsheet model showing both graphs and tables, they at least had access to both graphs and tables in their decision making.

By adjusting for this, we can group the results by what presentation forms the respondents used in their decision making process. Table 6.4 shows the results after this grouping:

No.	Task type	Pres. Form	Elective data	Computation	Graph	Level of info. Proc.	Index	Group Average
1	L	b	d	3		5	0,9993	
2	L	b		2		4	0,9698	
3	L	b		3		5	0,9998	
4	L	b		0		3	0,9965	
6	L	g*	d	3		7	0,9954	
7	L	g*	d	3	2	4	0,9587	
10	L	t*		2	2	5	0,9775	
11	L	t*		1	2	5	0,9801	
12	L	t*		3	2	5	0,9967	0,9860
5	L	g	d	3		4	0,9300	
8	L	g		0		3	0,9864	0,9582
9	L	t	d	2		4	0,9788	0,9788
13	H	b	d	1		4	0,9105	
14	H	b	d	2		5	0,9026	
15	H	b	d	1		4	0,9743	
16	H	b	d	3		7	0,9878	
17	H	b		1		4	0,7640	
18	H	b		0		3	0,8083	
19	H	b		0		5	0,9240	
20	H	b		0		3	0,8284	
21	H	b		0		4	0,8724	
26	H	g*	d	3		7	0,9358	
33	H	t*	d	3	2	5	0,9843	
34	H	t*	d	3	3	7	0,9663	0,9049
22	H	g	d	0		3	0,9028	
24	H	g	d	2	2	3	0,7828	
25	H	g	d	2	1	3	0,8128	
27	H	g	d	0		3	0,8530	
28	H	g		0		3	0,9331	
29	H	g		0		2	0,7838	
30	H	g		0		3	0,8061	
31	H	g		0		3	0,8896	
32	H	g		0		2	0,8274	0,8435
35	H	t	d	1		3	0,7747	
36	H	t	d	3		5	0,9844	
37	H	t	d	2		6	0,9184	
38	H	t	d	2		4	0,9163	
40	H	t		1		3	0,8394	
41	H	t		0		1	0,6917	
42	H	t		1		5	0,8782	0,8576
	L = low	b = both	d = data	1 = simple	1 = line	1=low		
	H = high	g = graph		2 = compr.	2 = XY	7=high		
		t = table		3 = margi/el.	3 = XY, compr.			

Table 6.4 - Adjusted for presentation forms used in the decision making

The table now shows a more powerful effect regarding use of a presentation forms consisting of *both* tables and graphs, see Table 6.5 for an overview of average scores on the contribution index.

		Presentation format		
		Table	*Graph*	*Table and Graph*
Task complexity	*Low*	**0,9788** N=1, st.dev.=N/A	**0,9582** N=2, st.dev.=0,040,	**0,9860** N=9, st.dev.=0,015
	High	**0,8576** N=7, st.dev.=0,099	**0,8435** N=9, st.dev.=0,054	**0,9049** N=12, st.dev.=0,073

Table 6.5 – Cross table: Presentation format and Task complexity

For the low complexity task, there are nine respondents categorized as having used both table and graph. Only two respondents are categorized as having used graph and just one is categorized as having used table. Therefore, it is no longer useful to compare means for the low-complexity task – there is simply not enough data to do so. However, for the high-complexity group, there is a clear tendency of higher results for respondents using both graphs and tables in their decision making process.

A closer inspection of Table 6.2 can give the impression that respondents with an elective course in data processing apparently attain a higher result than the rest. This needs further investigation.

6.6 The importance of the respondents data processing skills

To get a better understanding of the effects of having an elective course in data processing, I will use Table 6.2 (adjusted for economic knowledge), sorted by: 1) whether or not the respondents have an elective course in data processing and 2) presentation form. The result of these adjustments is presented in Table 6.6:

No.	Task type	Pres. Form	Elective data	Computation	Graph	Level of info. Proc.	Index	Group Average	Group Average 2
1	L	b	d	3		5	0,9993	0,9993	
5	L	g	d	3		4	0,9300		
6	L	g	d	3		7	0,9954		
7	L	g	d	3	2	4	0,9587	0,9614	
9	L	t	d	2		4	0,9788	0,9788	0,9725
2	L	b		2		4	0,9698		
3	L	b		3		5	0,9998		
4	L	b		0		3	0,9965	0,9862	
8	L	g		0		3	0,9864	0,9942	
10	L	t		2	2	5	0,9775		
11	L	t		1	2	5	0,9801		
12	L	t		3	2	5	0,9967	0,9852	0,9867
13	H	b	d	1		4	0,9105		
14	H	b	d	2		5	0,9026		
15	H	b	d	1		4	0,9743		
16	H	b	d	3		7	0,9878	0,9438	
22	H	g	d	0		3	0,9028		
24	H	g	d	2	2	3	0,7828		
25	H	g	d	2	1	3	0,8128		
26	H	g	d	3		7	0,9358		
27	H	g	d	0		3	0,8530	0,8574	
33	H	t	d	3	2	5	0,9843		
34	H	t	d	3	3	7	0,9663		
35	H	t	d	1		3	0,7747		
36	H	t	d	3		5	0,9844		
37	H	t	d	2		6	0,9184		
38	H	t	d	2		4	0,9163	0,9241	0,9071
17	H	b		1		4	0,7640		
18	H	b		0		3	0,8083		
19	H	b		0		5	0,9240		
20	H	b		0		3	0,8284		
21	H	b		0		4	0,8724	0,8394	
28	H	g		0		3	0,9331		
29	H	g		0		2	0,7838		
30	H	g		0		3	0,8061		
31	H	g		0		3	0,8896		
32	H	g		0		2	0,8274	0,8480	
40	H	t		1		3	0,8394		
41	H	t		0		1	0,6917		
42	H	t		1		5	0,8782	0,8031	0,8343
	L = low H = high	b = both g = graph t = table	d = data	1 = simple 2 = compr. 3 = margi/el.	1 = line 2 = XY 3 = XY, compr.	1=low 7=high			

Table 6.6 – Results adjusted for economic knowledge, sorted by elective course in data processing

My assumption has been that respondents having sufficient data processing skills are better capable of using the functionality of a spreadsheet program. This includes possibilities, such as building dynamic models for calculations, being able to utilize built-in functions and also being able to create graphs based on data in the spreadsheet. Used properly, the spreadsheet can support decision makers, e.g. by taking away some of the pressure on working memory. However, a premise for this is that the decision-makers master the spreadsheet.

For the present purpose, having an elective course in data processing is used as an objective criterion for whether or not respondents have the necessary data processing skills. Of the 40 respondents in the experiment, 20 had the elective course.

The probability of carrying out additional calculations when solving the decision problem is not known. However, of a total of 40 respondents, 26 carried out additional calculations (see Table 6.2). If we then assume the probability of carrying out calculations is the same for all respondents (both those having an elective course in data processing and those who have not), we can estimate the probability of calculations to be:

$$P = 26/40 = 0{,}65.$$

Table 6.6 supports my assumption regarding data processing skills. The group of respondents capable to carry out additional calculations (26) mainly consists of respondents having the elective course in data processing (18 out of 26). Furthermore, 20 of the 20 respondents having the elective course, 18 performed additional calculations. If we now assume the probability of carrying out calculations is the same for all respondents having the elective course in data processing, we can estimate the probability of calculations for this group to be:

$$P = 18/20 = 0{,}9$$

This indicates that these respondents, to a larger extent than the ones not having such an elective course, uses verbal processes, which in turn can lead to more accurate results.

An interesting observation is, however, that this tendency seems to be more obvious for the high-complexity task. 13 out of 15 having the elective course made additional calculations, whereas 3 out of 13 of those not having such an elective course made additional calculations. In the low-complexity task 4 out of 4 of those having an elective course in data processing made additional calculations, whereas 5 out of 7 of those not having such an elective course made additional calculations. Furthermore, in the high-complexity task, none of the participants without an elective course made any but simple calculations.

A possible explanation for these findings might be that the subjective complexity for the high-complexity group is perceived as higher for those not familiar with using spreadsheet as compared to those familiar with using a spreadsheet. A higher perceived complexity can lead to information overload, and consequently a reduction in level of information processing (see section 3.2). A parametric correlation matrix, controlled for the effect of mastering a spreadsheet supports this assumption. The correlation between level of information processing and those performing additional computations is significant (p=0,0001).

This confirms the assumption that mastering a decision aid (in this case, having sufficient skills in mastering a spreadsheet) is important for an effective decision making process to occur.

