Using Uncertainty to Inform Information Sufficiency in Decision Making

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Abstract. Decision making is a critical part of design. Designers must constantly compare, weigh and select design options throughout the design process. The effectiveness of those decisions impacts the effectiveness of the final design. In this paper, we compare two decision support systems, one that allows designers to enter and visualize the uncertainty in each alternative, and one that does not. We compared differences in the designers' perceptions of whether they had sufficient information to make a choice, and their confidence in their choice. The goal is *not* to make designers more confident of their decisions, but rather to help them evaluate realistically whether they have sufficient information to make a clear choice.

Keywords: Decision support system, decision making under uncertainty.

1 Introduction

The goals of this work are to develop and evaluate a decision support system (DSS) which helps decision makers to more accurately identify situations in which they need to gather more information before they can make a choice between several alternatives with confidence. Many decision methods, and computer tools that implement those methods, focus on helping designers to make the best decisions possible. However, in any complex decision with important consequences, many important facets of the decision situation are either unknown or uncertain. In many cases, the information may not yet be known that will allow the decision maker to know which is the best choice. Thus in this work, we have focused on helping decision makers to better assess whether or not they have enough information to make a clear choice though a simple visualization inspired by sensitivity analysis. We hope that by helping decision makers to recognize when they lack information, it will encourage them to seek clarifying information. We have focused our evaluation on the domain of product design, and have used designers to assess the tool. However, we believe the results to be applicable to almost any type of decision making.

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2 Literature Review

Engineering design is a complex and ill-defined task in which designers must make decisions even when critical information is unknown or uncertain [1, 2, 3, 4, 5]. Thousands of decisions must be made in the course of a design project, and the financial and other consequences of bad decisions can be catastrophic. Rational decision methods of various sorts [6] are often used by designers to improve decision making, especially for major decisions. For example, designers often create decision matrices on paper, in spreadsheets, or with the assistance of a DSS.

However, decision makers often find such methods problematic in several ways. It is inconvenient to enter all the information required for such a method [7]. Erev and Bornstein [8] found that simply allowing designers use DSS does not necessary to increase the quality of the design. Other studies [9, 10] investigated whether allowing designers to express uncertainty in design values would improve the quality of design choices. Not only did this study find that it did not have much impact on the quality of the final decisions, expressing uncertainty information also required significant additional time. Furthermore, Hayes and Akhavi [9] observed that entry-level designers did not always know when to seek more information or what information would be most valuable in clarifying a choice. Based on these results and observations, we came to the conclusion that helping decision makers to choose the "best" option may not necessarily make sense; given the lack of knowledge about the options on the table, in many situations it may be impossible to know which choice is the best, even with the help of the best tool. Thus, in the work reported in this paper, we have changed our focus from directly helping the decision maker to identify the "best" option, to helping decision makers identify whether they have enough information to make a choice. We hope that by focusing on information sufficiency, it will encourage decision makers to work more on gathering appropriate information, which will likely lead to better decisions in the end.

3 Methodology

3.1 Two Decision Support Systems

We developed a DSS tool that allows decision makers to specify their estimates of the uncertainty in each of design parameter, and to visualize the uncertainty in the overall suitability of each design. The top-level interface is shown in Figure 1, on the left hand side. In order to allow us assess the impact of the DSS and its visualization, we also created a second DSS which does not allow users to express or visualize uncertainty in the design parameters. This interface is shown on the right hand side of Figure 1. To distinguish the two interfaces, we will call the first one the "uncertainty" DSS, and the other the "certainty" DSS.

