# The Mobile Decision Maker

## Mobile Decisions Aids, Task Complexity, and Decision Effectiveness

Heijden, Hans Van Der; Sangstad Sørensen, Lotte

# The mobile decision maker: mobile decision aids, task complexity, and decision effectiveness

Hans van der Heijden and Lotte Sangstad Sørensen
Copenhagen Business School

Abstract

The increasing power of mobile computing devices raises the question to what extent traditional decision support systems theory can be applied to decision makers using a mobile decision aid. An experiment is reported on the use of a mobile information system to support product selection in a physical store. 86 participants were being subject to two treatments: decision task complexity and the availability of a decision aid supporting additive compensatory (AC) strategies. The study provides some limited evidence that the availability of AC decision aids increases the quality of the user's consideration set. We also show that the mobile user's confidence in the final decision increases if the AC decision aid is available and the task complexity is high.

The adoption of mobile computing devices in our society is increasingly widespread. Mobile computing devices are becoming as powerful as the traditional desktop personal computer, and increasingly, users are able to use these devices and carry out work outside their regular office environment. No longer restricted to their desk, users also become more flexible in their use of the technology. This leads to an increasing use of information systems throughout physical environments. Advanced systems operating in these environments are put forward under umbrella terms such as ambient intelligence (ISTAG, 2001), pervasive computing, and ubiquitous computing (Weiser, 1993).

Consider for example the use of a mobile information system for consumer decision making in a physical retail store. In the near future, we envision durable consumer products to be able to transmit their product data to a user's mobile device. This can be done for example by a radio frequency ID label or by an infrared beacon next to the product. In a retail store, the user's device will be able to receive this data when the user holds the device close to the product. A mobile information system could then provide decision support to the user, by comparing the product data to the preferences of the user.

From a research perspective, the question is whether such a new decision environment has any marked impact on current information systems (IS) theory. For example, can we apply theory on the effectiveness of decision support systems (DSS) to mobile decision making? In this paper, we describe a research project in which we have taken this research question as a starting point. By applying DSS theory to mobile decision makers, we develop four hypotheses on their behaviour. We then test these hypotheses in a mobile shopping experiment.

The archetypical decision maker faces two objectives: to maximise accuracy (decision quality), and to minimise cognitive effort (Payne, Bettman, & Johnson, 1993). These objectives often conflict, because more effort is usually required to increase accuracy. To balance effort and accuracy, decision makers use a variety of decision strategies (Johnson & Payne, 1985). The mobile user facing the consumer decision example described above is able to use at least the Additive Compensatory (AC) strategy. Using the AC strategy, a user examines all alternatives first along all relevant attributes. Then, he or she calculates a weighted score for each alternative, and continues with the next one. The use of this strategy is natural in a retail store environment, where the products are lined up on shelves and consumers need to move from shelf to shelf and from product to product to examine each alternative in more detail.

The purpose of decision aids is to reduce the cognitive effort involved in each strategy (Todd & Benbasat, 1992). By doing so, the benefits of decision aids are increased accuracy, decreased effort, or a combination of both. It is well known in the literature, however, that the benefits of decision support systems do not always become manifest (for overviews, see Dickson, Senn, & Chervany, 1977; Sanders & Courtney, 1985; Sharda, Barr, & McDonnell, 1988). Empirical results on the impact of decision aid availability are mixed: some researchers have reported an increase in decision quality (Benbasat & Schroeder, 1977), others reported no change, or even a decrease (Alavi & Joachimsthaler, 1992). Among other reasons, researchers have attributed these inconclusive results to the lack of attention of the decision strategy being supported by the decision aid. There has been growing evidence in the literature that the support of the appropriate decision strategy should reflect the impact of DSS on performance (Todd & Benbasat, 1999).