Furthermore, the result strengthens the assumption that respondents with an elective course in data processing are better able to take advantage of spreadsheet functionality in order to complement the data presentation format if needed. Also, in the high-complexity group, we see that all the respondents making additional graphs (24, 25, 33 and 34) are respondents with an elective course in data processing. Hence, the ability to effectively master the decision aid is highly important. By being able to complement the data presentation format, the respondents can reduce the load on working memory, and get a better view of the decision problem. However, respondents carrying out additional calculations did not use spreadsheets exclusively. Some of the respondents (24 and 25) used paper, pencil and calculator for their calculations.

Table 6.6 reveals that in the high-complexity task, respondents with an elective course in perform far better (0,9071) than respondents without this course (0,8343).

Also, if we, for the high-complexity task, compare results in sub-groups (graphical without elective course in data processing vs. graphical with an elective course in data processing etc.), we see that the mean results for respondents with an elective course are higher than for those without this course. The difference is, however largest for respondents receiving tabular data and least for respondents receiving a graphical presentation format. Table 6.7 summarizes average values for the contribution index in the high-complexity task:

		Presentation format		
		Table	*Graph*	*Table and Graph*
Elective course in data processing	*Yes*	**0,9241** N=6, st.dev.=0,079	**0,8574** N=5, st.dev.=0,063	**0,9438** N=4, st.dev.=0,043
	No	**0,8031** N=3, st.dev.=0,098	**0,8480** N=5, st.dev.=0,062	**0,8394** N=5, st.dev.=0,061

Table 6.7 – Cross table, high-complexity task: Presentation format and Elective course in data processing

During the interviews, the respondents' data processing skills have been evaluated subjectively. This was done to check for respondents not having an elective course in data processing, but who did still master the spreadsheet well. This exercise makes it possible to eliminate possible respondents that turn out to not master the spreadsheet well, even though they have completed the elective course in data processing. This is the case of respondents number 24 and 25. They did relatively poorly when working with the spreadsheet, even though they had completed the elective course. Number 24 even needed an explanation of how the spreadsheet functioned. In Table 6.8 the respondents 24 and 25 have been moved down to the category of respondents without the elective course in data processing (marked with d*). As we have already seen, doing this gives a strengthening of the result.

No.	Task type	Pres. Form	Elective data	Computation	Graph	Level of info. Proc.	Index	Group Average	Group Average 2
1	L	b	d	3		5	0,9993	0,9993	
5	L	g	d	3		4	0,9300		
6	L	g	d	3		7	0,9954		
7	L	g	d	3	2	4	0,9587	0,9614	
9	L	t	d	2		4	0,9788	0,9788	0,9725
2	L	b		2		4	0,9698		
3	L	b		3		5	0,9998		
4	L	b		0		3	0,9965	0,9862	
8	L	g		0		3	0,9864	0,9942	
10	L	t		2	2	5	0,9775		
11	L	t		1	2	5	0,9801		
12	L	t		3	2	5	0,9967	0,9852	0,9867
13	H	b	d	1		4	0,9105		
14	H	b	d	2		5	0,9026		
15	H	b	d	1		4	0,9743		
16	H	b	d	3		7	0,9878	0,9438	
22	H	g	d	0		3	0,9028		
26	H	g	d	3		7	0,9358		
27	H	g	d	0		3	0,8530	0,8972	
33	H	t	d	3	2	5	0,9843		
34	H	t	d	3	3	7	0,9663		
35	H	t	d	1		3	0,7747		
36	H	t	d	3		5	0,9844		
37	H	t	d	2		6	0,9184		
38	H	t	d	2		4	0,9163	0,9241	0,9239
17	H	b		1		4	0,7640		
18	H	b		0		3	0,8083		
19	H	b		0		5	0,9240		
20	H	b		0		3	0,8284		
21	H	b		0		4	0,8724	0,8394	
28	H	g		0		3	0,9331		
29	H	g		0		2	0,7838		
30	H	g		0		3	0,8061		
31	H	g		0		3	0,8896		
32	H	g		0		2	0,8274		
24	H	g	d*	2	2	3	0,7828		
25	H	g	d*	2	1	3	0,8128	0,8336	
40	H	t		1		3	0,8394		
41	H	t		0		1	0,6917		
42	H	t		1		5	0,8782	0,8031	0,8295
	L = low H = high	b = both g = graph t = table	d = data	1 = simple 2 = compr. 3 = margi/el.	1 = line 2 = XY 3 = XY, compr.	1=low 7=high			

Table 6.8 - Results adjusted for economic knowledge and the ability to master a spreadsheet

Table 6.8 shows that the largest difference between those mastering the spreadsheet and those who do not, is among the respondents that have been presented tables in one way or the other. This shows that access to raw data is essential – graphs will not by itself give enough details to enable effective calculations.

Furthermore, the results support the assumption that having access to a decision aid in itself is not enough. It is also necessary to be able to apply the decision aid efficiently, if one is to gain any advantages from using it.

6.7 Total adjustment

Table 6.9 displays raw data adjusted for economic knowledge and presentation formats used in the decision making process, sorted by the ability to master the spreadsheet.

No.	Task type	Pres. Form	Elective data	Computation	Graph	Level of info. Proc.	Index	Group Average	Group Average 2
1	L	b	d	3		5	0,9993		
6	L	g*	d	3		7	0,9954		
7	L	g*	d	3	2	4	0,9587	0,9845	
5	L	g	d	3		4	0,9300	0,9300	
9	L	t	d	2		4	0,9788	0,9788	0,9725
2	L	b		2		4	0,9698		
3	L	b		3		5	0,9998		
4	L	b		0		3	0,9965	0,9862	
8	L	g		0		3	0,9864	0,9942	
10	L	t*		2	2	5	0,9775		
11	L	t		1	2	5	0,9801		
12	L	t		3	2	5	0,9967	0,9884	0,9867
13	H	b	d	1		4	0,9105		
14	H	b	d	2		5	0,9026		
15	H	b	d	1		4	0,9743		
16	H	b	d	3		7	0,9878		
26	H	g*	d	3		7	0,9358		
33	H	t*	d	3	2	5	0,9843		
34	H	t*	d	3	3	7	0,9663	0,9517	
22	H	g	d	0		3	0,9028		
27	H	g	d	0		3	0,8530	0,8779	
35	H	t	d	1		3	0,7747		
36	H	t	d	3		5	0,9844		
37	H	t	d	2		6	0,9184		
38	H	t	d	2		4	0,9163	0,8985	0,9239
17	H	b		1		4	0,7640		
18	H	b		0		3	0,8083		
19	H	b		0		5	0,9240		
20	H	b		0		3	0,8284		
21	H	b		0		4	0,8724	0,8394	
28	H	g		0		3	0,9331		
29	H	g		0		2	0,7838		
30	H	g		0		3	0,8061		
31	H	g		0		3	0,8896		
32	H	g		0		2	0,8274		
24	H	g	d*	2	2	3	0,7828		
25	H	g	d*	2	1	3	0,8128	0,8336	
40	H	t		1		3	0,8394		
41	H	t		0		1	0,6917		
42	H	t		1		5	0,8782	0,8031	0,8295
	L = low H = high	b = both g = graph t = table	d = data	1 = simple 2 = compr. 3 = margi/el.	1 = line 2 = XY 3 = XY, compr.	1=low 7=high			

Table 6.9 - Results adjusted for presentation form and economic knowledge, sorted by the ability to master a spreadsheet

Also this time, the sample size of the low-complexity task is too small to make any inferences of the effects of data processing knowledge and presentation form. However, for the high-complexity task, there is enough data to see a pattern. Average values for the contribution index in the high complexity task are presented in table 6.10.

		Presentation format		
		Table	*Graph*	*Table and Graph*
Mastering a spreadsheet	*Yes*	**0,8985** N=4, st.dev.=0,88	**0,8779** N=2, st.dev.=0,035	**0,9517** N=7, st.dev.=0,035
	No	**0,8031** N=3, st.dev.=0,098	**0,8336** N=7, st.dev.=0,057	**0,8394** N=5, st.dev.=0,061

Table 6.10 - Cross table, high-complexity task: Presentation form and the ability to master a spreadsheet

The table exhibits a clear distinction between those mastering the spreadsheet and those who do not. Furthermore, Table 6.10 shows that the largest difference in decision effectiveness is among the respondents that have been presented with some form of a data table.

A possible explanation why respondents with a tabular presentation format gain the highest scores might be that this presentation format anyhow stimulates verbal processes. Consequently, it is possible to go deeper into details and perform more accurate calculations. However, I expected the need to get a visual overview to be higher.

