THE EFFECTIVENESS OF DATA PRESENTATION FORMATS: AN EXPLORATORY STUDY

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Abstract:

This paper contributes to the understanding of how data presentation formats may affect decision-making. We report on two experiments, one using verbal protocols and one including eye tracking as methods for data collection. Compared to previous studies, our experiments were characterised by complex tasks with a requirement for accuracy (problem tasks) and by allowing our subjects to use decision aids. We found that decision-makers used both verbal and perceptual processes to handle the task. Furthermore, we found that the subjects needed both tables and graphs to support their decision-processes. The tables facilitated the subjects' calculations, while the graphs gave overviews when studying the trends in the development of the solutions.

Key words: Data presentation format, verbal protocols, eye-tracking, decision effectiveness

1   INTRODUCTION

Data presentation formats and effects on problem solving is an important topic to information systems research, see, for example, reviews by Kelton, Pennington and Tuttle (2010) and Dilla, Janvrin and Raschke (2010). Developments within information and communication technology have increased decision-makers' possibilities to search for, collect, organise and analyse data. On the one hand, this development has increased their possibilities to enhance the understanding of their task environments and, thus, make decisions that are more effective. On the other hand, more data increase the load on the decision-makers' cognitive capacity, which is a limited resource (Anderson, 2013). Therefore, understanding of the relationships between data presentation formats and decision processes may help designers of information systems design more effective screen displays.

The purpose of this paper is to enhance the understanding of how data presentation formats may affect managerial decision-making. In particular, we focus on enhancing the understanding of how presentation formats may influence the decision-makers' mental representation and processing of a task. By doing so, we are responding to a call for research from Kelton et al. (2010). According to these authors (ibid. p. 99), the relationship between presentation formats and mental problem representation and processing is one of the least understood areas in the research on how presentation formats influence problem solving.

Numerous studies have examined presentation format issues in connection with factors such as characteristics of the task and the individual. Most of this research focuses on how presentation formats affect problem-solving performance. In line with the recommendations by Kelton et al. (2010), we have applied process-tracing methodologies to assess possible mental representation differences related to various presentation formats.

We present the preliminary results from two experimental studies. 79 MBA students were asked to make decisions related to managing a summer restaurant. The tasks varied in complexity, and the presentation formats were graphs, tables and combined graphs and tables. The tasks were constructed so that they had optimal solutions. The subjects' handling of the tasks was studied using verbal protocols, eye tracking and observation.

The rest of the paper proceeds as follows: In the next section, we give an overview of the literature, emphasising our research contribution. In section three our research model and research design are

presented. In section four, we present our findings. Finally, implications of our research is discussed together with proposals for further research.

2 LITERATURE REVIEW

A comprehensive research stream assessing the effects on problem solving performance of various display formats has led to the widely shared belief that there is not one optimal format, but that the effectiveness of a specific presentation format depends on the type of task to be performed (Speier, 2006). Much of the foundation for studying the effects of data presentation formats on problem solving is the cognitive fit theory (Vessey, 1991).

2.1 Cognitive fit theory

The cognitive fit theory is a special case of cost-benefit theory (Vessey, 1994). Since humans' capacity for information processing is a limited resource, this theory suggests that humans change information-processing strategy so that they minimise the joint cost of effort and error when solving a problem. The term "strategy" denotes a general approach to information processing involving elementary mental processes. Examples of such strategies are holistic and analytic (Umanath and Vessey, 1994). Holistic strategies involve 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 responses that are more accurate.

According to the cognitive fit theory, for most effective and efficient problem solving to occur, data presentation formats should match the task to be accomplished (Vessey, 1994, 1991). Vessey and Galetta (1991) describe two basic types of tasks, spatial tasks and symbolic tasks. An example of a spatial task is (Vessey and 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 and Galetta, 1991): "Provide the amount of withdrawals in April." This task requires a specific amount as response and is best accomplished using verbal processes.

Examples of data presentation formats are graphs and tables. Graphs are spatial presentation formats, i.e. they emphasise relationships among the data. Tables are numeric, i.e. they emphasise presentation of discrete data values. According to the cognitive fit theory, graphs are the appropriate representation format for spatial tasks, whereas tables support symbolic tasks. The argument is that when the data presentation format and the task type match, the decision-makers can formulate 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 to act on the data and to solve the problem, which will require more cognitive effort. Thus, cognitive fit between the (external) presentation format and the task type is supposed to lead to an effective (accurate) and efficient (fast) solution (Vessey, 1994).