The decisions that consumers make in a retail store have been subject to extensive study (for overviews, see Howard & Sheth, 1969; Simonson, Carmon, Dhar, Drolet, & Nowlis, 2001). There is substantial evidence in the consumer behaviour literature that consumers decide on the purchase of a durable product in two cycles (Hauser & Wernerfelt, 1990; Howard & Sheth, 1969). The first one is the alternative selection cycle, where each product that is potentially interesting becomes part of the *consideration set*. The second one is the alternative consideration cycle, where each product is considered in more detail. This cycle leads to the eventual product being chosen.

The experiment reported in this paper examines the impact of a mobile purchase decision aid on decision quality. Specifically, we are interested in the support of the AC strategy. The mobile device we have developed allows for scanning of the product and the mobile information system displays the attributes of the product to the user. A decision aid examines the user's preferences for these attributes and recommends whether the product should be included in the consideration set.

We develop four hypotheses in the context of this experiment. The first hypothesis deals with the impact of the decision aid on the quality of the consideration set. Because a decision aid assists the user in the evaluation of the product as a whole, the user can better decide whether an alternative should be part of the consideration set or not. Because of this, we expect the quality of the consideration set to improve if an AC decision aid is available on the mobile device.

*Hypothesis 1*

Mobile decision makers with an AC decision aid will reach a better quality consideration set than unaided individuals.

Quality of the consideration set can be measured objectively (for the procedure, see below), but how does the user subjectively evaluate the decision he or she finally makes? Would this differ between aided and unaided individuals? Our hypothesis here is that users would have more confidence in their final decision if the mobile device aided them. The argument is that the shopping service will strengthen and reinforce their attitude towards a specific alternative. Also, the service may evoke feelings of reassurance in that it will consistently recommend a product based on the user's preferences. Both attitude reinforcement and reassurance will contribute to an increase in confidence in the final decision.

*Hypothesis 2*

Mobile decision makers with an AC decision aid will have more confidence in their decision than unaided individuals.

One of the factors that will have an impact on the relationships between presence and absence of the decision aid and decision quality is task complexity. There are various ways of looking at the complexity of a decision task (Campbell, 1988), but in this paper we have narrowed down the scope to the number of alternatives to be considered. The more alternatives the user needs to consider, the higher the complexity of the decision task.

We hypothesise that the impact of the decision aid on consideration set quality is dependent on this type of task complexity. If complexity is low, the user will not feel the urge to save cognitive effort, and therefore the decision accuracy will not be markedly different between groups with and without the mobile decision aid. On the other hand, if complexity is high, we hypothesise that the user will try to economise on cognitive effort, and settle for less than accurate decisions. This implies that his or her consideration set quality will increase more if the complexity of the decision is higher.

*Hypothesis 3*

Complexity of the decision task positively affects the relationship between AC support and consideration set quality.

We also hypothesise an impact of task complexity on the relationship between the availability of the decision aid and decision confidence. Again, if complexity increases, then the impact of decision support will be higher on subjective decision confidence. In a low complexity environment, we expect the user feeling less need to economise on cognitive effort. Consequently, the availability of the decision aid may be perceived of lesser value. This in turn implies that subjective decision confidence may be lower. In the case of high decision complexity, the impact of the decision aid on confidence is expected to be higher.

*Hypothesis 4*

Complexity of the decision task positively affects the relationship between AC support and decision confidence.

## Method

The experimental task was to select one camera that would best fit with the participant's preferences on five attributes: resolution, photo capacity, digital zoom performance, weight, and price. We chose cameras because the number of attributes to take into account for purchase selection is not trivial, because a number of attributes would not require senses other than visual, and because a number of these attributes can be associated with objective performance, and not to taste. These three conditions were needed to calculate objective measures for consideration set quality, as will be explained below.

We constructed an artificial camera store with digital camera pictures on stands. The stands were placed in a circle with equal distance between each stand, so as not to introduce shelf space bias. Also, a consideration set table was set up. We instructed the participants to put each the camera stand that they considered purchasing on the consideration set table. This way, we attempted to make them adopt the two-cycle process.