6.8 Level of information processing

There are significant differences in level of information processing between the low and the high complexity task when comparing means. However, level of information processing is ordinal scaled data; hence comparing means is not the optimal way of analyzing the data. Nevertheless, for this purpose it serves as a useful indication of tendencies in the data set. The average value of level of information processing for the low complexity task is 4.5 whereas the average value for the high complexity task is 3.93. It might sound strange that the high-complexity group attain a lower the level of information processing than do the low-complexity group. However, this is in accordance to cognitive complexity theory (see section 3.2), which argues that level of information processing is influenced by the complexity of the task. Handling of a complex task places a heavy demand on an individual's cognitive capacity, and therefore the level of information processing may be reduced (information overload).

A nonparametric correlations matrix shows significant correlation between the contribution index (result) and level of information processing (p=0,000). This sounds fear, since those attaining a higher level of information processing also are expected to able to achieve higher quality in the decision making process. This, in turn, should lead to a better result (see section 3.2). However, there are also significant correlations between level of information processing and a) those who have performed additional calculations (p=0,000), b) those who have made additional graphs (p=0,014) c) those who have attended an additional course in data processing (p=0,014). Furthermore, there are significant correlations between those having made additional calculations and a) those having an elective course in data processing (p=0,000) and b) the contribution index (p=0,000). No significant correlations where found between those having an elective course and those having made additional graphs. See Table 6.11.

Nonparametric correlations

			Result (contribution index)	Level of info. Proc.	Additional graph	Additional comp	Elective data
Spearman's rho	Result (contribution index)	Correlation Coefficient	1,000	,634(**)	0,218	,555(**)	0,160
		Sig. (1-tailed)	.	0,000	0,302	0,000	0,162
		N	40	40	8	40	40
	Level of info. Proc.	Correlation Coefficient	,634(**)	1,000	,761(*)	,741(**)	,349(*)
		Sig. (1-tailed)	0,000	.	0,014	0,000	0,014
		N	40	40	8	40	40
	Additional graph	Correlation Coefficient	0,218	,761(*)	1,000	0,418	0,000
		Sig. (1-tailed)	0,302	0,014	.	0,151	0,500
		N	8	8	8	8	8
	Additional comp.	Correlation Coefficient	,555(**)	,741(**)	0,418	1,000	,572(**)
		Sig. (1-tailed)	0,000	0,000	0,151	.	0,000
		N	40	40	8	40	40
	Elective data	Correlation Coefficient	0,160	,349(*)	0,000	,572(**)	1,000
		Sig. (1-tailed)	0,162	0,014	0,500	0,000	.
		N	40	40	8	40	40

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

Table 6.11 – Nonparametric correlations

As we have seen earlier in the analysis, data processing skills are important in order to perform additional calculations, which in turn have had a positive effect of the result (contribution index). Therefore, it is reasonable to ask if maybe the correlation between level of information processing and the contribution index indirectly caused by having sufficient data processing skills. This needs further investigation.

A partial correlation matrix was generated. Here, I controlled for those having an elective course in data processing. Still, after this controlling, the matrix reveals significant correlations between level of information processing and result (p=0,000). See Table 6.12.

Partial correlations

Control Variables			Additional comp.	Additional graph	Level of info. Proc.	Result (contribution index)
Data	Additional comp	Correlation	1,000	0,438	0,654	0,518
		Significance (1-tailed)	.	0,163	0,000	0,000
		df	0	5	37	37
	Additional graph	Correlation	0,438	1,000	0,891	0,499
		Significance (1-tailed)	0,163	.	0,004	0,127
		df	5	0	5	5
	Level of info. Proc.	Correlation	0,654	0,891	1,000	0,629
		Significance (1-tailed)	0,000	0,004	.	0,000
		df	37	5	0	37
	Result (contribution index)	Correlation	0,518	0,499	0,629	1,000
		Significance (1-tailed)	0,000	0,127	0,000	.
		df	37	5	37	0

Table 6.12 - Partial correlations

The new correlation matrix shows no significant correlation between result (contribution index) and having made additional graphs. However, level of information processing correlates well with a) having made additional graphs (p=0,000) and b) having made additional computations (p=0,000). This shows that those having made additional graphs or tables also have attained a higher level of information processing, even when controlling for the effect of having adequate data processing skills. Furthermore, this finding supports the assumption that decision makers need both tables and graphs in order achieve a high quality decision making process.

This is interesting, and supports the This finding support the assumption that sufficient skills in handling a decision aid (in this case mastering a spreadsheet) is extremely important a decision aid

6.9 Possible sources of errors

One of the most striking weaknesses of this study is certain characteristics of the data set. First of all, the number of respondents participating in the experiment is too small in order to make significant conclusions. However, we see clear traces of possible effects from both presentation form, task complexity and the ability of mastering a decision aid (spreadsheet). Second, the data set should have included more accurate measures of the respondents' time consume. This includes total time used by each respondent, but also how this time was divided between problem understanding and problem solving. By including clear measures of time consume in the data set, I would have been able to look for possible trade-offs between accuracy and effort. Both the number of respondents and a clear measure of time consume should be taken into account in a potential follow up study.

Another weakness of the study is related to the respondents and their motivation for attending and performing well in the experiment. A measure of motivation should have been developed and incorporated in the study.

The assessment of cognitive processes used by the respondents is especially hard to do when the respondents neither create additional calculations, nor create graphs. Therefore it was particular important that the respondents thought aloud during the interviews. Nevertheless, a focus on use verbal protocol as a source of research data and the validity in such should have been taken into considerations.

In this experiment, the respondents' grade in economic analysis has not been taken into consideration. Although this would have been desirable, it has not been possible to get hold of such data. However, economic skills might partly explain differences in decision effectiveness, since adequate economic knowledge is a important to fully understand the present decision problem. This was confirmed in the results of respondents' no. 23 and no. 39 as well.

The data in this research has been gathered by two researchers, and the data collection procedure has not been fully coordinated between the two. Consequently, different ways of interpreting the respondents' thoughts might have occurred when observing them.

Such differences in interpretations are a potential source of error. For instance, if a respondent indicates need for additional graphs but does not know how to make them, the observer could, or could no, explain how to use Excel to create such graphs. If the respondent were “helped” to make a graph, this would have to be equal for all respondents indicating such a need for help.

7 Conclusion

The results presented in this thesis show that both tables and graphs are useful presentation formats when aiming at effective decision making processes. Tables are necessary in order to obtain details, and form the basis for further calculations. Graphs, on the other hand, provide a visualization of relations between decision variables and are useful for getting an overview of the decision problem. This corresponds with the results from research on decision making in lower complexity by Fuglseth and Grønhaug (2000).

Nevertheless, the results also show that graphs alone are not sufficient as data presentation format. Decision makers *do* need raw data. Therefore, graphs alone should never be used as basis for a decision. This limits the decision makers’ ability to carry out accurate calculations which is a requirement for achieving a good result. This is especially important in complex decision tasks.

Access to decision aids is significant regarding decision making effectiveness. However, results from this study show that a decision makers’ ability to master the decision aids is a premise for effective utilization.

The results in this research calls for a follow up study. Both the number of respondents and a clear measure of time consume should then be taken into account. Furthermore, a measure of motivation should be developed and applied in such a study.

8 References

Anderson, J. R. 1978. Arguments concerning representations for mental imagery. Psychological Review. Vol. 85, No. 4, pp. 249-277.

Beach, L. R., Mitchell, T. R. 1978. A contingency for selection of decision strategies. Academy of Management Review. Vol. 3, pp. 439-449

Beattie, V. A. Jones, M. J. 1993. Effect of graphical presentations on insights into a copany’s financeial position – an innovative educational approach to communicating financial information in financial reporting: a comment. Accounting Education, Vol. 2, No. 4, pp. 303-309.

Bricker, R., and R. Nehmer. 1994. Information presentation format, degree of information processing, and decision quality. Working paper, Case Western Reserve University.

Brarud, P. Ø. 2001. Subjective task complexity and subjective workload: Criterion validity for complex team tasks. International Journal of Cognitive Ergonomics Vol 5, No 3, pp. 261-273.

DeSanctis, G. 1984. Computer graphics as decision aids: Directions for research. Decision Sciences Vol. 15, No. 4, pp. 463-487

Edwards, W. 1992. Organizational behavior and human decision processes. Vol. 53. pp. 267-277.

Frownfelter-Lohrke, C. 1998. The effects of differing information presentations of general purpose financial statements on users’ decisions. Journal of Information Systems. Vol. 12, No 2, pp. 99-107.

Fuglseth, A.M, Grønhaug, K. 2000. The effectiveness of data presentation forms. IAREP/SABE 2000.

Fuglseth, A.M., Grønhaug, K. 2002. Theory-driven construction and analysis of cause maps. International Journal of Information Management. Vol. 22, pp. 357-376.

