

# Visualisation Tools for Exploring the Uncertainty-Risk Relationship in the Decision-Making Process: A Preliminary Empirical Evaluation

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## Abstract

Models play an important part in the decision-making process. However, due to uncertainty in a model's input variables, making decisions involves a degree of risk. We have developed two visualization prototypes for exploring the influence of uncertainty in the values of the input variables on the risk associated with the decision-making. The first prototype is the interactive tornado diagram, which is considered as an extension to the static tornado diagram. The second prototype is the Uncertainty Influence Explorer (UIExplorer). This paper presents and discusses the results of an experiment conducted to assess the efficacy of these prototypes and compare their ability to help people answer meaningful questions related to the risk associated with decision-making. The results show that participants using UIExplorer performed better in terms of accuracy and time taken to complete the questions. Also, they found it easier to use and had higher confidence in the decisions being made.

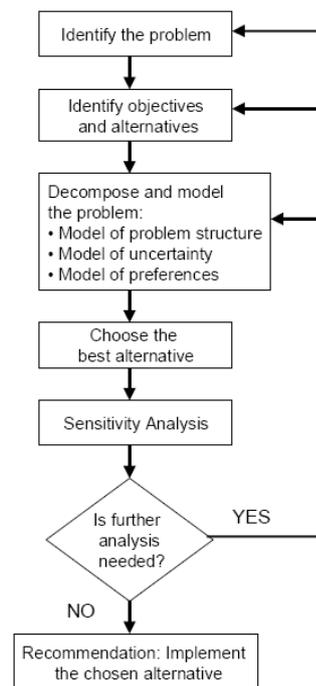
**Keywords:** Information visualization, Interaction Design, Decision-making process, Uncertainty, Risk, Sensitivity analysis.

## 1 Introduction

All decisions are intended to bring about some future benefit to someone or something, and involve choices (e.g. whether to buy a new machine, whether to implement design A or B, etc.) (Willows & Connell, 2003). Systematic approaches to decision-making usually involve models which give a quantitative estimate of the value for the decision-maker to base a decision on (Clemen & Reilly, 2001). For example, financial managers use net present value and internal rate of return for analysing investment alternatives (Dayananda, Harrison, Herbohn, & Rowland, 2002; Jovanovic, 1999). In another decision context such as water management, decision-makers use more complex models to rank multiple water management options or compare the frequency and extent of various flooding events (Hyde, Maier, & Colby, 2005; Xu & Tung, 2008; Xu, Tung, Li, & Niu, 2009).

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There are different kinds of decisions (Harris, 1998); some decisions such as which company's shares to buy, involve making a choice among alternatives while others such as whether or not to invest in a new business are more "yes/no" decisions. Whatever the type of decision, the decision-maker can never be certain of the values of the variables or parameters used in the model and there may also be errors or approximations in the model itself (Jovanovic, 1999). For this reason, descriptions of the decision-making process include a sensitivity analysis step once the "best" decision has been identified (Clemen & Reilly, 2001; Larichev & Moshkovich, 1995; Roy & Vincke, 1981). This is evident in Figure 1 which shows a typical decision-making process (Clemen & Reilly, 2001).



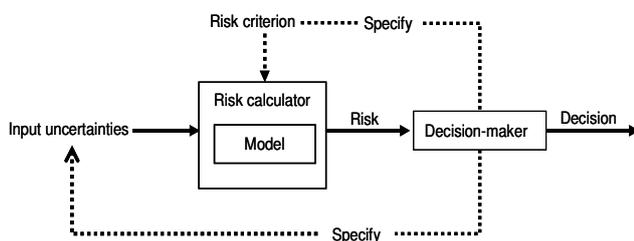
**Figure 1: A Decision Analysis Process flowchart (Clemen & Reilly, 2001).**