In tasks involving complex evaluations, cost-benefit theory suggests that the information processing strategy may occur as a result of a 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 verbal processes, which are facilitated by tables. Complex symbolic tasks place significant strain on humans' cognitive resources. As the complexity of a symbolic task increases, humans may prefer – or may have to – use perceptual rather than verbal 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).

The cognitive fit theory has been largely successful in explaining outcomes in fairly simple tasks involving data acquisition and well-defined evaluations (for an overview, see Vessey, 2006, 1994; Umanath and Vessey, 1994; Tuttle and Kershaw, 1998; Speier, 2006). Evaluating the results of three published graph versus table studies using more complex tasks, Vessey (1994) also finds empirical support for strategy shifts, i.e. using perceptual rather than verbal processes in complex symbolic tasks.

2.2　Task complexity

In the previous section, the terms "simple", "more complex" and "complex" have been applied somewhat intuitively – which is also done in the literature (Speier, 2006; Vessey, 1994). In order to categorise tasks we need a typology. In our research, we have used Campbell's (1988) typology of complex tasks, which is based on the work by Schroder, Driver and Streufert (1967). The advantage of building on Schroder et al. (1967) is that their constructs provide a common language both for analysing objective task complexity and for translating these attributes into cognitive processes (Campbell, 1988 p. 43). In line with Schroder et al. (1967), Campbell distinguishes between objective and subjective or experienced task complexity. Objective task complexity is a function of the task per se, and subjective task complexity is related to the individual's perception and handling of the task. As argued by Campbell (1988), subjective and objective task complexity are related. Subjective task complexity can explain how objective task complexity is handled, and the relationship between objective and subjective task complexity can be moderated by, for example, familiarity with the task domain, the availability of decision aids and the data presentation formats (Campbell, 1988).

In accordance with Schroder et al. (1967), Campbell (1988) applies three properties of an objective complex task: (1) the number of dimensions requiring attention, (2) the number of alternatives associated with each dimension and (3) the relationships among the dimensions and alternatives, including the degree of uncertainty. Elaborating then on the relationships, Campbell (1988) distinguishes among four main types of complex tasks: choice tasks[1], judgement tasks, problem tasks and fuzzy tasks. Choice tasks involve selecting the best alternative from a set of possibilities. Judgement tasks require the subjects to evaluate diverse sources of information and then make a judgement or prediction of some future event. Problem tasks are characterised by a multiplicity of paths to a well-specified outcome, i.e. they require the subject to search for and find the best way to achieve the outcome. Fuzzy tasks are characterised by the presence of both multiple desired outcomes and multiple ways of attaining each of the desired outcomes. Tasks representative of this category are often found in business contexts. Within each of these four main categories, there are subcategories related to the interdependences and uncertainty of the linkages among the dimensions and alternatives, for a detailed discussion, see, Campbell (1988).

2.3　Positioning of our research

In our opinion, the cognitive fit theory has mainly been tested in choice tasks and judgement tasks with little conflicting interdependence and/or uncertainty among the dimensions and alternatives. For example, Speier (2006) claims that she has extended cognitive fit theory to complex tasks. However, the task she presents as a complex-symbolic task involves five dimensions and six alternatives associated with each dimension (i.e., 30 information cues) and 18 rather simple calculations/comparisons. In Campbell's (1988) typology, the task would characterise as a choice task with some interdependence among the alternatives.

Most studies investigating the relationships between data presentation formats and decision quality use tasks that can be characterised as either spatial or symbolic, and they assume a decision processing strategy that is either holistic (using mainly perceptual processes) or analytic. Real-life managerial decision tasks are, however, often "fuzzy" as described above. They can be achieved using a variety of spatial and symbolic subtasks, and they usually require both perceptual and analytic processes. How decision-makers choose to structure such tasks into subtasks may have significant implications for the accuracy of the outcome. In order to enhance the understanding of how data presentation formats may support decision-makers, we should test cognitive fit theory in tasks that are more similar to real-life managerial decision tasks.