Fuglseth, A.M., Grønhaug, K. 2003. Can computerized marked models improve strategic decision-making? An exploratory study. Journal of Socio-Economics, Vol. 32, pp. 503-520

Jarvenpaa, S.L., Dickson, G.W. 1988. Graphics and managerial decision making: research based guidelines. Communications of the ACM. Vol. 31, No. 6, pp. 764-774.

Helstrup, T. Kaufman, G. 2000. Kognitive Psykologi. Fagbokforlaget.

Kaufman, G. 1988. Problem Solving and Creativity. In K. Grønhaug and G. Kaufman (eds), Innovations: a cross-disciplinary perspective. Oslo: Norvegian University Press, pp. 87-137

Kleinmuntz, D. Schkade, D. A. 1993. Information displays and decision processes. Psychological Science. Vol 4, No. 4, pp. 1-7

Mayer, E. M., Anderson, R. B. 1991. Animations need narrations: An experimental test of a dual-coding hypothesis. Journal of Educational Psychology. Vol. 83, No. 4, pp. 484-490

Meyer, J. 2000. Performance with tables and graphs: effects of training and visual search model. Ergonomics 43 (11). pp. 1840-1865.

Olshavsky, R. W. 1979. Task complexity and contingent processing in decision making: A replication and extention. Organization Behavior and Human Performance. 24. Pp. 300-316.

Paivio, A. 1986. Mental Representations: a dual coding approach. New York: Oxford University Press

Paivio, A.1971. Imagery and verbal processes. New York: Holt, Rinehart, and Winston. (Reprinted 1979, Hillsdale, NJ: Lawrence Erlbaum Associatiotes).

Paquette, L., Kida, T. 1988. The Effect of Decision Strategy and Task Complexity on Decision Performance. Organizational behavior and human decision processes 41. Pp. 128-142.

Payne, J. W. 1982. Contingent Decision Behavior. Psychological Bulletin. No. 2, pp. 382-402.

Santa, J. L. 1977. Spatial Transformations of Words and Pictures. Journal of Experimental Psychology: Human Learning and Memory. Vol. 3, No. 4. pp. 418-427.

Schroder, H. M., Driver, M. J., Streufert, S. 1967. Human Information Processing – Individuals and Groups Functioning in Complecs Sosial Situations.

Simon, H. A. 1955. A behavioral model of rational choice. Quarterly Journal of Economics. 69. pp. 99-118.

Speier, C. 2006. The influence of information presentation format on complex task decision-making performance. International Journal of Human-Computer Studies. 64. pp. 1115-1131.

Tutle, B. M., Kershaw, R. 1998. Information Presentation and Judgment Strategy from a Cognitive Fit Perspective. Journal of Information Systems. Vol. 12. No. 1. pp. 1-17.

Vessey, I. 1994. The effect of information presentation on decision making: A cost-benefit analysis. Information & Management 27. pp. 103-119.

Vessey, I. 1991. Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature. Decision Sciences. 22, 2. pp. 219-240.

Vessey, I, Galetta, D. 1991. Cognitive Fit: An Empirical Study of Information Acquisition. Information System Research. 2, 1. pp. 63-84.

Wood, R. E. 1986. Task Complexity: Definition of the Construct. Organizational behavior and human decision processes 37. Pp. 60-82.

Appendix

Appendix 1: *Task description of Bonanza AS.*
Presents a decision problem related to managing the summer restaurant Bonanza AS.

Appendix 2: *Prints of recordings from respondent no. 32 and no. 37.*

Appendix 3: *Prints of spreadsheet models*.
Shows different spreadsheet models used in the experiment: A graphical model, a tabular model and a model using combined display of graph and table.

Appendix 4: *Prints of historical data.*

Shows historical data related to managing Bonanza AS. Data are presented as graphs and as tables.

Appendix 1

Task description of Bonanza AS

Bonanza A/S – (high-complexity)

Du har fått sommerjobb i biffrestauranten Bonanza som assistent for restaurantsjefen. På grunn av sykdom har restaurantsjefen overtatt ledelsen av et hotell i København på kort varsel, og du er bedt om å overta den delen av restaurantsjefens jobb som angår økonomiske beslutninger.

Bonanza er en sommerrestaurant knyttet til en fornøyelsespark. Gjestene i restauranten er besøkende i parken. Restauranten er i drift hvert år fra mai til og med september.

I Bonanza serveres biff av høy kvalitet. Gjestene har flere muligheter for å variere menyen, for eksempel velge mellom bakt potet, pommes frites, fløtegratinerte poteter, ris, og de kan velge mellom forskjellige typer grønnsaker, brød, sauser og dressinger. Dessuten kan de avtale hvordan de vil ha biffen tilberedt. For å redusere administrasjonen av restauranten brukes en enhetspris.

Det er flere serveringssteder knyttet til parken, men de er ikke i direkte konkurranse med hverandre. Andre serveringssteder tilbyr hamburgere, pølser, kebab, og. Serveringsstedene er uavhengige av hverandre når det gjelder selve driften. De samarbeider likevel på den måten at barn som ikke vil ha biff, kan gå til et annet utsalgssted og kjøpe for eksempel en hamburger og spise den i restauranten.

I tilknytning til alle utsalgsstedene, også Bonanza, er det salg av fatøl, brus og mineralvann. Prisen på disse drikkevarene er den samme i hele parken, og regnskapet fra salg av drikkevarer holdes atskilt fra middagsserveringen.

Serveringen i restauranten foregår på den måten at gjestene tar kontakt med en av personalet. Hvis det er kapasitet i restauranten, anvises et bord. Hvis det ikke er ledig kapasitet, blir gjestene informert om når det forventes å bli ledig kapasitet, og de får da muligheten for å reservere plass. Restauranten er stor, og det er mulighet for å stenge av deler av den. Kapasiteten i restauranten er derfor ikke bestemt av antall bord, men av antall servitører på vakt, og av kapasiteten på kjøkkenet til å betjene gjestene. Alle henvendelsene blir registrert og brukes som et estimat for etterspørselen.

Den faste staben består av restaurantsjefen og to hovmestre. På kjøkkenet har kjøkkensjefen ansvaret for kvaliteten av driften. Han har fem erfarne kokker med seg.

Restauranten har avtale med husmødre i nærheten om å ta vakter som servitør eller kjøkkenassistent. Slike vakter avtales for en uke om gangen. Totale utgifter til ett vaktskifte pr. uke, dvs. en person på hver vakt hver dag, er kr 13.368 for servitører og kr 12.655 for kjøkkenassistenter.

Bonanza åpner hver dag kl. 10 om formiddagen og er i drift til parken stenger kl. 23. Det tas ikke inn nye gjester etter kl. 22. Det er to pressperioder i løpet av dagen. Første gang mellom kl. 12 og kl. 14. Deretter fra kl. 16 til kl. 20, med en topp i antall besøkende mellom kl. 16.30 og kl. 17.30. De ansatte arbeider på skift. Første skift møter kl. 10 og slutter kl. 17.30. Annet skift møter kl. 16 og slutter kl. 23.30, slik at begge skiftene er på vakt når den daglige etterspørselen er størst. Erfaringsmessig fordeler etterspørselen seg utover dagen som illustrert i tabell 1:

Tidsrom	%-vis fordeling
kl. 10 - 12	5 %
kl. 12 - 14	20 %
kl. 14 - 16	10 %
kl. 16 - 18	30 %
kl. 18 - 20	20 %
kl. 20 - 22	10 %
kl. 22 - 23	5 %
	100 %

tabell 1 – prosentvis fordeling av etterspørselen i løpet av dagen

På grunn av at gjestene overveiende er turister, er det jevn fordeling av etterspørselen over hele uken.

Kjøkkensjefen har avtale med faste leverandører om levering av prima oksekjøtt, ferske grønnsaker, osv. På grunnlag av disse avtalene har han satt opp følgende kostnadskalkyle for en biffmiddag i Bonanza:

kjøtt	61.05
andre ingredienser	15.80
totale variable enhetskostn.	76.85

tabell 2 - kostnadskalkyle

Restautantsjefen har drevet restauranten i to år. Han har tatt kurs i bedriftsøkonomi og i bruk av personlig datamaskin. I de to årene har han tatt i bruk regneark til registrering av etterspørsel, inntekter og utgifter. Han har dessuten laget en enkel modell som skal støtte ham ved beslutninger om hvilken pris han skal ta for en middag, og hvor mange servitører og kjøkkenassistenter han skal kalle inn hver uke. Når du overtar, får du tilgang til både data og modellen.