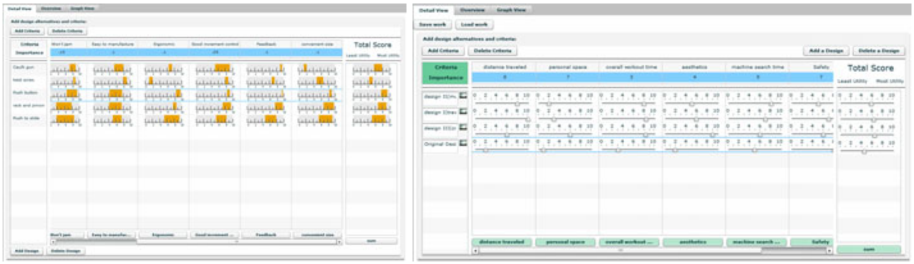

Fig. 1. Interfaces for two DSSs. On the left is the interface for the “uncertainty” DSS, on the right is the interface for the “certainty” DSS.

Both interfaces are structured like traditional weighted decision matrices, which are already familiar to many designers. Designers can enter the name of a design alternative at the start of each row. They can enter the names of their criteria at the top of each column, along with a number representing the weight or importance of that criterion. Each cell in the matrix created by these rows and columns represents a value indicating the degree to which that design alternative fulfills that criterion.

The “certainty” DSS allows users to enter only one value for each design parameter, and the overall scores are also displayed as single “point” values, as shown in the interface on the right-hand side of Figure 1. However, the “uncertainty” DSS allows users to enter values as ranges, using a pair of sliders. Thus, if the designer is uncertain about what exact value to enter, for example for the manufacturing cost, he or she can enter a range of values. The distance between the sliders (e.g. the width of the bar) indicates how much uncertainty is associated with each value.

Similarly, the “uncertainty” DSS computes an overall value score for each alternative (a weighted sum of minimum and maximum values), and is displayed in the right-hand column as a bar representing a range of values. Sometimes, one alternative stands far above the others. But more often, several “best” alternative may “overlap” in their overall value, as shown in Figure 1; the overall value scores of the third, fourth and fifth design alternatives are “better” than the other alternatives, but since their ranges overlap, it is not possible to tell which is really the best alternative. To clarify which is really the best, it is necessary to gather more information about the criteria that most contribute to the uncertainty in those alternatives.

By providing this simple set of bars to visualize the uncertainty in each alternative, designers can tell at a glance if there is one clear “winner” – e.g. a bar with the highest value and no overlap with the others, or whether there are several contenders -- indicating by overlapping bars. It is designed to be both simple and familiar so that users can learn to use it with relatively little training.

3.2 Research Questions

In this research, we wanted to investigate the following questions. 1) Can uncertainty visualizations be used to give designers a more accurate awareness of information sufficiency (e.g. whether or not they have sufficient information to evaluate which choice is best)? 2) Can uncertainty visualizations help designers to have more realistic confidence in their decisions (i.e. to be less confident when there is not enough information to make a clear choice)? 3) Can uncertainty information be used to encourage designers to seek clarifying information when appropriate? Finally, 4) Does domain experience change the benefits that decision makers derive from the DSS?

3.3 Experimental Design

We used a 2 x 3 within subjects design. The independent variables were *expertise level* (entry-level or intermediate-level designer), and *Design Comparison Method* (control system, "certainty" DSS, or "uncertainty" DSS). Dependant variables were perceived information sufficiency, effort to reach a decision, decision confidence, plans to seek additional information, and preference between the methods. Our hypothesis was that the "uncertainty" DSS would appropriately reduce designers' perceived information sufficiency and decision confidence when there were "overlaps" between the top alternatives, and that the others would not. In other words, it would help designers to notice when more information was needed before they could make a choice between alternatives with any confidence.

Subjects. We recruited 22 designers from mechanical engineering and medical device design backgrounds. Of these, 12 were entry-level designers (senior undergrads and one junior) and 10 were intermediate-level designers (graduate students from mechanical engineering department and center for medical devices). Entry-level designers had on average 1.5 years (SD = 0.84) of design experience, while intermediate-level designers had 3.1 years (SD = 1.22). The entry-level designers were on average 25.83 years old (SD=6.10), while intermediate-level designers were on average 31.80 years old (SD=4.87). All participants were currently working on design projects which had been underway for at least 4 weeks.