*Participants*

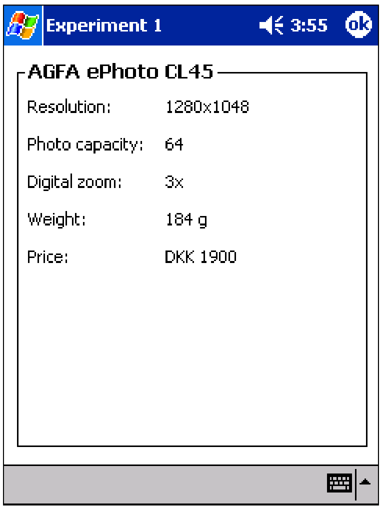
86 undergraduate students of a Danish business school (48 male, 38 female, mean age = 22.1 years, *SD* = 2.95) participated in the experiment as part of a course requirement. 15 students had English as their native tongue, 42 had Danish as their native tongue, and 29 had neither English nor Danish as their native tongue. All students followed an international curriculum which was entirely taught in English, so it was natural for the experiment to be conducted in English as well. To encourage involvement, we awarded one digital camera to a random participant at the end of the experiment. Participants signed an informed consent form in which they agreed to participate seriously and to the best of their ability.

*Context, device, and information service*

We developed a mobile purchase service that provides information about the cameras. Each camera stand was accompanied by a barcode. The mobile information service could retrieve data about the digital camera from the barcode, and display this data to the user on his mobile device. This way, the user could inform himself about the cameras and then select the one that best meets his needs.

We developed two versions of the mobile service. One version produced data about five attributes of the scanned digital camera. The other version did this too and also featured a AC decision aid. The aid produced a colour-coded indication of the camera's attractiveness to the user. This attractiveness was computed according to preferences that could be input into the device. Shades of a single colour (blue) were used to display this attractiveness to the user. Darker shades indicated better fit with revealed preferences. There was neither a comparison function, nor an archive function: the device could display information about only one camera at a time.

The mobile device that we used was an iPaq H3850 (Hewlett Packard) with an SPS 3000 barcode jacket (Symbol). Together, the device weighed 262g. We built the software using Microsoft Windows Platform SDK for PocketPC 2002, Symbol Windows CE SDK, and Embedded Visual Basic 3.0 (Microsoft). Figure 1 displays screenshots of the two versions of the mobile information service, the first version without the decision aid, and second version with the decision aid.



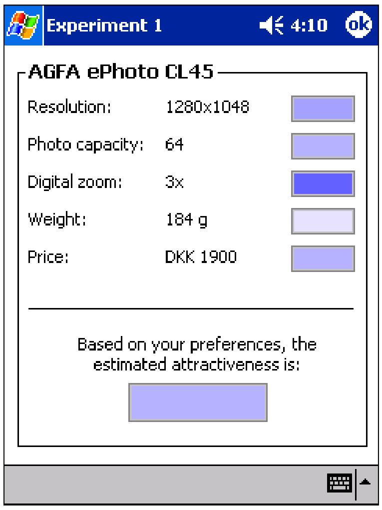



**Figure 1 Screenshots of the mobile information service. The first is without decision aid, the second with decision aid. The darker the colour blue, the better the fit with the user's revealed preferences**

*Procedure*

The cameras had five attributes each. To be able to measure consideration set quality, we followed a procedure identical to (Haubl & Trifts, 2000), and manipulated the data such that no matter what the preferences were, some cameras were always better than others. These cameras are the so-called non-dominated alternatives, because they do not dominate each other, but they do dominate every other alternative in their respective brand. The appendix lists the values and attributes for each alternative.

Using a 2 x 2 factorial design, we worked with two treatments: 1) task complexity and 2) availability of the decision aid. The 86 participants were randomly assigned to each of the four cells. Task complexity was reflected in the number of digital cameras that participants could choose from (10 and 20). All five non-dominated alternatives were available in each task complexity treatment.

After entering the artificial store, the participant was given written instructions about the experiment. The participant then signed the informed consent form, and filled out a pre-experiment survey. This survey included demographic questions, control questions, and a scheme where participants could fill in their personal preferences on the five camera attributes.