Bonanza A/S – (low-complexity)

Du har fått sommerjobb i biffrestauranten Bonanza som assistent for restaurantsjefen. På grunn av sykdom har restaurantsjefen overtatt ledelsen av et hotell i København på kort varsel, og du er bedt om å overta den delen av restaurantsjefens jobb som angår økonomiske beslutninger.

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Den faste staben består av restaurantsjefen og to hovmestre. På kjøkkenet har kjøkkensjefen ansvaret for kvaliteten av driften. Han har fem erfarne kokker med seg og seks kjøkkenassistenter. Restauranten har avtale med husmødre i nærheten om å ta vakter som servitør. Slike vakter avtales for en uke om gangen. Totale utgifter til ett vaktskifte pr. uke, dvs. en servitør på hver vakt hver dag, er kr 13.368.

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Appendix 2

Transcripts of recordings of respondent no. 32 and no. 37

Kandidat nr. 32

TV:

J: Skal vi se, hvis jeg prøver meg med en pris på 140… og så må eg ha 6 stk. på jobb.. servitører… Ehh.. tre av de ()…. Ups
Dvs at omsetningen gikk veldig ned.
Hva betyr det (peker)

TV:Det er omsetningen

J: Åja. Dvs at det var egentlig ganske lurt profittmessit

TV: Mmm.. Du ser der, hvis du holder over her så får du fram de forskjellige punktene, dvs verdiene her.. For eksemepl 492.

J: Det er DB
Og det var jo det han ville maksimere

TVJ: Ja

J: Hvis eg da prøver med 140, og tar kanskje en mindre av de der.. og en mer av de der på jobb

TV: Det hadde vært fint hvis du sier hva du gjør, hva de forskjellige tallene betyr

J: 5 servitører og 3 kjøkkenassistenter, samme pris… Ser hva som skjer, kanskje ikke så veldig lurte?.... Jo, det var det! Veldig lurt! Ser du det.. hehe
… og hvis… tar kanskje… øker prisen litt… og seks personer på jobb igjen og 3 på kjøkkenenet… Så gikk vi litt ned igjen.. kanskje ikke så lurt…
Hvis vi da forsøker med fem på jobb, tre på kjøkkenet…. Det var ganskje lurt.. hmm.. ka var den blå?... Selger jo lite da?

TV: Hva?

J: Totalomsetningen går jo ned

TV: Ja

J: Det var jo ikke så lurt…. Så hvis vi da setter… prisen lik 135, fire på jobb, tre på kjøkkenet… det var nå ikke lurt… Kan eg gå tilbake og endre?

TV: NeiJ: OK

TV: Hva ser du nå ut fra grafen da?

J: Jeg ser at totalomsetningen, den går ned

TV: Ja

J: DB pr.. gikk jo opp.. men nå gikk den ned igjen.. det var jo ikke lurt.. skulle ikke gjort det i det hele tatt.. Så da tenker jeg vi må… øke prisen littegranne kanskje… skal vi se.. jeg begynte i uke 33 sant?

TVJ: Ja

J: Setter prisen opp igjen da kanskje.. nei… 135, og hvis jeg da forsøker med 5 servitører på jobb og tre på kjøkkenet….. kanskje dumt og da.. kan jo forsøke å redusere til to på kjøkkenet.. se om det går… ahh.. det var ikke lurt…. Hmmm.. nå gikk den jo opp igjen ganske bra.
Øker prisen til 140, har fem… fem servitørere.. to på kjøkkenet.   Det var ganske lurt…. Hvor lang skal jeg lede dette her?

TV: ..

J: Det vil si at.. .jeg har ikke noen prognoser på hvordan han drev det?

TV: DU har bare de fire første periodene.

J: Degt var da han drev det?

TV: Ja

J: …………… Hvis jeg fremdeles forsøker meg på…………… tror kanskje jeg øker den littegranne.. skal vi se, fem kroner.. Fem servitører…. Nå gikk jeg litt ned igjen.. hvorfor det? ………………. Er det totalomsetningen han er interessert i eller dekningsbidraget?

TV: Det er jo profitt han er interessert i..

J: Omsetningen?

TV: Nei

J: Dekningsbidrag?

TV: Ja, det er jo dekningsbidraget han ønsker

J:Så det er det han ønsker å maksimere, og det var jo ganske høyt/bra der

TV: Mmm.

J: Så hvis… kan jo ikke drive å endre prisen hele tiden heller..

TV: Du kan jo se på de grafene der nede.. om det gir noe hjelp eller?

J: Hmm. Omsetningen, det var den der?

TV:Ja

J: Men det er jo totalomsetningen, er det ikke? Eller er det dekningsbidraget?

TV: Nei, det er omsetningen, totalomsetningen

J: OK
Men totalomsetningen kan jo være høy selv om DB er relativt lavt

TV: Ja

J: Så da er det kanskje lurt at den ikke er alt for høy hvis det er det……….
Men han begynner jo der da……. Hmmm… Det har vel ingenting å si……
Hvis jeg øker da? Det er kanskje ikke så lurt.. skal vi se.. prisen.. prisen pr. middag… øker etterspørselen………….. Så ligger vi rundt her kanskje……………………………. DB er jo høyest er jo høyest på 140, fem servitører og 2 kjøkkenassistenter hittil, er den ikke det? For kjøkkenassistenter?

TV: Mmm

J: ……………. Hvis vi da kanskje tar fire servitører i stedet for to.. hmm.. da gikk det ned.. Da får de sikkert ikke betjent alle som vil ha mat…

TV: mmm

J: Litt dumt.. hvordan vet jeg det da?....... Spiller det noen rolle? Om jeg driver og tar samme hele tiden?

TV: Neida

J: ………..Hvis jeg synes at jeg var ganske fornøyd med det resultatet jeg fikk der da? Jeg ligger jo over det han fikk da.. så det er jo egentlig ganske bra..

TV: Jada.

J: Så må han må jo være fornøyd med meg. Kan jeg ta det samme i alle resten?

TV: Ja, hvis du ønsker det, så kan du det…   Men da kan vi egentlig si at du er ferdig. At du setter pris litk 140, fem….

J: Ja, men hvis jeg kanskje skulle sette prisen… Hvis jeg økte prisen der så gikk den jo ned igjen.. Da skjer det gjerne ikke noe hvis jeg øker prisen enda mer.. da må den jo i så fall ansette.. hvis jeg prøver bare en periode for å se….. men det er kanskje ikke så lurt.. da blir prisen kanskje litt høy……   Men hvis jeg tar 160 i pris, 6 på jobb.. og 3 på kjøkkenet.. bare for å forsøke…

TV: Ja

J: Jeg skulle kanskje regnet gjennom det?

TV: Det du må se, hvis du ser på grafen hvordan for eksempel etterspørselen utvilker seg etterhver tsom du har satt de ulike prisene..

J: Etterspørsel….. det var………… Faktisk gjennomsnittlig etterspørsel.. den mørkeblå…. Den sank jo…. Den lyse, hva var det?.... Her selger vi jo mer enn….. går det an da?

TV: Ja, jeg ser.. det må jeg ordne på.. Bare glem det nå..

J: Ja.. hvis etterspørselen.. den har jo lagt her.. .det var jo…. Nei, jeg tror jeg går tilbake til det der jeg, 140, 5 og 2.   Tror det var lurt, jeg

TV: Mmm.. Så da er du fornøyd med det hele veien?

J: Ja.

TV: OK, men da kan vi egentlig si at du er ferdig her, så da trenger du ikke å fylle ut hele her..

J: OK

TV: Jo da, vi kan fylle ut verdiene ganske fort her, så ser du hva resultatet blir.

J: Det va jo ikke så mange igjen

TV: Sånn..

J: Er det noen totalløsning her..

TV: Nei, det lager jeg ferdig etterpå.

J:Ok

TV: Men det var veldig bra. Takk skal du ha

Kandidat 37

05: Etterspørsel pr. dag ja…… Ja, dette blir ikke enkelt.
Kan jeg skrive på dette, eller skal jeg bruke et annet ark?

TV: Jada, bare skriv i vei.

05:Det er en klar sammenheng mellom prisen her og antall vakter man trenger.. så setter vi prisen bestemmer vi jo hvor mange kjøkkenassistenter og servitører vi må ha på vakt.. så det viktigste er kanskje å finne prisen.
Kan jeg regne her på dette regnearket?

TV: Jada, det kan du.. eller du kan lage et helt nytt et..

05: Neida, jeg bare gjør det her enkelt, jeg.

TV: Det er fint hvis du sier litt hva du tenker og gjør.

05: Ja, nå bare regner jeg på et priseksempel her.. en pris på 148 kroner.. for å se hva han har..
Skulle hatt et DB her da.. hadde gjort det litt enklere.
Har vi en oversikt over sessongvarisajoner her?