Many researchers have emphasized the role of sensitivity analysis in decision-making (Clemen & Reilly, 2001; French, 1986; Triantaphyllou, 2000). After choosing the "best" alternative and following the completion of the decision analysis, sensitivity analysis should be carried out to investigate how uncertainty in the input variables and criteria weights (preferences) affects the values of decision criteria, as well as the final ranking

of alternatives (Clemen & Reilly, 2001). Several sensitivity analysis methods have been proposed (Guillen, Trejos, & Canales, 1998; Hutton & Charles, 1988; Mareschal, 1988; Ringuest, 1997; Soofi, 1990; Triantaphyllou & Sanchez, 1997). These methods are carried out to investigate the relationship between changes in the criteria weights and the subsequent alteration that occurs in the ranking of alternatives (Hyde et al., 2005). Despite this, decision-making processes are often applied with little consideration given to uncertainty in the input variables and propagation of such uncertainties through the decision model (Basson & Petrie, 2007; Xu & Tung, 2008). We suggest this is because the way in which the sensitivity analysis step should be used as part of the overall decision-making is not at all clear.

We are investigating the use of visualization tools to enable the consideration of the uncertainty to be an integral part of making the decision rather than treating it as an add-on step which does not have a clear role in the process. To date we have applied these ideas to "yes/no" decisions. Application to decisions involving multiple alternatives will be the subject of later work.

We have proposed three visualization tools to allow the consideration of uncertainty to be better integrated into the decision-making process for "yes/no" decisions. The first visualization we investigate is the well known static tornado diagram (Cooke & Van Noordwijk, 2000; Koller, 2005, 2007) which is commonly used to explore sensitivity in financial decision-making. For the second visualization we have added interactivity to the tornado diagram. The third visualization is a prototype of our Uncertainty Influence Explorer (UIExplorer). It has been developed to explicitly allow the decision-maker to explore how the risk of making an undesirable decision is affected by the uncertainty in the input variables as depicted by the process shown in Figure 2. The decision-maker specifies the risk criterion to be used (e.g. that the NPV is less than zero) and also the uncertainty range for each input parameter.



**Figure 2: Uncertainty-Risk relationship in the decision-making process.**

This paper describes an empirical evaluation and presents its results. We introduce an experimental design with two parts: a quantitative part that measures and compares the performance of participants during the experiment. Two variables of performance (accuracy of the answers and time to complete questions) for each visualization were measured. In the qualitative part, the participants answered a number of questions regarding

their experience and satisfaction with these visualizations in the decision-making process.

This paper is structured as follows. Section 2 briefly describes the visualizations using a widely used financial model for investment decisions called Net Present Value (Dayananda et al., 2002; Jovanovic, 1999). Section 3 describes the evaluation. Section 4 presents and discusses the experiment results. Future work and conclusions are discussed in Section 5.

## 2 Description of the Visualization Tools

In this section, we describe the visualizations using a widely used financial model for investment decisions called Net Present Value (Dayananda et al., 2002; Jovanovic, 1999). NPV is a financial model used in capital budgeting to analyse the profitability of an investment or project. A positive NPV indicates that the investment is acceptable. If NPV is negative, the investment should properly be rejected. However, there are many estimations and subtle interactions between variables that have significant effects on the profit outcomes. A basic version of calculating NPV is given by equation 1:

$$NPV = \sum_{t=0}^N \frac{C_t}{(1+r)^t} \quad (1)$$

Where

$t$  is the time of the cash flow.

$N$  is the total time of the project.

$r$  is the discount rate (the rate of return that could be earned on an investment.)

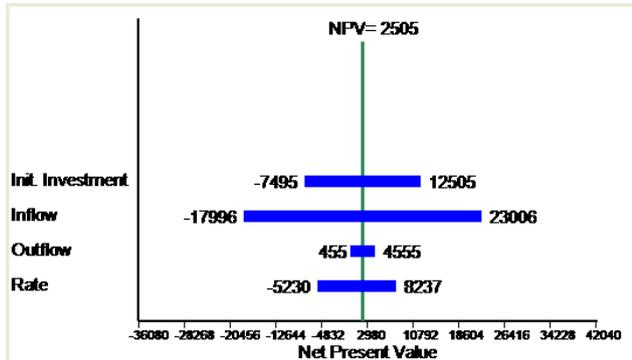
$C_t$  is the net cash flow (inflow minus outflow) at time  $t$ .