The theory of cognitive fit (Vessey, 1991, 1994) builds on the dual coding theory of cognition (Paivio, 2007, 1986, 1971). This theory states that human beings have developed different types of mental representation and operation that are assigned to different information processing functions. There is one system specialised for the representation and processing of information concerning nonverbal objects and events, and there is one system specialised for dealing with language. Paivio refers to the two systems as the nonverbal or imagery system and the verbal system. The two systems are assumed to be independent in

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[1] Termed decision tasks by Campbell (1988).

the sense that either system can be active without the other. At the same time, they are supposed to be interconnected so that activity in one system can initiate activity in the other. In the studies performed so far, data presentation formats are usually presented as if they were mutually exclusive. Exceptions are studies by DeSanctis and Jarvenpaa (1989), Frownfelter-Lohrke (1998) and Lucas (1981).

The interconnections of the two mental systems support the idea of examining the effects of combined displays of graphs and tables. In tasks with limited strain on working memory, we would expect that humans can mentally visualise the relationship between variables from a table and do not need the graphic display. In tasks placing a high cognitive load on the subject, the graphic display may give an overview, but not detail enough to reach a high decision quality, while a table may not give sufficient overview to handle the details appropriately. We therefore expect that graphs will increase humans' general understanding of the relationships among variables in such tasks, and that additional tables will increase the understanding of details.

Furthermore, most research in this area is based on the notion of the unaided decision-maker. However, unless compelled to work under unfamiliar constraints, decision-makers are usually not unaided. We agree with Edwards (1992) that researchers should take this aspect into consideration in their research design.

As stated in the introduction to this paper, most studies focus on the outcomes. There have been few efforts to understand how the various data presentation formats influence decision-makers' mental representations and processes. With our research, we will enhance the understanding of the relationships between data presentation formats and problem solving performance by studying how subjects represent and process tasks that are similar to real-life decision-making tasks involving the use decision-aids.

3   RESEARCH MODEL AND RESEARCH DESIGN

Based on the above discussion, we developed the research model shown in figure 1:
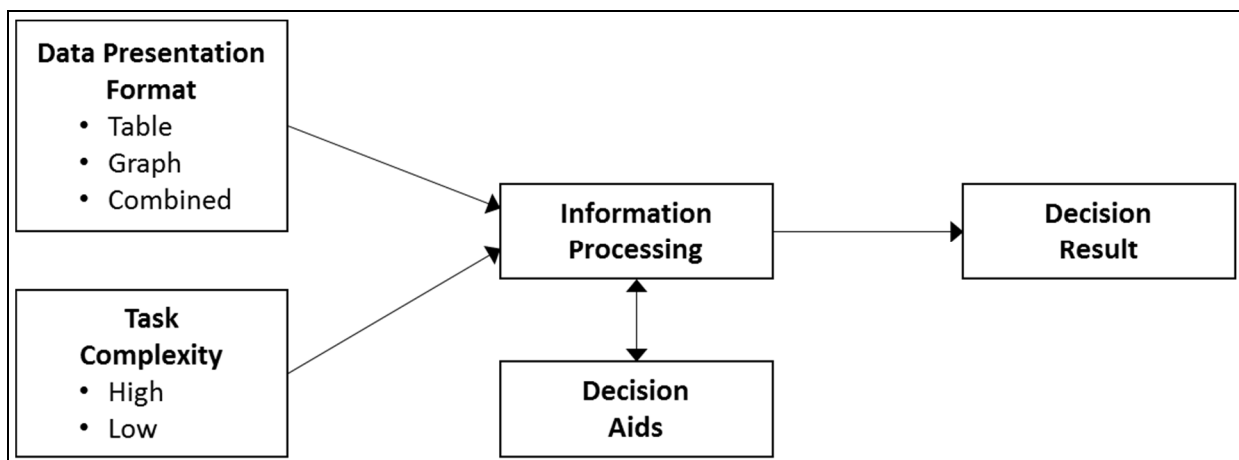

Figure 1   Research model

As can be seen from the figure, the independent variables are data presentation format and task complexity. The dependent variable is decision result with information processing including the use of decision aids as mediating variables. The subjects could not change the format presented to them. However, as indicated by the relationship between information processing and decision aids, they could copy/extract data from the presentation format and thus extend the presentation formats to support their information processing. For example, they could make a graph from the table format, set up a table based on data values in the graph format. They could also use a calculator, pen and paper.

In order to explore the relationships among the concepts, we constructed a laboratory experiment with six treatments as shown in table 1.

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

Table 1   *Experimental treatments*

3.1   Experimental setting

The experimental setting was the management of a summer restaurant. The subjects were given the task to run the restaurant for a period of four months (17 decisions, one each week), with the object to maximise the total contribution. Thus, the experimental task had a requirement for accuracy, and there was no time pressure.