TV: Neida, du kan anta at det ikke er det.. at det er jevnt i hele perioden.
Og så har du jo denne oversikten med historiske tall som du kan bruke

05: ja, riktig, riktig.. kan jo bruke denne til å se hva han hadde som tilsvarende tall tidligere imåneden. Om det er stigende med en høyere pris. Kommer forventet etterspørsel?

TV: Nei, det er der du kan skrive inn hva du forventer at den blir..

05: Så da kan jeg bare kjøre på der da.

TV: Nei, det er kun forventningene dine.. det er ikke nødvendigvis de som gjelder.

05: OK.
Burde finne den prisen som har størst DB her da.. så skulle vi hatt en DB her som jeg kunne sett på.. hehe
(lang pause – foretar beregninger i regnearket.)
Ehh.. nå er jo også de kjøkkenassistentene og kelnerne variable kostnader, så man bør jo lage et estimat med antall kelnere/servitører pr kunde for å få et korrekt DB. For kjøkkensjefene og restauranten er vel faste kostnader.. Hvis du har for få ansatte, får du da noen negativ utvikling i modellen.. Du kan tilby dårligere service og få høyere DB.

TV: Det kan jeg ikke si noe om.

05: Hvis vi ikke har med kelnerne så har vi et større DB.

TV: Hva har du satt opp, Du har satt opp en liste over pris, etterpsørsel, DB pr dag.

05: Tallene stemmer jo utrolig bra med modellen da.. med inndata og utdata.. det skal man ha.

Her ligger det fast på antall kjøkkenassistenter og antall servitører da.. det har vi vel muligheten til å endre.
Opprerer med rimelig lave priser og høy etterspørsel her.. Men hvis vi har en høyere pris.. jeg ser DB er høyere ved en høyere pris. 144 er den prisen jeg har høyest DB på. Og da vil man trenge færre kelnere og assistenter.. så det må jo lønne seg å ha en høyere pris enn de som har vært operert med her.   Det er vel den som har best vel.
Er det noen rangeringsverktøy her.. i Excel? Nei, får ta det manuelt.
Skal vi se på disse kelnerne da.. hvor mye det blir..
Så det er ikke noe som tilsier noe om bruk av servitører?

TV: Nei, ikke noe annet enn det som står i teksten.

05: For hvis jeg opprerer med en pris på 148 så vil antallet måltider gå betraktelig ned.. så vil kanskje klare meg med færre folk. Ehh.. prøver å finne ut hvor mye det koster å ha servitrisene pr. gjest her. Eller pr. måltid.
Hvor mange dager i uken er det åpent, står det noe om det?

TV: 7 dager.

05: Ikke noe forskjell på dagene?

TV: Nei

05: Da koster det altså, med de tallene som er brukt her, 18,7 kr. Pr. person for å ha kelnere eller servitører.. mens da koster …
For å opprettholde samme servicenivå som i modellen, så forsøker eg å regne ut hvor mye hver kelner jobber med hver kunde.   Det var ikke mye..
I modellen har de en servicegrad på 0,009.   mens jeg med en pris på 144 som har størt DB, vil ha en servicegrad på 0,01.. så setter ned antall ansatt på jobb. Ja..
Da ble det dårlige service hvis jeg har fire og høyere hvis jeg har fem.

TV: Du må bestemme hvilket servicenivå du vil ha selv.

05: Ja, riktig, det er opp til meg
Jeg går for en høyere pris og burde jo egentlig hatt en høyere service.. Ehh. Den servicen som betyr mest er jo den servicen du får hos servitrisen.. Det på kjøkkenet ser du jo ikke..
Så siden min etterspørsel går ned til 478 fra 656 så tror jeg vi kjører med pris 144, 5 servitriser og to kjøkkenassistenter tror jeg.. da vil vi ha en høyere service på hos personalet hos kunden og litt mindre på kjøkkenet. Og forventet etterspørsel fra tabellen her er 478,.. da knuser jeg dine tall her.. hehe
TV: Dette er første uken i juni

05: Det er bare å kjøre på her hvis jeg fant en modell jeg likte

TV: Jada

05: Bør kanskje forsøke meg litt for å se hvordan det utvikler seg.. Men var det ikke bare en ukes frist på å si i fra hvor mye man vil jobbe.

TV: Det kan du bestemme pr. uke. Hva du vil.

05: Men jeg har jo ikke noen nye tall å jobbe med.. eller er det det her.. sånn det gikk

TV: Ja, dette viser hvordan det gikk ut fra dine beslutninger

05: OK
Men jeg bestemmer jo selv etterspørselen. Oi, se her da.. det blir jo forskjellig.. eller har jeg tastet feil. Det blir forskjellig..

TV: Jada:

05: Eller er det lagt inn noe lureri her.. hehe.. . Det mangler jo kanskje den viktigste variabelen her.. Korrekt etterspørsel.
Å, der har du faktisk, ja.. den er jo bygget på... den så ikke jeg i det hele tatt. Jeg trodde den var estimert, jeg... OK
Kan jeg spørre hva denne bygger på? Bygger den på servicenivå?

TV: Etterspørselen vil variere litt, og den bygger på flere forhold

05: OK, ja
Har det noe å si hva servicenivået er da?

TV: Det er jo likt for dine uker i juni - så som du ser så har det ikke noe å si egentlig.

05: OK, så servicegraden er ikke lagt inn som en variabel i antallet som kommer, faktisk etterspørsel.?

TV: Jeg kan nok ikke si hvordan modellen er bygget opp da!

05: Jeg kan jo se på koden da

TV: Ja, du kan se på formlene i dette regnearket her.
TV: Du begynner på juli nå?

05: JA!
Det er ingen sessongsvingninger?

TV: Neida

05. ok. Jeg er ikke helt fornøyd med utviklingen i DB siste uke. Men det har jo steget... Ehh.. Jeg har jo ikke noen nye tall her da..
Jeg satt opp prisen til 158 kroner.. for å prøve det.. siden det var den prisen som gav størst DB etter.. Opprettholder samme servicenivå, men med en lavere pris. DB ble omtrent det samme - litt lavere enn i de høyeste månedene, litt høyere enn de laveste månedene.
Setter prisen ned til 138 for å prøve å se hvordan det går.. Det beste DB generelt sett.. Det gikk ikke så bra! Går tilbake til 144 kroner, da det gav best DB. Ehh... Estimerer med litt færre kunder enn det som sies i modellen, da antall kunder har vært lavere ved alle observasjoner. 170 ser ut som et bra tall. Prøver igjen med 144 kroner, og får denne gangen et meget godt DB.
Fortsetter med 144 kroner.

Et par ikke så veldig gode uker nå!
Men jeg fortsetter ut måneden med samme pris. Den har gitt best resultater.

TV: Da har du fylt ut alle?

05: Ja, jeg forsøkte meg med litt andre priser som gav et litt annet DB, gikk først opp i pris til 152. Det gav omtrent samme DB, litt dårligere.. men omtrent det samme. Prøvde meg videre på 138, men da fikk jeg et meget skuffende DB.. Dessuten så ble salget da så høyt at det ble for få servitriser og folk på kjøkkenet. Men her er det såpass mye lavere. Når etterspørselen er på 420 så synes jeg det er mer mening å endre på kjøkkenet.. Så må du også se for deg at på kjøkkenet er det en del fast personale som er der hele tiden, så variasjonen blir ikke så stor som det ser ut her.. Den blir ikke 33%.

TV: Hva fant du som optimal pris da?

05: 144 gikk jeg tilbake til, for det var den som gav best.

TV: OK
Og den fant du ut i fra regning der nede?

05: ja, men det kan jo være det er feil.

TV: Nei, men dette var greit. Da må jeg bare få lagre her.