### 2.1 Static Tornado Diagram

A tornado diagram is a pictorial representation of the contribution of each input variable to the output of the decision making model (Clemen & Reilly, 2001; Cooke & Van Noordwijk, 2000; Koller, 2005). It consists of stacked horizontal bars, each one associated with one input variable. Each horizontal bar represents the range of the output (NPV) as the corresponding variable is varied over its specified range while all other variables remain constant at their nominal values. The length of the bar indicates the variable's effect on the model output. The model output has a nominal value which is calculated for the nominal values of all the input variables and displayed as a vertical line on the diagram.

A typical diagram is shown in Figure 3. The left and right bar ends indicate the corresponding upper and lower bounds of NPV as the related variable is varied within its specified range while the other variables remain constant at their nominal values. The example in Figure 3 shows that, for the given values of the other parameters, the NPV is mostly influenced by varying the inflow, while the variation in the outflow has little effect on NPV. One of the main drawbacks of the tornado diagram is that it assumes all of the input variables are independent. Thus, it ignores the influence of the interaction between input variables that might have a significant effect on the output (Koller, 2005). In addition, it is a static representation of

the sensitivity and thus it doesn't allow users to interactively explore and compare possible outputs under different scenarios.



**Figure 3: The static tornado diagram shows the sensitivity of NPV to the variation in each input variable while other variables are held constant (Source: own Figure).**

## 2.2 Interactive Tornado Diagram

This visualization prototype is an extension of the static tornado diagram where users can change the nominal values of the input variables interactively and so explore the effects of the interaction between input variables on the model's output. As shown in Figure 4, this can be investigated by varying an input variable (with its scroll bar) and observing how the bars on the diagram for the other input variables change. For example, if the user scrolls the inflow scroll bar, he/she will notice that the length of the rate bar will change. This means that the uncertainty in the model's output resulting from the variation in the rate variable is affected by the inflow value, as can be seen from Figures 4b and 4c. In this way, the prototype can help in exploring the influence of the interaction between input variables on the overall output uncertainty.

One drawback with the interactive tornado diagram is due to how the displayed information is calculated. The calculation used to display the horizontal bars depends on varying one input variable at a time while keeping the other inputs at constant values. The problem with this way of calculation is that, in most cases, the true influence on the output variable depends not only on the values of the input variables, but also on the interaction between input variables over all ranges. Thus, varying one input variable while keeping the others constant might not, reveal the true influence of any input variable. This led to the development of another prototype that rectifies this drawback.

## 2.3 Uncertainty Influence Explorer (UIExplorer)

The aim of this prototype is to visualize the risk due to uncertainty in the model's input variables, and its sensitivity to the variation in these input variables. The UIExplorer uses colours to convey the risk magnitude (in

this case the probability of making a loss). Figure 5 shows a screenshot of the prototype. Yellow means no risk (i.e., probability of making a loss =0) and dark orange represents the highest risk (i.e. probability of making a loss =1). The colour of a cell shows the risk associated with that value of the input variable. It is calculated by taking every possible value of all the other variables and calculating what proportion of these combinations will result in a loss. The user can retrieve the numerical value of the risk (i.e., the probability of a negative NPV) by pointing to any of the cells. For example if the inflow is \$30000 (highlighted cell in Figure 5) then if we consider all other possible combinations of values for the other variables about 44% will result in a loss (probability 0.44).

By looking at the displayed range of colours that represent the risk magnitude, the user can quickly and easily see where the investment is potentially risky or where it is not. In addition, he/she can readily see the values of the input variables for which the investment will likely be profitable (i.e., low risk). For example, in Figure 5, if the inflow varies within the range [\$33000, \$35000], the user can have confidence that the NPV will be positive (i.e., there is no risk of making a loss if the other variables stay within the given ranges).