We constructed a demand function for the relationship between the price of a meal and the demand for meals. The sale of meals in the restaurant generated the income. Costs for ingredients and staff then had to be deducted to calculate the contribution. The subjects entered the values of the decision variables into a computerised system, which calculated and displayed the values of the result variables. The user interface of the system is a spreadsheet, see figures 2a and 2b. The system was displayed with indata and outdata for four "historic" periods as shown in the figures. These "historic" data were supposed to hint at the optimal solution.

The experiment was designed with two tasks of different complexity. The differences were related to the number of variables and the degree of uncertainty in the relationships between the decision variables and the result variables. In the task low in complexity, the subjects were asked to make weekly decisions regarding the price of a meal and the number of waiters needed. Random variation in the demand function was limited to 1%. In the high complexity task, the subjects also had to make decisions regarding the number of kitchen assistants, and the random variation in the demand function was set to 3%.

Related to Campbell's (1988) typology of task complexity, both tasks can be characterised as problem tasks, i.e. they have a well-specified outcome (maximise contribution), but there are a multiplicity of paths with interdependences among the variables involved in finding the optimal combination of meals and number of waiters/kitchen assistants.

The computerised system had been designed to display the output data related to the experimental treatments as graphs, tables or as a combination of graphs and tables. In the table versions, all data were presented as tables. In the graph versions, the same data were presented as graphs as illustrated in figures 2a and 2b.

3.2   Two experimental studies

Two experimental studies were conducted to explore our ideas. In the first study, we used verbal protocols to assess the subjects' information processing. We then experienced that the subjects often stopped "thinking aloud" when they focused attention on graphs. Therefore, we decided to include eye tracking in a second study. Furthermore, in the first study, we observed that there were differences among the subjects in the time spent before they started to make decisions. Therefore, in the second study we recorded the time the subjects spent until they had made the first decision. This phase we called the problem-definition phase. The time spent from the first decision was made until they finished the task we termed the problem-solving phase.

Decision result was measured as the total contribution divided by the maximum contribution. The two tasks did not have the same optimal solution, so the division was done to make the decision results comparable.

Level of information processing was measured based on the theory of cognitive complexity (Schroder et al., 1967). A 7-point scale was developed from the description of the four levels of information processing

in the theory (ibid. p. 14-23) and by adaptation of a general manual for scoring structural properties from verbal responses (ibid. p. 186-189). In this paper, we do not go into detail about these measures, but we have applied them in our interpretation of the verbal protocols in the section of findings.

In study 2, we have additional measures of the subjects' eye movements while solving the tasks as scan-path diagrams, see figures 2a/b and 3. A scan-path diagram shows the paths (lines) between eye fixations, indicated by circles. The centre of the circle marks the fixation, and the size of the circle indicates the duration of the fixation. It is widely accepted that eye movements indicate where subjects direct their attention. During decision-making tasks allowing subjects to freely view the data as in our experiments, eye movements are generally considered to provide a valid measure of the spatial distribution of attention (Glaholt and Reingold, 2010).

In study 2, we also assessed the subjects' tendency to engage in and enjoy effortful information processing by applying the "Need for cognition scale" (Cacioppo, Petty and Kao, 1984). In this paper, we do not go into details regarding these data, but they will be mentioned in the discussions of findings.

3.3   Subjects and procedures

The subjects in the two studies were 42 and 37 MBA students, respectively. All subjects were in their final year when the experiments were conducted. Thus, the subjects should have a relevant background for handling the experimental task described above. We also expected them to be acquainted with spreadsheets for data presentation and calculations. The subjects were randomly assigned to the six experimental treatments.

All subjects were paid NOK 200 for participating in the experiment. In addition, in order to motivate the subjects to perform as well as possible, the highest performing subjects in each experimental group received an extra reward of NOK 1000.

The subjects were introduced to their new "job" as managers of the summer restaurant. We explained the task they were supposed to handle. The computerised system was also explained, i.e. the decision variables and the result variables, and how to run the system. In addition, we emphasised that the subjects were allowed to use decision aids.

The method of data collection in study 1 was tape-recording of the subjects "thinking aloud" while they were interpreting the data displays and making decisions. The results of using the spreadsheet system including additional spreadsheets for calculations and/or making graphs were saved. The results from using paper and calculator were also saved.