Design Tasks. Instead of giving each subject the same set of design tasks, we asked each subject to compare several options currently under consideration in their own on-going design projects. The reason was that we wanted to observe the impact in tasks that were both real and complex. It was also important that the subjects had had time to become reasonably knowledgeable about the specific design projects, and were highly vested in the decision outcome. None of that would be possible to recreate using and artificial "laboratory" design task.

Design Comparison Methods. Each subject was asked to compared different sets of design alternatives of their own choosing, using 3 different methods: using their normal practices (control condition), the "certainty" DSS, and using the "uncertainty" DSS. In the control condition subjects were allowed to use whatever methods or tools they would normally use to compare design alternatives. In some cases this was pencil and paper, and in others, a spreadsheet. The order in which they used the DSSs was systematically varied, so as to counter-balance learning effects.

Procedure. Each participant completed all tasks in the experiment individually. Participants were randomly assigned to one of the two experiment groups. The difference between groups was the order in which they used the "certainty" and "uncertainty" DSSs. Both groups used their normal method (control condition) first, then one group used the "certainty" DSS followed but the "uncertainty" DSS, while the other group did the reverse.

1. At the beginning of each experiment, participants were given a brief introduction to the study. Participants signed a consent form which included agreement to audio recording, and answered questions on their demographics and design experience.
2. Subjects were given a brief training session on both DSSs. The training sessions took roughly 10 minutes on each system (20 minutes total).
3. Participants were to use the three different methods in the order specified by the experimenter for their experimental group. They were asked to use the methods to identify one design from a set of alternatives which they would choose further development. Participants were given no time limit for completing design tasks.
4. Immediately after using each system, participants were asked to complete a questionnaire measuring all dependent variables, except "system preference".
5. The "system preference" question was answered after completion of tasks on all decision support systems.
6. At the end of the session, after using the three methods, participants were asked to reproduce the tasks they used in the "certainty" and control condition on "uncertainty" system. The purpose was to find out the degree of uncertainty (e.g. overlap) that existed between those alternatives.
7. A week later, the participants were asked to report what information they had gathered for their design projects.

3.4 Data Collected

Preference between methods was measured by asking subjects to "Please split 100 points among the three decision methods you have just used. The most preferred system should get the most points." *Effort to use decision support system*, *decision confidence*, and *perceived information sufficiency* were measured based on subjects answers to the statements: "I feel this method required more effort than should be necessary." "I am not very confident that the design(s) I chose were the best ones." "I feel I had sufficient information to make an informed decision." The answers to these questions were marked on 7-point Likert scales from "*Strongly Disagree*" (scored as 1) to "*Strongly Agree*" (scored as 7). *Plans to seek additional information* were assessed by first asking, "Is there a particular aspect of the design(s) on which you would like to know more in order to be confident of your decision?" and "If so, please elaborate below and indicate how strongly you want to know about it." The degree of desire was measured by a 7-point Likert scales ranging from "*Strongly Undesired*" (scored as 1) to "*Strongly Desired*" (scored as 7).

4 Results and Discussions

Method Preference. A repeated measure ANOVA, with expertise-level as between subject variable, was used to analyze the preference of the systems and effort to use the systems. We found a significant main effect on design comparison method

($F_{(2,40)}$ = 309.430, $p < 0.001$). As shown in Figure 2. There was also a significant interaction effect between design experience and decision support system ($F_{(2,40)}$ = 4.726, $p = 0.014$). These results indicate that both entry-level and intermediate-level designers preferred the "uncertainty" DSS much more than certainty DSS and control. This preference was stronger for the designers more experience, the intermediate-level designers.