Clicking on a cell in the first grid fixes the value of that input variable. The chosen cell is highlighted, and the colours in the lower grid change to convey a new range of risks associated with the values of the other input variables. For example, the lower grid in Figure 6 shows the risk associated with the values of inflow, outflow, and rate based on fixing the Initial Investment at \$90000 and allowing the other input variables to vary within their ranges. The new range of colours in the lower grid represents the recalculated risk which is calculated by fixing the initial investment at \$90000 and taking every possible value of the other variables and calculating what proportion of these combinations will result in a loss. This is useful when the user wants to fix a value for a certain variable and explore the risk range associated with the other input variables.

The range of input variables can be modified by changing their minimum and maximum values and as a result, the range of colours in both grids will change to convey the new values of risk. For example, Figure 7 shows the effect of changing the range of Inflow, from (\$25000, \$35000) to (\$20000, \$30000). It can be seen from Figure 7 that the colours in the upper grid are darker which means that the risk is very high for almost all of the values of the input variables. However, this does not mean that the risk associated with all possible scenarios is very high. For example, when the user chooses the value \$30000 from inflow (the highlighted cell), he/she can notice from the lower grid that there are some combinations of the other variables which have low or no risk. This is helpful when the decision maker wants to assess the risk of choosing different scenarios and allows him/her to answer many different "what-if" questions.



Figure 4: (a) Screenshot of interactive tornado diagram. (b) The influence of decreasing the Inflow value on the Rate bar length. (c) The influence of increasing the Inflow value on the Rate bar length.



Figure 5: A screenshot of the UIExplorer showing the ranges of risk.



Figure 6: A new range of colours in the second grid after holding the Init. Investment at \$90000.



Figure 7: The influence of changing the Inflow Range on the calculated risk and the colour range.

In this version of UIExplorer, we display the information in a uniform grid. The use of a grid layout facilitates the presentation of uncertainty and the associated risk in an organised way. In addition, it makes it easier to see and follow the change in the risk magnitude across the rows, which in turn facilitates the discovery of trends and relationships between uncertainty and risk. In addition, all input variables are bounded by a known maximum and minimum and, for this case study, we have made the assumption that all values in between occur with equal likelihood. Therefore, they can be mapped onto equal-sized cells. This way, the user can run through or compare several scenarios with various values and easily determine the risk associated with each value or scenario.

In this version of UIExplorer there is a limit to the number of divisions. We have divided each input variable into eleven divisions although there is no specific reason for that number. However, for finer-grained analysis and representation the user can change the min and max values. This facilitates more detailed assessment over a small range, and consequently more precise and effective decision making. In the future versions we plan to make the UIExplorer more flexible and amenable to larger number of variables.

Colour was chosen for the purpose of presenting risk because it is widely used for risk visualisation and communication (Bostrom, Anselin, & Farris, 2008). Also

it is an important visual attention guide that can highlight levels of risk (Wolfe & Horowitz, 2004). Several studies have addressed the influence of colours on risk perception and decision-making processes (Lipkus & Hollands, 1999; Rogers & Groop, 1981; Soldat & Sinclair, 2001; Wogalter, Conzola, & Smith-Jackson, 2002). A study by Wogalter et al. (Wogalter et al., 2002) supports the following hierarchy of colours to convey risk level: red/dark orange riskier than yellow, yellow riskier than green. Scaling based on lightness or brightness may be helpful in presenting risk information (Bostrom et al., 2008). Davis and Keller (Davis & Keller, 1997) asserted that using colour hue and colour value are the “best candidates” for presenting risk information using static methods. Brewer (Brewer, 2006) advises use of light-to-dark colour for low-to high values with a constant hue.

### 3 Evaluation

We evaluated the visualizations by testing and observing how people used them in a controlled experiment. The aim was to determine whether answering questions using the three visualizations would differ with respect to accuracy, completion time, ease of use, and confidence in the decisions that have been made. Specifically, we try to address the following questions:

1. How easily and quickly can users assess the magnitude of risk of making a loss associated with a certain value or a range of values?