Before beginning the actual task of selecting a camera, the participant was shown how to work with the mobile device. After the participant had successfully tried the service and expressed readiness to proceed, the actual purchase selection task started. The participants were told that there were no constraints on how much time they could spend on the task or how many times they could scan a camera. As the participant proceeded in the experiment, we noted down all cameras that were put down on the consideration set table. On average, the actual decision making time was 7.02 minutes (*SD* = 3.20 minutes, minimum 2.10 minutes, maximum 20.03 minutes).

After the participant had selected the final camera, he or she was asked to fill out a post-experiment survey. In this survey we asked the participants to rate their confidence in the final decision, on a scale from 1 (not confident at all) to 7 (very confident).

## Results

Table 1 presents an overview of the number of participants in each cell.

**Table 1 Number of participants in each cell**

| | *Task complexity* | |
|---|---|---|
| *Decision aid* | 10 cameras | 20 cameras |
| Not available | 22 | 22 |
| Available | 21 | 21 |

Consideration set quality was measured using two indicators. One was the number of non-dominated alternatives in the consideration set. The other was the number of non-dominated alternatives divided by the total number of alternatives in the consideration set (Haubl & Trifts, 2000). The resulting variable "share of non-dominated alternatives" ranged between 0% and 100%. Decision confidence was measured by the participant's rating on the decision confidence question. Table 2 presents an overview of the descriptive statistics of the three decision quality measures.

**Table 2 Mean scores and standard deviations for measures of decision quality as a function of decision aid presence and task complexity (*N* = 86)**

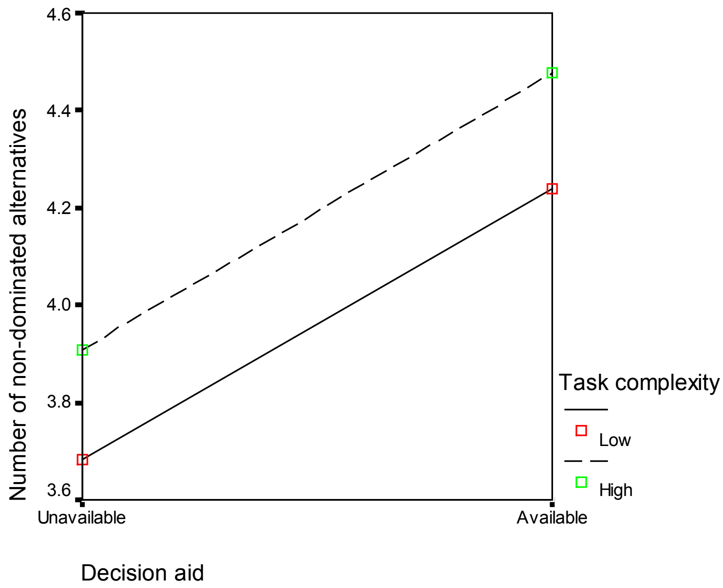
| | Decision quality measure | | | | | |
|---|---|---|---|---|---|---|
| | Number of non-dominated alternatives | | Share of non-dominated alternatives in consideration set | | Perceived decision confidence | |
| Group | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| No decision aid | | | | | | |
| Low complexity | 3.68 | 1.21 | 92% | 13% | 6.32 | .65 |
| High complexity | 3.91 | 1.41 | 71% | 20% | 5.32 | 1.49 |
| Decision aid | | | | | | |
| Low complexity | 4.24 | .83 | 97% | 8% | 6.14 | .66 |
| High complexity | 4.48 | .93 | 77% | 18% | 6.00 | .78 |