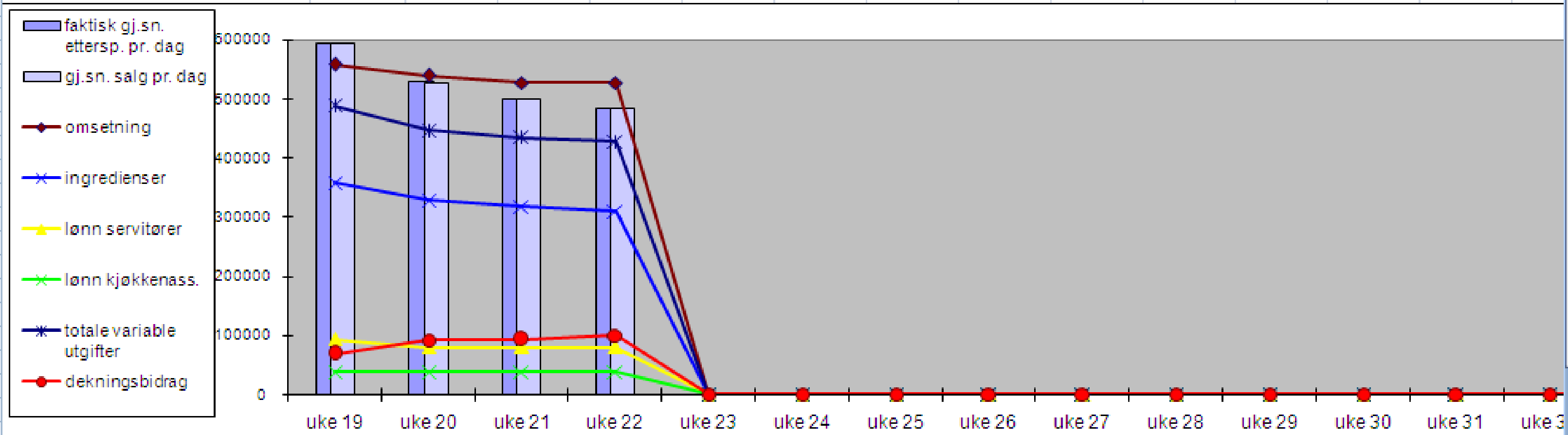
Appendix 3

Prints of spreadsheet models

BKB.xls [Kompatibilitetsmodus] - Microsoft Excel

Bonanza A/S - driftsoversikt

	mai				juni				juli				
	uke 19	uke 20	uke 21	uke 22	uke 23	uke 24	uke 25	uke 26	uke 27	uke 28	uke 29	uke 30	uke 31
Inndata													
Handlingsvariabler													
Pris pr. middag	120	126	128	131									
antall servitører pr. vakt	7	6	6	6									
antall kjøkkenassistenter pr. vakt	3	3	3	3									
Ikke-kontrollerbare variabler													
forventet etterspørsel pr. dag	655	611	611	565									
Utdata													
Inntekter													
faktisk gj.sn. etterspørsel pr. dag	664	612	589	575	0	0	0	0	0	0	0	0	0
gj.sn. antall middager solgt pr. dag	664	611	589	575	0	0	0	0	0	0	0	0	0
omsetning	557760	538902	527744	527275	0	0	0	0	0	0	0	0	0
Variable kostnader													
ingredienser	357199	328687	316853	309321	0	0	0	0	0	0	0	0	0
lønn servitører	93575	80207	80207	80207	0	0	0	0	0	0	0	0	0
lønn kjøkkenass.	37965	37965	37965	37965	0	0	0	0	0	0	0	0	0
totale variable utgifter	488738	446859	435024	427493	0	0	0	0	0	0	0	0	0
Dekningsbidrag	69022	92043	92720	99782	0	0	0	0	0	0	0	0	0

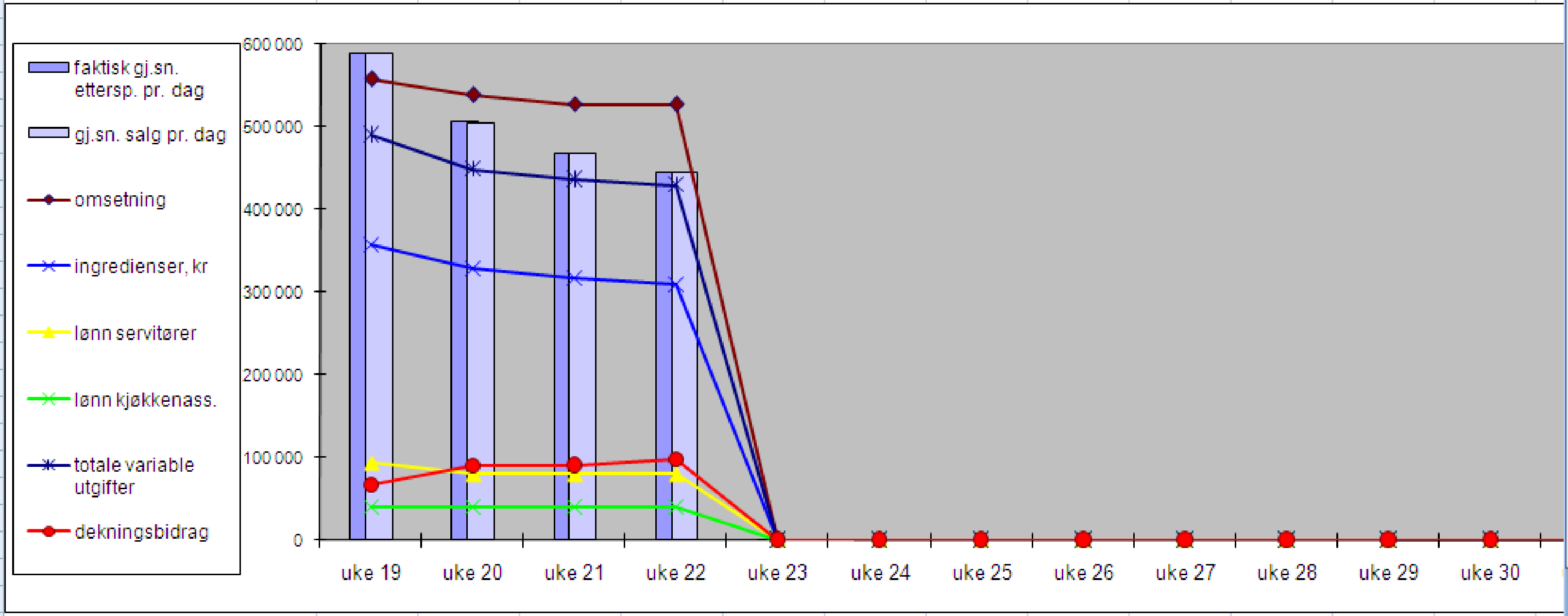


Modell

BKG.xls [Kompatibilitetsmodus] - Microsoft Excel

Bonanza A/S - driftsoversikt

	mai				juni				juli			
	uke 19	uke 20	uke 21	uke 22	uke 23	uke 24	uke 25	uke 26	uke 27	uke 28	uke 29	uke 30
Inndata												
Handlingsvariabler												
pris pr. middag	120	126	128	131	0	0	0	0	0	0	0	0
antall servitører pr. vakt	7	6	6	6	0	0	0	0	0	0	0	0
antall kjøkkenassistenter pr. vakt	3	3	3	3	0	0	0	0	0	0	0	0
Ikke-kontrollerbare variabler												
forventet etterspørsel pr. dag	655	611	611	565	0	0	0	0	0	0	0	0