2. How easily and successfully can users answer a variety of “what-if” questions?
3. Can users successfully use the interactive options to assist the risk assessment process?
4. How confident are users in the decisions they make using these tools?

In the following sections, the method of the evaluation will be explained, and then the results will be discussed.

### 3.1 Experimental Design

For this experiment, the Net Present Value (NPV) model is used. The four input variables are Initial investment, cash inflow, cash outflow, and discount rate. The output is the net present value, calculated over a number of years. We put the participant in the situation of deciding whether or not to make an investment as follows:

“You are planning to make an investment and you need to make a decision based on the value of the NPV. You are uncertain about the exact values of the model’s input variables so there is a risk involved in your decision. You need to deal with this uncertainty and assess the risk of your decision. The risk here means the probability of making a loss.”

### 3.2 Participants

We recruited 10 participants from the Lincoln University community. All participants had some understanding of the use of financial models and information to analyse and interpret data relating to business activities. Five were undergraduate students; all of them have enrolled in the Financial Information for Business Paper (ACCT103). One MSc student, with research experience in developing models for financial forecasting using neural networks, also participated. The other four participants were PhD students in the Faculty of Commerce studying marketing, business management, finance, and accounting respectively. The latter participant was also working as a part time lecturer in accounting. Of the sample, 6 were male and 4 were female ranging in age from late teens to 40+. All of them agreed to spend 30 minutes with our experiment and receive a \$20 voucher in compensation. The motivation behind recruiting students from Faculty of Commerce is their good knowledge and understanding of the basic NPV model.

### 3.3 Procedure

The method used in the experiment was as follows: The participants filled out an entrance questionnaire to determine their background experience. It asked the participants to rate their experience in three areas on a four-point scale (1-None, 2-Beginner, 3-Intermediate, 4-Advanced). Figure 8 shows the average rating of participants’ familiarity with financial modelling, decision making under uncertainty and risk assessment. Participants rated their familiarity with financial modelling between none and intermediate, but rated their familiarity with decision making under uncertainty and risk assessment between beginner and intermediate level. This suggests that the participants were well placed to

evaluate the visualizations and would have little trouble understanding the scenario.

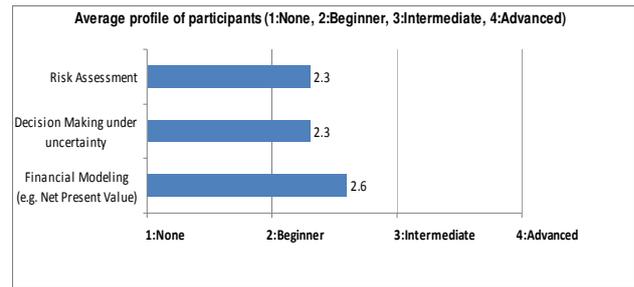


Figure 8: Background of participants.

The participants were given a brief introduction to each visualization and the experimental method and were then asked to answer a set of questions using each visualization. During this time they were observed and their performance was recorded. Upon completion of the questions, the participants were asked to complete an exit questionnaire. Participants took part in the experiment individually with an observer present to record the time taken to answer the questions.

### 3.4 Test Questions

The task of the participants in the experiment was to answer questions about the impact of input uncertainty on the risk associated with making a decision for the given scenario. The questions addressed tasks common to the decision making process and required finding facts and information to answer them correctly. The five questions below were repeated for each visualization:

Q1. For the displayed ranges, which variable do you think has the most effect on the risk of making a loss? (Purpose: to find the most influential variable on risk)

Q2. Approximately, for what range of cash inflow can you be assured that the NPV will stay  $> 0$  i.e. there is no risk of making a loss? (Purpose: to find a range of values associated with a specified risk)

Q3. What do you think the risk of making a loss will be if the Discount rate becomes 10%? (Purpose: to determine the risk associated with a specified input value)

Q4. Given that Initial investment is fixed at \$90000, approximately what is the minimum Cash Inflow that will ensure a positive NPV? i.e. probability of making a loss is zero. (Purpose: to find a value within a particular scenario)

Q5. If the Inflow is \$30000, what is the range of rate values that will ensure no risk of making a loss? (Purpose: to determine a range of values resulting in a specified outcome).