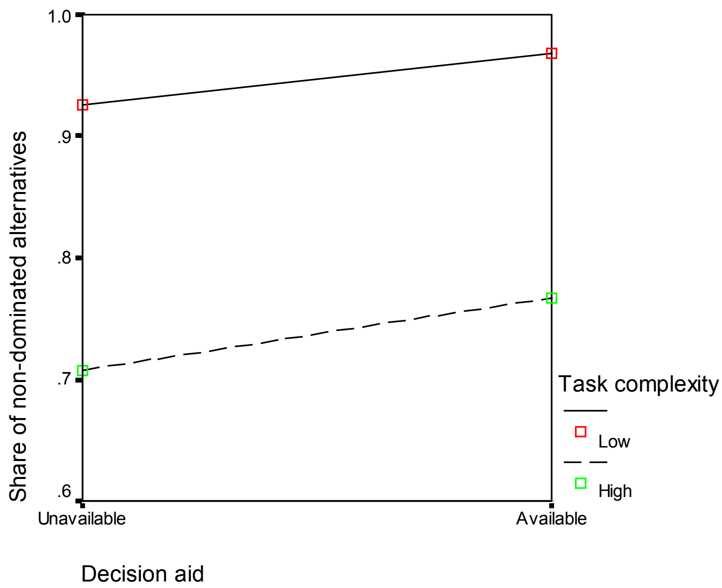
Table 3 provides the correlations between the three measures of decision effectiveness. One would expect the measures to correlate at least to some extent, but the correlations between them are all non-significant.

**Table 3 Correlation coefficients for relations among three measures of decision effectiveness**

| Measure | Share of non-dominated alternatives in consideration set | Perceived decision confidence |
|---|---|---|
| Number of non-dominated alternatives | -.06 | .07 |
| Share of non-dominated alternatives | -- | .09 |
| Perceived decision confidence | -- | -- |

To allow the reader to graphically examine the effects, Figure 2 displays three profile plots, one for each effectiveness measure.


Number of non-dominated alternatives
4.6
4.4
4.2
4.0
3.8
3.6
Unavailable
Available
Decision aid
Task complexity
Low
High


Share of non-dominated alternatives
1.0
.9
.8
.7
.6
Unavailable
Available
Decision aid
Task complexity
Low
High

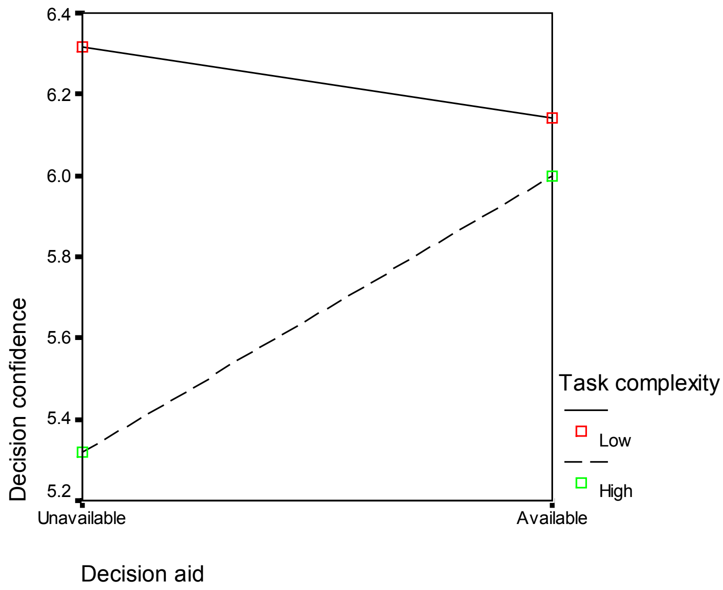



**Figure 2 Profile plots for number of non-dominated alternatives in the consideration set, share of non-dominated alternatives, and decision confidence**

A multivariate analysis of variance (MANOVA) would be the most appropriate statistical test to examine the simultaneous effects on the two decision effectiveness measures. Many of the statistical assumptions for a MANOVA, however, were not met. The cell sizes just exceeded the recommended minimum cell size of 20 observations to conduct a MANOVA, so only large effect sizes would be detected at a power level of .80 (Hair, Anderson, Tatham, & Black, 1998). Also, the assumption of multivariate normality has been violated because the three distributions were highly skewed and departed from normality. Finally, Box's M was significant at 60.49 ($F_{18, 23651} = 3.14$, $p < 0.001$), indicating that the covariance matrices of the groups were not equal. Although the effect of violating the assumptions in a MANOVA analysis is unclear (Hair et al., 1998), we decided not to risk unwarranted interpretations. Instead, we ran multiple two-way ANOVAs to examine the effect on each decision measure individually.