Effort Required. Figure 2 shows that Entry-level designers found that it required significantly less effort to use the "certainty" DSS than their own method (i.e. no DSS) ($F_{(2, 22)}$ = 21.020, $p < 0.001$), but no significant difference between the two DSSs. For the intermediate-level designers, there was no significantly difference in the effort required to use the three different design comparison methods (control, and two DSSs).

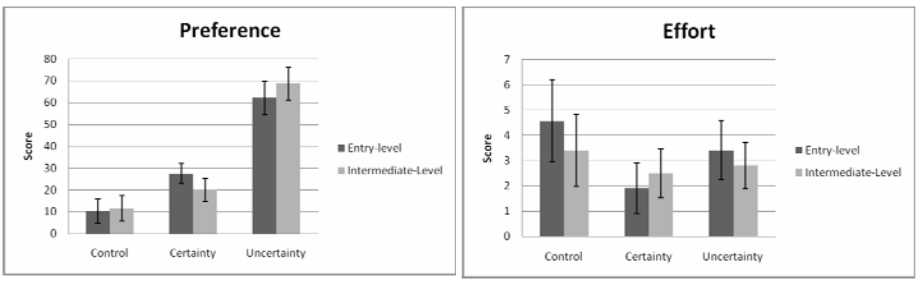

Fig. 2. Designers' preferences for the various design comparison methods, and the effort of using each method

Overall, both experienced and entry-level designers preferred the "uncertainty" DSS. Subjects' comments after the study confirmed this finding. They expressed that the "uncertainty" better reflected the uncertain nature of the design tasks. One subject stated, "it (the "uncertainty" DSS) adds another dimension of what I can do" and "it is intuitive to draw uncertainty as a range."

4.1 Perceived Information Sufficiency and Decision Confidence

During the study, we found that in some cases there were overlapping values between the set of alternatives considered, while in others cases there were not. Our expectation was that whenever there was overlap between the top alternatives, users of the "uncertainty" DSS would perceive less information sufficiency, and lower confidence in a decision that had to be made under such circumstances. Our results showed that this was true. There was a significant main effect of *decision making method* on *perceived information sufficiency* ($F_{(2,40)}$ = 4.158, $p = 0.023$) and *decision confidence*($F_{(2,40)}$ = 3.307, $p = 0.047$). When there was an overlap between top alternatives, entry-level designers who used the "uncertainty" DSS perceived less information sufficiency ($F_{(1,10)}$ = 8.095, $p = 0.017$), and expressed less confidence

($F_{(1,10)}$= 3.447, p = 0.093) in their decisions, as shown in Figure 3. In the control, and when using the "certainty" DSS, users did not perceive and difference in information sufficiency, regardless of whether the alternatives overlapped or not, nor did their decision confidence change.

We did not find significant effects for the intermediate-level designers, but the trends were in the same direction.

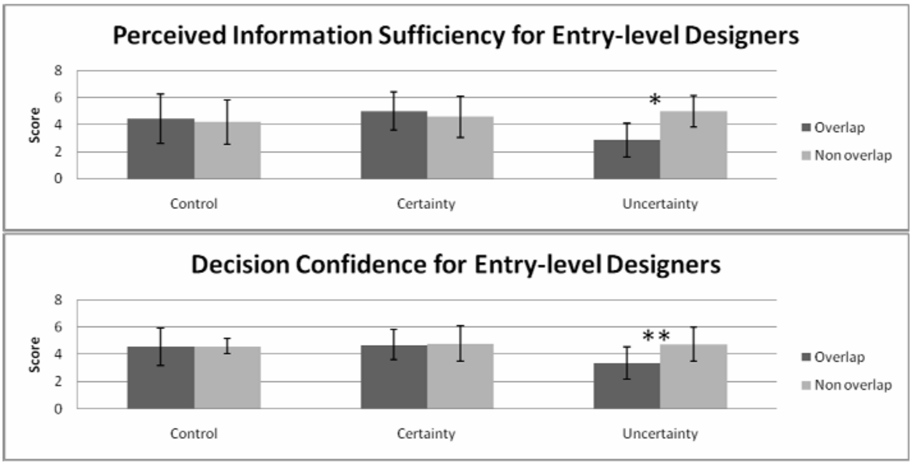

Fig. 3. Entry-level designers found the "uncertainty" tool to help them identify situations in which they lacked sufficient information to make a decision. *Significant at the 0.05 level. ** Significant at the 0.10 level.