In addition to the total time to complete questions using each visualization and the accuracy of answers overall, we looked at each question individually. Each participant was asked to rate the ease of use of each visualization to answer each question on a four-point scale (1-Very difficult, 2-Difficult, 3-Easy, 4-Very easy). Participants were also asked to explain why they found a

question easy or difficult to answer. After completing the questions for each visualization, participants were required to rate their confidence in the decisions they had made with these visualizations on a 5 point scale (where 1 meant Not Confident and 5 Highly Confident).

## 4 Evaluation Results

The results revealed considerable differences between the visualizations.

### 4.1 Accuracy

In terms of the accuracy of answers, the results showed that there is a noticeable difference between the three visualizations. Figure 9 shows the number of accurate answers for each question using each visualization. 7 out of 10 participants answered the question on finding the most influential variable on risk (Q1) correctly using the three visualizations. This is because this question doesn't need interaction from participants to find the answer. For the questions on finding a value or range of values (Q2 and Q4), the static tornado diagram failed to give very accurate answers. This is because these questions could not be answered without interaction. The number of correct answers for Q2 and Q4 increased for the interactive tornado diagram. However, moving the sliders did not give high accuracy (5 out of 10 were incorrect for both Q2 and Q4). Using UIExplorer, participants gave more accurate answers for Q2 and Q4 than using static tornado or interactive tornado diagram.

For the questions on determining the risk associated with a certain value (Q3) or the risk associated with a range of values within a scenario (Q5), the results show that participants did better using UIExplorer than using both the static tornado and the interactive tornado. This suggests that both interactive tornado and UIExplore helped in finding precise answers to the questions that are related to finding the risk (Q3 and Q5). On the other hand, interactive tornado failed to give high accuracy for the questions that are related to finding the values that affect the risk (Q2 and Q4), while UIExplore succeed to give high accuracy for the same questions, as shown in Figure 9.

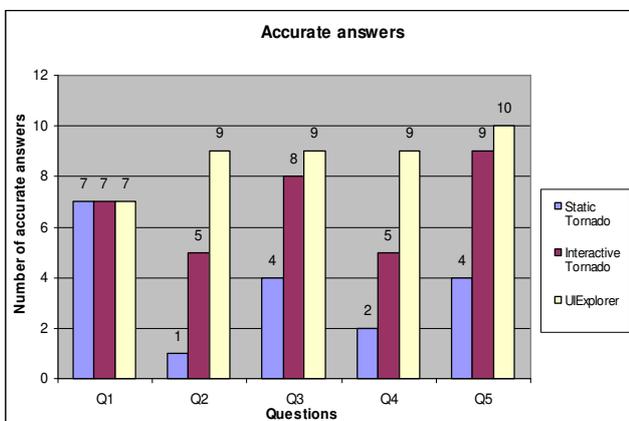


Figure 9: Comparison between the three visualizations in terms of accuracy.

### 4.2 Time Taken

Participants took from 5 to 10 minutes to complete the five questions using each visualization. Figure 10 shows that the mean time taken to answer the questions was 7.3 minutes using static tornado, 6.2 minutes using interactive tornado, and 6 minutes using UIExplorer. The mean time was shorter for UIExplorer than interactive tornado perhaps because, as some participants expressed, moving the sliders in interactive tornado prototype to find the answer takes longer than observing the colour change in UIExplorer. Table 1 summarizes the results of the time taken by the participants to answer the questions using each visualization.