Table 4 presents an overview of the ANOVAs carried out on the three decision effectiveness measures. Levene's test for equal variance was significant at $p = 0.04$ for the number of non-dominated alternatives and significant at $p < 0.001$ for the other two measures. This indicates that we cannot confidently assume that the variances of the different groups are homogeneous. These violations, however, are not rendering the ANOVA unsuitable, as it is relatively robust against these violations, in particular for equal cell sizes as is the case here (Hair et al., 1998).

Let us first consider the number of non-dominated alternatives in the consideration set. The impact of task complexity is insignificant. The impact of the decision aid however is significant, but the interaction is not. This result supports hypothesis 1 (the effect of the decision aid) but does not support hypothesis 3 (the interaction of complexity on this effect).

**Table 4 Summary of two-way analysis of variance for the number of non-dominated alternatives in consideration set, share of non-dominated alternatives, and decision confidence**

| | *SS* | *MS* | $F$ (1, 82) |
|---|---|---|---|
| | Number of non-dominated alternatives | | |
| Decision aid (D) | 6.78 | 6.78 | 5.36* |
| Complexity (C) | 1.16 | 1.16 | 0.92 |
| D x C | 0.00 | 0.00 | 0.00 |
| | Share of non-dominated alternatives | | |
| Decision aid (D) | 0.05 | 0.05 | 2.37 |
| Complexity (C) | 0.95 | 0.95 | 40.47*** |
| D x C | 0.00 | 0.00 | 0.07 |
| | Decision confidence | | |
| Decision aid (D) | 1.38 | 1.38 | 1.49 |
| Complexity (C) | 7.02 | 7.02 | 7.56** |
| D x C | 3.95 | 3.95 | 4.25* |

*$p < .05$, **$p < 0.01$, ***$p < .001$

Looking at the share of non-dominated alternatives in the consideration set, we find that the effect of the decision aid was insignificant and the effect of task complexity was significant. No interaction between complexity and the decision aid could be detected. This result does neither support hypothesis 1 (the effect of the decision aid) nor hypothesis 3 (the interaction of complexity on this effect).

Looking at perceived decision confidence, there was no effect of the decision aid on decision confidence, although there was a significant effect of task complexity. There was also a significant interaction effect of complexity on the perception of decision confidence. These results do not provide support for hypothesis 2 (the effect of the decision aid on confidence) but they do provide support for hypothesis 4 (the interaction of complexity of this effect).

## Discussion

This study provides some limited evidence that the availability of AC decision aids increases the quality of the consideration set. The study also shows that the mobile user's confidence in the final decision increases if the AC decision aid is available and the task complexity is high. It follows that we can at least partially extend current decision support theory to the realm of mobile decision aids.

These results are subject to the following qualifications. First, some statistical tests produced equivocal results. This may be partly due to the small sample size upon which the tests were applied. Second, the research design has a potential weakness in that it used a potentially unrepresentative sample (Gordon, Slade, & Schmitt, 1986). Students may not be representative because they are likely to be more analytical than non-students. Because the decision aid appealed to the analytical mind, non-analytical users may find the device less useful. We did not control for decision style in this experiment, so we must acknowledge this limitation.

Contrary to our expectations, there were no correlations between the three decision effectiveness measures. It seems that users hold opinions about accuracy which are decidedly unrelated to actual consideration set quality. From a broader perspective, this is an unsettling result. It may indicate that other factors than quality have a countereffect on perceived decision confidence. One such countereffect may be the sheer number of products displayed in a retail store, which can overwhelm the mobile decision maker. The initial state of discomfort may decrease decision confidence irrespectively of the actual decision quality. Another explanation may be the problem novelty for the participants (see Kasper, 1996, for a discussion).