In study 2, we recorded subjects' eye movements using an eye-tracker unit mounted under the computer screen. Thus, the subjects were not physically connected to the eye-tracker, and they were not supposed to be disturbed by the eye-movement recording. Before the recording started, the subjects went through a calibration process to adjust the eye-tracking device to each individual's eyes. During the experimental sessions, the eye-tracker recorded the subjects' eye fixations as time stamped coordinates on the screen with a sampling rate of 50 Hz (i.e., 50 samples pr. second). After each session, the eye-movement data were loaded into software that converted the time stamped coordinates into eye fixations and subsequently into the scan-path diagrams (Holmqvist et al., 2011).

4   FINDINGS

Table 2 summarises the results of our initial findings including both studies. Of the 79 subjects that participated in the experiment, we considered five as outliers. These five subjects had misunderstood the task and attempted to maximise the sales instead of the contribution, so we ended up with N = 74. Table 2 shows a clear difference in the decision results between the low and high complexity tasks. The average value of the contribution index for the low complexity task is 0,9795, and the average value for the high complexity task is 0,8648 ($p<0,001$), indicating that the experimental tasks are perceived as having different degrees of subjective complexity.

Table 2 shows the outcomes of the experiments measured as the average contribution index values. The table shows the outcomes based on the data presentation formats that the subjects received at the start of the experiment.

		Presentation format		
		Table	*Graph*	*Table and Graph*
Task complexity	*Low*	**0,9850** N=8, st.dev.=0,012	**0,9713** N=10, st.dev.=0,027	**0,9839** N=9, st.dev.=0,019
	High	**0,8768** N=16, st.dev.=0,083	**0,8423** N=15, st.dev.=0,068	**0,8739** N=16, st.dev.=0,081

Table 2   *Average results based on original presentation format*

Even though not significant, the table indicates that the subjects that received the graphical presentation format generated a lower contribution than subjects presented with a table or a combination of table and graph. Furthermore, in both task types, the subjects presented with the table actually performed best.

Table 3 presents the outcomes when we have taken into consideration the presentation formats that the subjects actually used when solving the experimental tasks. Six subjects that received the table format (three in each task category) generated a graph during the session. Five subjects (three in the low-complexity task and two in the high-complexity task) copied data from the graphs and generated table data for their analyses.

		Presentation format		
		Table	*Graph*	*Table and Graph*
Task complexity	*Low*	**0,9851** N=5, st.dev.=0,014	**0,9655** N=7, st.dev.=0,028	**0,9842** N=15, st.dev.=0,017
	High	**0,8588** N=13, st.dev.=0,081	**0,8330** N=13, st.dev.=0,067	**0,8882** N=21, st.dev.=0,077

Table 3   *Average results based on presentation format as adapted by subjects*

Comparison of tables 2 and 3 reveals that 11 subjects that received either a table or a graph format felt a need for the combined format. The comparison also reveals that particularly in the high-complexity task the generation of the additional format has improved the outcome. In this task, the difference in contribution index values for the "Graph" and the "Table and Graph" cells is significant at the 0,05 level with a rather large effect size (Cohen's d = 0,78) (Cohen, 1988). The results indicate that decision-makers need both presentation formats in problem tasks.

The economic result is an objective measure of performance used in the study. In the following, we will analyse the differences in outcome by comparing the verbal protocols and eye-tracking data from subjects that attained the highest contribution, and subjects that attained the lowest contribution. The object is to improve the understanding of the problem solving behaviour that may explain the differences in performance.

4.1   Low-performing subject: high complexity task, graph format

Subject S215 is an example of a low-performing subject. He attained a contribution index value of 0,6721, which is well below the average. Analysing the verbal protocol for subject S215 revealed that he had long tacit periods, even though we encouraged him to verbalise his thoughts. The eye-tracking data were, therefore, useful when we tried to understand why this student did not perform well.

Figure 2a shows a scan-path diagram for ten seconds of the student's eye fixations at the beginning of the session, i.e. when the subject attempted to understand the task. The figure illustrates that the subject mainly had horizontal eye movements in the problem-definition phase, and that he particularly had his attention directed at the prices of the meals (large circles). When S215 later entered his decisions, the prices were limited to NOK 130 – 135, i.e. close to the "historic" prices, while the optimal price for the high-complexity task is NOK 154.