We feel that this demonstrates that the visualization of uncertainty did help users, particularly entry-level designers to correctly identify when they lacked sufficient information to make a decision. These findings are in line with the research reported by Cole [11] and Hoffman et al. [12] who found that visualization of uncertainty information helps convey the sense of uncertainty. Also, Nadav-Greenberg [13] found that decision makers are able to recognize the value of uncertainty information, and evaluate the information to have a more realistic understanding of the situation.

4.2 Plans to Seek Additional Information

While it is important to recognize when one does not have enough information to make an informed decision, it is also important to take action to get more information, and to get the right information. We also analyzed to what extent users realized what specific information they should get to most reduce the overlap between alternatives, and whether they followed through on these intentions a week later. The criteria that contribute most to the overall uncertainty are those that have a high importance weight and have great uncertainty in their values. A very uncertain parameter which is not very important does not contribute greatly to the overall uncertainty for an alternative.

We wished to see whether the criteria which designers planned to investigate further correlated to the criteria that actually contributed most to the overall uncertainty. The results of correlation are shown in Figure 4. While the correlations were positive, they were not strong enough for either the entry-level (r = 0.418, n = 48) or intermediate-level designers (r = 0.551, n = 31). From this we concluded that they could use more assistance identifying what specific information would be most useful for clarifying the decision.

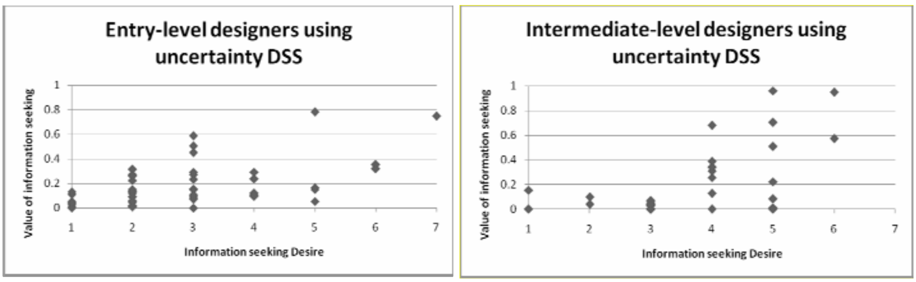

Fig. 4. Correlation results of information seeking desire and value of information seeking

One week after the experiment, we sent a follow-up survey to the participants to inquire what they did in the week following the experiment. The entry-level designers were less likely than intermediate-level designers to have followed through on their expressed plans to seek information. Much of entry-level designers' information seeking effort was spent seeking information on criteria which they had identified to be non-critical, while the intermediate-level designers' more often focused their efforts on the criteria which they had identified as important. We feel further efforts are needed to identify how to help entry-level designers carry through on appropriate information seeking plans.

5 Conclusions and Future Work

The results of this study showed that use of DSS which allows designers to express uncertainty in design parameters, and more importantly, to visualize uncertainty in the overall value of each alternative helps entry-level designers to identify when information is insufficient to allow an informed choice of the "best" from a set of alternatives. Without the visualization, designers did not perceive any difference between situations in which clarifying information was needed, and those in which it was not. This relatively simple visualization empowered designers to think more clearly about the uncertainty in the design, and its implications on their decisions. Further work is needed to identify how to help entry-level designers identify what specific additional information will help the most to inform their decision, and how to motivate them to carry through on plans to gather that information.

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