Apart from strengthening these results through replication, many opportunities for future research can be put forward. One opportunity concerns the signalling of preference fit. The use of colour shades to indicate the degree of preference fit improved consideration set quality, and it improved decision confidence in the high complexity treatment group. We therefore encourage researchers to build upon theories on the effectiveness of colour (Benbasat & Dexter, 1985) and examine this in a mobile decision environment. Researchers may look into the effect of the number of colour shades, the number of colours, and the number of (aggregated) attributes that should receive colour codes. Cues other than visual can be explored as well, such as audio cues (e.g. pitch) and sensitive cues (e.g. trembling of the mobile device).

The success of personal mobile services is dependent on the service being aware of the correct preferences of the user. A second opportunity for further research concerns the entry of user preferences. In our example, the user was allowed to assign weights to attributes. Also, we calculated the overall preference fit on the mobile device by assuming that the user's utility function would be linear in every domain. Researchers may look into different preference entry formats for these and other decisions, building on the work by Widing & Talarzyk (1993).

A third opportunity is the exploration of supporting decision strategies other than the AC strategy could be explored. If the support is restricted to a certain type of decision strategy, the users may be directed towards using that strategy even though other strategies may be more effective (Silver, 1990). Researchers may want to explore the effects of supporting different types of strategies in an experimental setting similar to this one.

The mobile consumer scenario that we have advanced with our experiment can not yet be implemented in real life. One important precondition for successful implementation is the willingness of vendors and retailers to let their products beam out standardised product descriptions truthfully. We realise that fulfilling this condition requires a societal effort of substantial size. It is hoped that our research will contribute to the discussion to what extent such an effort would be feasible and desirable.

Author note

Hans van der Heijden, Faculty of Economics and Business Administration, Vrije Universiteit Amsterdam, The Netherlands.

Lotte Sangstad Sørensen, Copenhagen, Denmark.

The experiment was conducted when the first author was a visiting associate professor of Information Systems at the Department of Informatics, Copenhagen Business School.

We thank the department of Informatics at Copenhagen Business School for the financial support of this research.

Correspondence concerning this paper should be addressed to the first author, e-mail: hheijden@feweb.vu.nl.

Appendix

The following matrix is the list of attributes used in the consumer purchase task. The brands and models were derived from public consumer reports, all attribute values are fictitious. Alternatives were randomly assigned to an ID and attributes were randomly assigned to display order on the decision aid, except for price which was last. Dominated alternatives for a brand are displayed in italics.

| ID | Brand | Resolution | Photo Capacity | Digital zoom | Weight | Price (in DKK) | Low compl |
|---|---|---|---|---|---|---|---|
| 1 | AGFA ePhoto CL45 | 1280x1048 | 64 | 3x | 184g | 1900 | |
| 2 | AGFA ePhoto CL50 | 640x480 | 66 | 2.5x | 188g | 1975 | |
| 3 | Sony DSC-P20 | 2400x1800 | 60 | 3x | 176g | 2200 | |
| 4 | AGFA ePhoto CL60 | 2400x1800 | 62 | 2x | 180g | 1825 | x |
| 5 | Sony DSC-P50 | 640x480 | 56 | 2.5x | 168g | 2050 | x |
| 6 | Panasonic PV-DC 2500 | 2400x1800 | 64 | 2.5x | 184g | 1900 | |
| 7 | Kodak DC 225 | 640x480 | 58 | 2.5x | 172g | 2125 | |
| *8* | *Toshiba PDR M-63* | *2400x1800* | *70* | *3x* | *156g* | *1750* | *x* |
| 9 | Kodak DC 215 | 2400x1800 | 60 | 3x | 176g | 2200 | x |
| *10* | *AGFA ePhoto CL55* | *2400x1800* | *72* | *3x* | *160g* | *1750* | *x* |
| *11* | *Panasonic PV-DC 1500* | *2400x1800* | *68* | *3x* | *160g* | *1600* | *x* |
| 12 | Toshiba PDR M-62 | 640x480 | 64 | 2x | 184g | 1900 | x |
| *13* | *Sony DSC-P30* | *2400x1800* | *72* | *3x* | *164g* | *1675* | *x* |
| 14 | Panasonic PV-DC 2000 | 1280x1048 | 66 | 2x | 188g | 1975 | x |
| 15 | Kodak DC 230 | 1280x1048 | 56 | 2x | 168g | 2050 | |
| *16* | *Kodak DC 220* | *2400x1800* | *70* | *3x* | *164g* | *1600* | *x* |
| 17 | Sony DSC-P40 | 1280x1048 | 58 | 2x | 172g | 2125 | |
| 18 | Toshiba PDR M-61 | 1280x1048 | 66 | 2.5x | 188g | 1975 | |
| 19 | Panasonic PV-DC 3000 | 640x480 | 62 | 3x | 180g | 1825 | |
| 20 | Toshiba PDR M-60 | 2400x1800 | 62 | 3x | 180g | 1825 | |