ModellGr EtterspOmsGr EtterspGr

BKV.xls [Kompatibilitetsmodus] - Microsoft Excel

Hjem Sett inn Sideoppsett Formler Data Se gjennom Visning

AB50

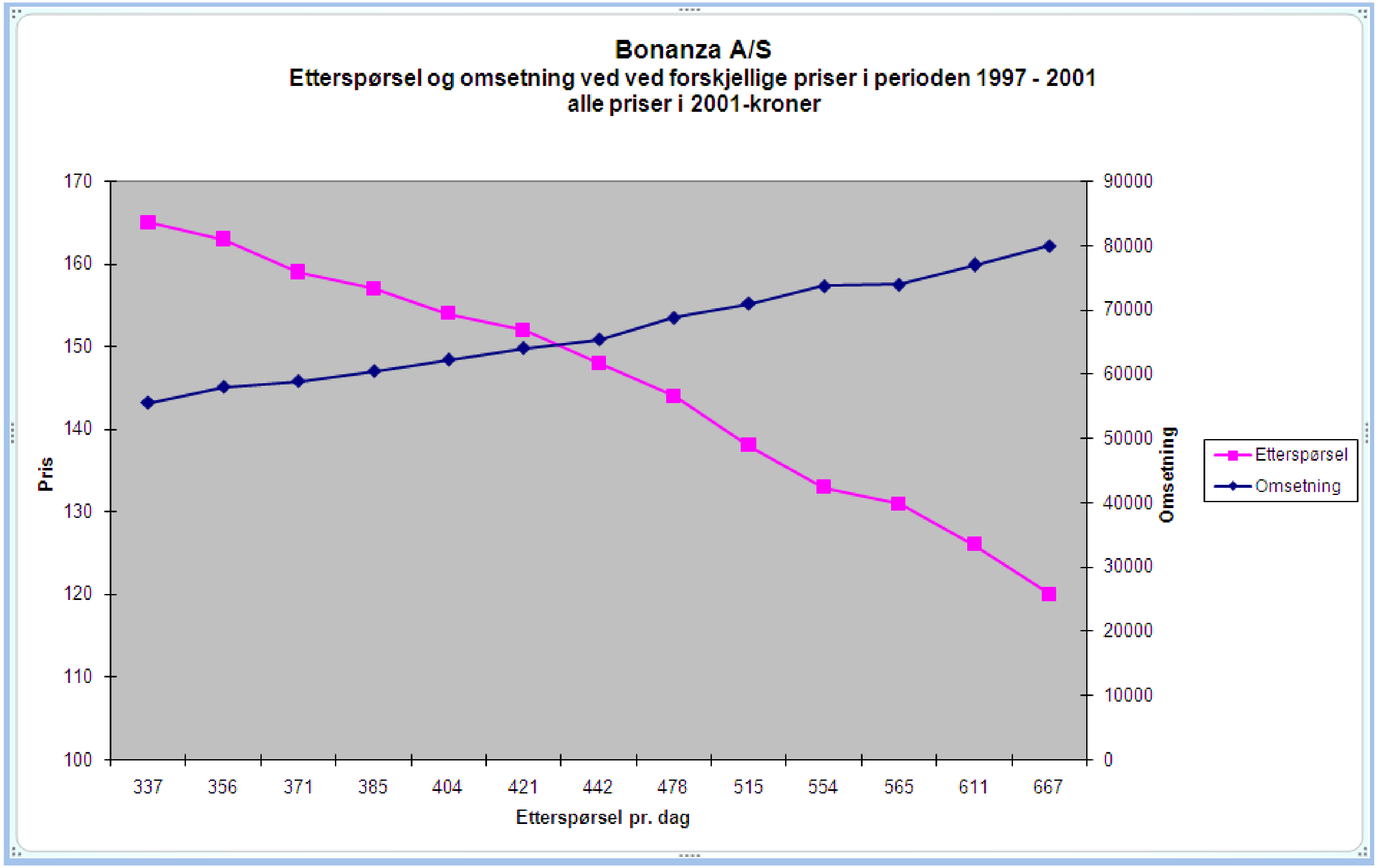
	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Bonanza A/S - driftsoversikt**												
2		mai				juni				juli			
3		uke 19	uke 20	uke 21	uke 22	uke 23	uke 24	uke 25	uke 26	uke 27	uke 28	uke 29	uke 30
4	**Inndata**												
5	***Handlingsvariabler***												
6	pris pr. middag	120	126	128	131	0	0	0	0	0	0	0	0
7	antall servitører pr. vakt	7	6	6	6	0	0	0	0	0	0	0	0
8	antall kjøkkenassistenter pr. vakt	3	3	3	3	0	0	0	0	0	0	0	0
9													
10	***Ikke-kontrollerbare variabler***												
11	forventet etterspørsel pr. dag	655	611	611	565	0	0	0	0	0	0	0	0
12													
13	**Utdata**												
14	***Inntekter***												
15	faktisk gj.sn. etterspørsel pr. dag	664	612	589	575	0	0	0	0	0	0	0	0
16	gj.sn. antall måltider solgt pr. dag	664	611	589	575	0	0	0	0	0	0	0	0
17	omsetning	557760	538902	527744	527275	0	0	0	0	0	0	0	0
18	***Variable kostnader***												
19	ingredienser, kr	357199	328687	316853	309321	0	0	0	0	0	0	0	0
20	servitører, kr	93575	80207	80207	80207	0	0	0	0	0	0	0	0
21	kjøkkenassistenter, kr	37965	37965	37965	37965	0	0	0	0	0	0	0	0
22	totale variable utgifter	488738	446859	435024	427493	0	0	0	0	0	0	0	0
23	***Dekningsbidrag***	69022	92043	92720	99782	0	0	0	0	0	0	0	0

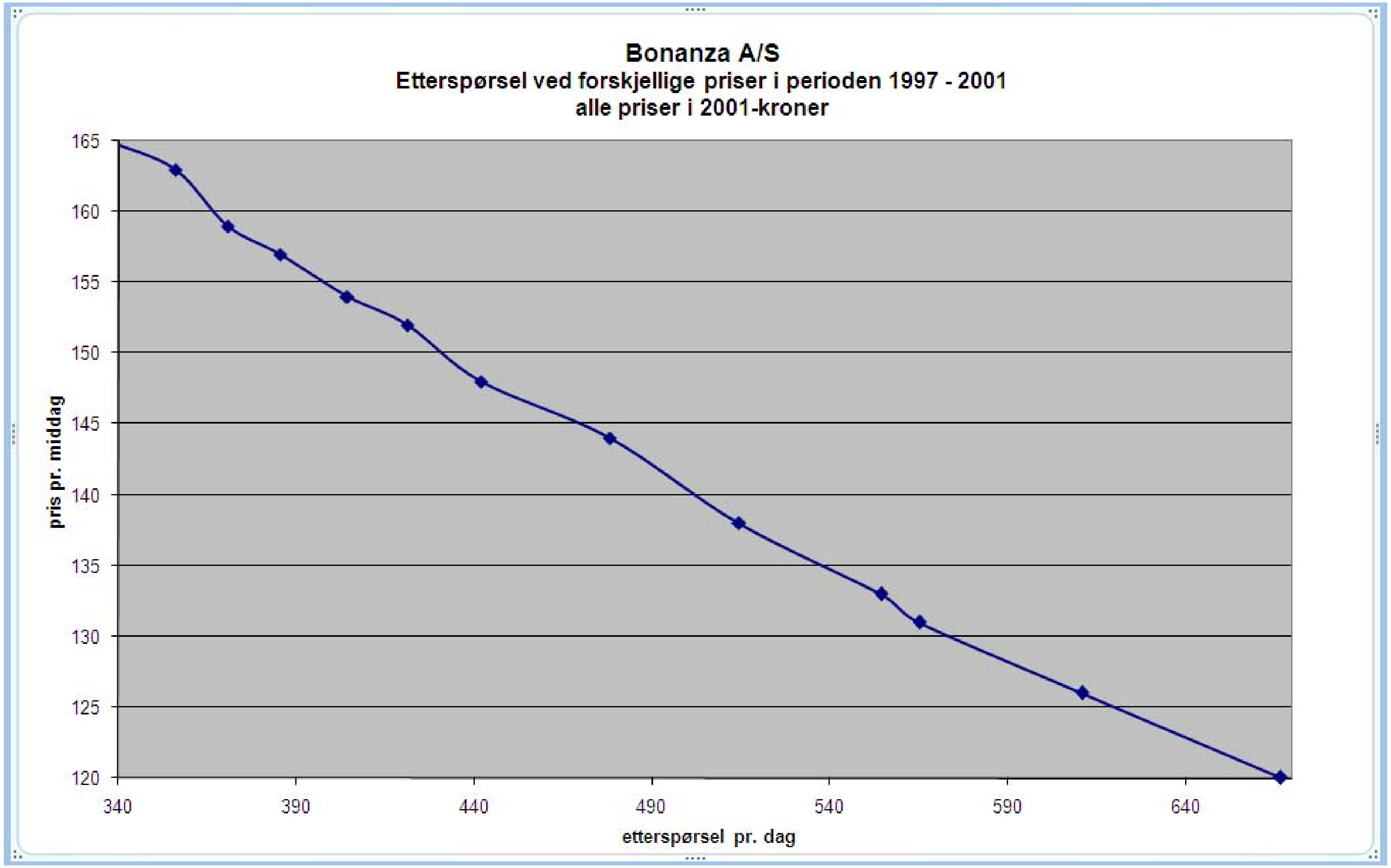
Modell

Klar 100 %

Appendix 4

Prints of historical data


Bonanza A/S
Etterspørsel og omsetning ved ved forskjellige priser i perioden 1997 - 2001
alle priser i 2001-kroner
Pris
170
160
150
140
130
120
110
100
Omsetning
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
337
356
371
385
404
421
442
478
515
554
565
611
667
Etterspørsel pr. dag
Etterspørsel
Omsetning


Bonanza A/S
Etterspørsel ved forskjellige priser i perioden 1997 - 2001
alle priser i 2001-kroner
pris pr. middag
165
160
155
150
145
140
135
130
125
120
340
390
440
490
540
590
640
etterspørsel pr. dag

Bonanza A/S - Etterspørsel pr. dag ved forskjellige priser i perioden 1997 - 2001

alle priser i 2001-kroner

pris	etterspørsel	omsetning
120	667	80005
126	611	76974
131	565	74044
133	554	73745
138	515	71001
144	478	68855
148	442	65395
152	421	64029
154	404	62273
157	385	60516
159	371	58945
163	356	58035
165	337	55611