When S215 started to make decisions, the graph clearly showed that the number of employees were not able to meet the demand, but S215 did not handle the problem. The eye-tracking data reveals that S215 did not pay attention to the specific area of the graph where the lack of capacities was displayed, i.e. the gap between the demand for meals and the actual sale of meals. Figure 2b illustrates this point, and the video before and after this scan-path diagram strengthens the interpretation.
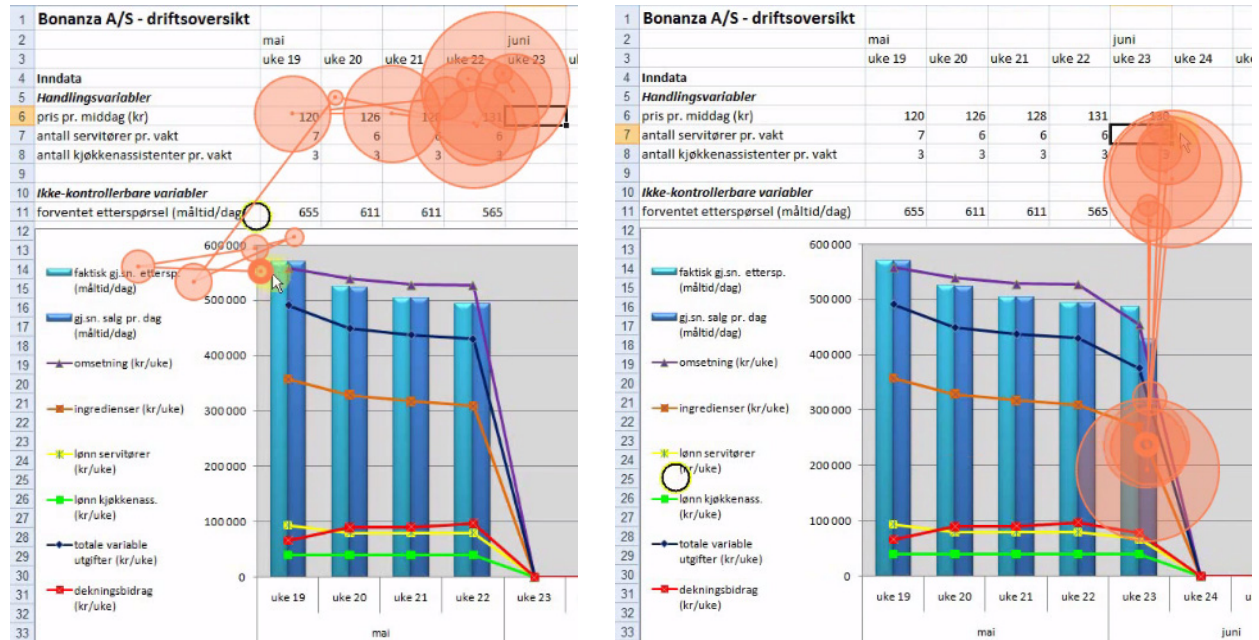

Figure 2   a) Horizontal eye movements, b) Vertical eye movements

Mainly based on the eye-tracking data we then conclude that the main reasons for S215's low performance are that he did not understand the problem with the maximum capacities of the employees and the interrelationships among the variables when he started to make decisions. With his focus mainly on prices, he never detected the possibilities to increase profit by reducing the staff and increasing the price of the meals.

S215 did not make any calculations on a spreadsheet or on paper. He seems to have solved the problem mainly based on spatial processes supported by the graph, which is in accordance with the cognitive fit theory, i.e. he reduced the cognitive load, but did not perform well in terms of accuracy. S215 had a low score on the "Need for cognition" scale, which indicates that he was not particularly motivated to make an effort to solve the task.

4.2   High-performing subject: high complexity task, combined format

Subject S205 is one of our high-performing subjects. In fact, he is the highest-performing subject in the high-complexity task with a contribution index value of 0,9815. S205 received the combined format as shown in figure 3.

Analysis of the verbal protocols show that S205 found the capacity for waiters from the "historic" periods before he started to make decisions. He had also estimated the capacity for the kitchen assistants, which he then checked in the following decisions. S205 actually found the optimal solution after the second trial, but used the following three decisions to test whether he could improve the solution.

The verbal protocols reveal that S205 performed calculations on marginal costs and profits. For example, he found out that reducing the number of kitchen assistants together with an increase in the price of meals would give a higher profit, i.e. he had understood the interdependencies in the relationships among the variables.