References


Alavi, M., & Joachimsthaler, E. A. (1992). Revisiting DSS implementation research: a meta-analysis of the literature and suggestions for researchers. *MIS Quarterly*(March), 95-116.

Benbasat, I., & Dexter, A. S. (1985). An experimental evaluation of graphical and colour-enhanced information presentation. *Management Science, 31*(11), 1348-1364.

Benbasat, I., & Schroeder, R. G. (1977). An experimental investigation of some MIS design variables. *MIS Quarterly*(March), 37-49.

Campbell, D. J. (1988). Task complexity: a review and analysis. *Academy of Management Review, 13*(1), 40-52.

Dickson, G. W., Senn, J. A., & Chervany, N. L. (1977). Research in management information systems: the Minnesota experiments. *Management Science, 23*(9), 913-923.

Gordon, M., Slade, L. A., & Schmitt, N. (1986). The "science of the sophomore" revisited: from conjecture to empiricism. *Academy of Management Review, 11*(1), 191-207.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th ed.). Upper Saddle River, NJ: Prentice-Hall.

Haubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: the effects of interactive decision aids. *Marketing Science, 19*(1), 4-21.

Hauser, J. R., & Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research, 16*(March), 393-408.

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

ISTAG. (2001). *Scenarios for Ambient Intelligence in 2010; Final Report*: European Commission.

Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. *Management Science, 31*(4), 395-414.

Kasper, G. M. (1996). A theory of decision support system design for user calibration. *Information Systems Research, 7*(2), 215-232.

Payne, J. W., Bettman, J., & Johnson, E. J. (1993). *The adaptive decision-maker*. New York: Cambridge University Press.

Sanders, G. L., & Courtney, J. F. (1985). A field study of organisational factors influencing DSS success. *MIS Quarterly*(March), 77-93.

Sharda, R., Barr, S. H., & McDonnell, J. C. (1988). Decision support system effectiveness: a review and an empirical test. *Management Science, 34*(2), 139-159.

Silver, M. S. (1990). Decision support systems: directed and nondirected change. *Information Systems Research, 1*(1), 47-70.

Simonson, I., Carmon, Z., Dhar, R., Drolet, A., & Nowlis, S. M. (2001). Consumer research: in search of identity. *Annual Review of Psychology, 52*, 249-275.

Todd, P., & Benbasat, I. (1992). The use of information in decison making: an experimental investigation of the impact of computer-based decision aids. *MIS Quarterly*(September), 373-393.

Todd, P., & Benbasat, I. (1999). Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection. *Information Systems Research, 10*(4), 356-374.

Weiser, M. (1993). Some computer science issues in ubiquitous computing. *Communications of the ACM, 36*(7), 75-84.

Widing, R. E., & Talarzyk, W. W. (1993). Electronic information systems for consumers: an evaluation of computer-assisted formats in multiple decision environments. *Journal of Marketing Research, 30*(May), 125-141.