The eye-tracking data support our interpretations of the verbal protocols. S205 spent most of the session time on problem identification (10,92 min. of 14,92 min.). Figure 3 shows ten minutes of scan-paths projected onto a still picture. The figure shows S205's eye-movements until he made the first decision.
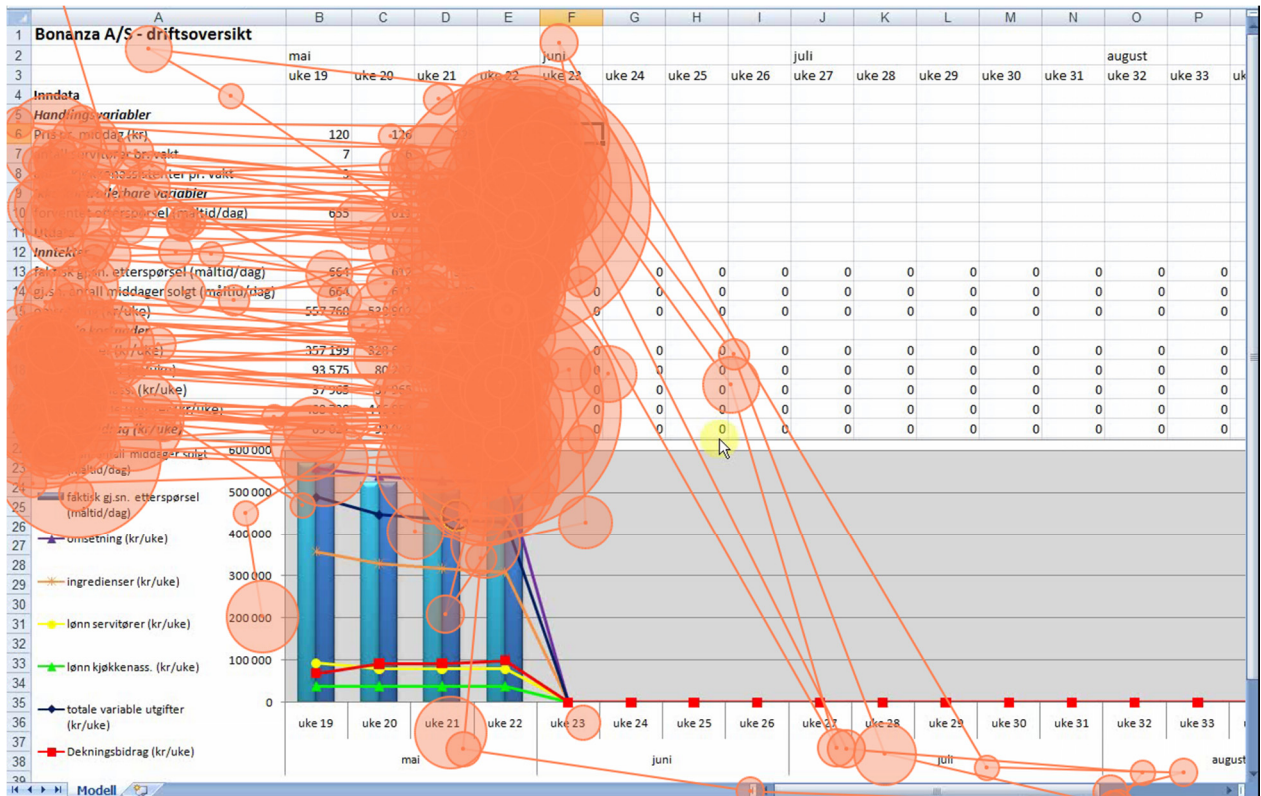
Figure 3   Eye movements during the problem-definition phase

Figure 3 seems "messy", but the point is to illustrate that S205 had many horizontal shifts to understand the variables and the accompanying values. Furthermore, he had many vertical shifts illustrating that he tried to understand capacity constraints and the causal relationships among the variables.

Figure 3 also shows that S205 mainly used the table format in the problem identification phase. However, the video of the problem-solving phase shows that S205 mainly used the graph when he checked for the optimal solution.

4.3   Comparison of low- and high-performing subjects

S215 and S205 illustrate some of our findings that may explain differences between low- and high-performing subjects in our experiments.

One of the differences is related to the time spent on problem identification, i.e. understanding the problem. For example, S215 spent 4,93 min. before making the first decision, while S205 used 10,92 min.

Analysis of the verbal protocols for low- and high-performing subjects indicates that low-performing subjects made rather simple calculations, before they started to make decisions. Most of them tried to find capacities based on the "historic" data. In the verbal protocols, such calculations were expressed as conditions, for example: "If I reduce the number of waiters to five, they will be able to serve about 500 guests". In the high-performing group, more subjects were able to integrate the various conditions and relate them to the contribution as illustrated for subject S205. Very few subjects developed the conditions for the optimal solution. Two subjects entered the optimal solution in the first trial in the low-complexity task. One subject needed only one trial decision in the high-complexity task to find the optimal solution.

Relating the analysis of the verbal protocols to the presentation formats, we find that most of the subjects with the graph format stopped their considerations with calculations of the capacities, while most of the subjects with the table and the combined formats managed to integrate the capacities. Our interpretations of the subjects' level of information processing are based on the work by Schroder et al. (1967).

Related to the eye-tracking data, the low-performing subjects seemed to have a trial and error strategy, while the high-performing subjects had a systematic approach to understanding the results from the various decisions as illustrated by S205.

With the support of decision aids, there were high-performing subjects in all six categories of our experiments. Still, an analysis of the time the subjects spent on the task indicates that subjects receiving the graph format had the hardest time finding a solution that they found satisfactory. On average, they spent 48 min. on the task, whereas subjects receiving the table and the combined format spent 28 min. and 35 min. respectively.

5   DISCUSSION AND CONCLUSION

Our research attempts to enhance the understanding of how (external) presentation formats support decision-makers' decision processes, i.e. their mental representation of the problem and how they solved it. Compared to previous research, we have examined decision-makers' need for data presentation formats in tasks of high complexity, termed problem tasks (Campbell, 1988). Characteristics of our experimental tasks are that they have a well-defined optimal solution, but the subjects have to find the "best" path to this solution. The relationships among decision variables are characterised by interdependencies and uncertainties. Another characteristic that distinguishes our studies from previous studies is that the subjects were allowed to use decision aids, such as spreadsheets and a calculator.

With tasks having a requirement for accuracy, our results indicate that subjects presented with the table format on average generated the highest contribution. However, when we correct for the presentation formats actually used by the subjects, the combination of tables and graphs gave the highest contribution in the high-complexity task.

The problem tasks designed for the experimental studies had both spatial and verbal subtasks. The tasks concerned time-series data, i.e. they included spatial elements of detecting and comparing trends in the output data. They included verbal elements of calculating capacities and dependencies.

Our results support the cognitive fit theory (Vessey, 1991, 1994) that subjects receiving the graph format had a hard time solving the problem when there was a requirement for accuracy. However, for most subjects we did not detect a strategy shift toward spatial processes. Subject S215 was actually one of the few exceptions. With access to decision aids, most subjects took the time they needed to extract values from the graphs and calculate capacities and costs in order to search for the optimal solution.

Our study indicates that decision-makers need both presentation formats. However, the graphs were used differently from what we had expected. We had expected the subjects to use the graphs early in the problem-identification phase to get an overview of relationships among the variables. However, the tendency among the subjects that had the combined format or generated graphs was mainly to use the table in the problem-identification phase and to use the graph in the problem-solving phase to check whether the development in the result variables was as expected.

The subjects in our study were MBA students in their final year. We expected them to know how to handle a spreadsheet. This expectation was only partly confirmed. Some students were not able to use the spreadsheet to support their analyses. They had to use calculator and paper. Some students with the table format explicitly expressed the need for a graph, but did not manage to generate it. Several students with the graph format expressed a need for numeric values.

Our research has implications for designers of information systems. In computerised systems designed to support decision-makers in problem and fuzzy tasks, designers should include both tables and graphs. Not all decision-makers are able to generate the graphs they need from table data. Furthermore, for data presented on the web, it should be possible to export data to a spreadsheet format so that decision-makers can use the data in additional analyses.

Our experiments are exploratory. They should be followed up in experiments with more subjects increasing the possibilities to achieve statistical significance at even the 0,05 level. Furthermore, the tasks in our studies are problem tasks that only require basic economic insights. They are closer to real-life decision-making than other studies within this area that we know of. Still, they only reflect aspects of the complexity that managers must handle in real-life situations characterised by global competition and cost pressures. There is a need to study how managers actually use the variety of data presentation formats they are introduced to on the web, on dashboards and other decision aids.

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