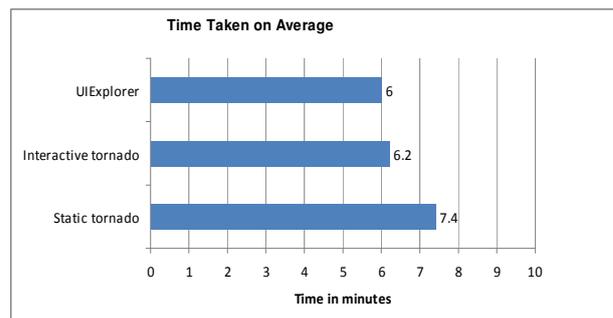


Figure 10: The average time taken by participants to complete the questions using each visualization.

visualization	average	sd	min	max
Static tornado	7.4	2.1187	5	10
Interactive tornado	6.2	1.3166	5	9
UIExplorer	6	1.1547	5	8

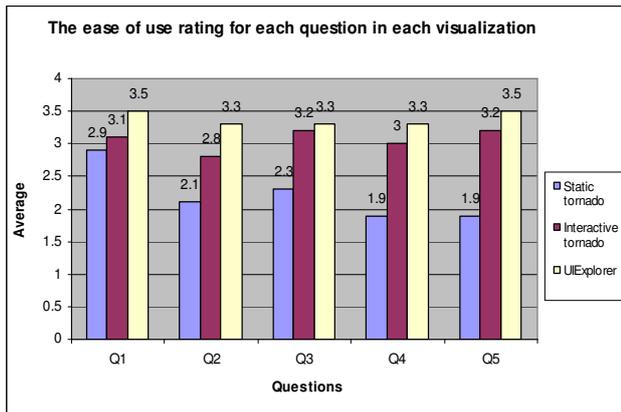
Table 1: Summary of the time taken Results.

### 4.3 Ease of Use

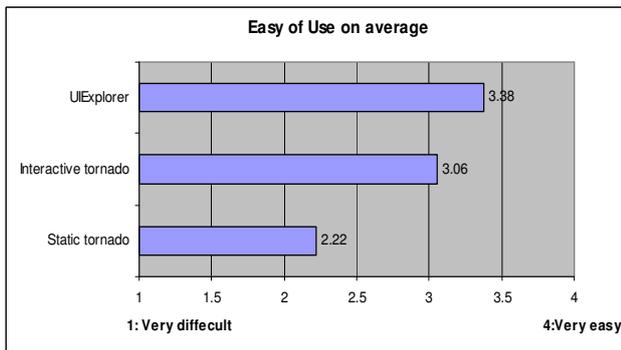
Figure 11 shows that there is a clear distinction between the three visualizations in terms of their ease of use. While it was difficult to find answers using static tornado, it becomes easier using interactive tornado and UIExplorer. For example, using the static tornado prototype, participants found it difficult to obtain answers to the questions related to finding the values of the input variables (Q2 and Q4) and the risk associated with these values (Q3 and Q5). However, using the interactive tornado prototype, participants found that the search for the answers became easier and even much easier when using UIExplorer.

Using the static tornado prototype, participants found that the question related to finding the most influential input variable on the risk (Q1) easier than the other questions. On the other hand, although the ease of use for the interactive tornado prototype and UIExplorer was rated between very easy and difficult, users found UIExplorer much easier than the interactive tornado. This was consistent with the feedback from the participants, who mostly expressed their satisfaction with the use of UIExplorer.

On average, participants found UIExplorer easier to use than the static tornado and interactive tornado as shown in Figure 12. Table 2 summarizes the results of the participants' evaluation to the ease of use. It is noted here that two of the participants who answered Q2 and three participants who answered Q4 incorrectly assessed finding the answers as easy. This gives the impression that the interactive tornado prototype is misleading because some of the participants have been unable to identify the correct answers despite what they perceived as a reasonable ease of use.



**Figure 11: Comparison between the ease of use for each question in each visualization.**



**Figure 12: A comparison between the three visualizations in terms of ease of use.**

Visualization	average	sd	min	max
Static tornado	2.22	0.6788	1	4
Interactive tornado	3.06	0.5858	2	4
UIExplorer	3.38	0.6023	2	4

**Table 2: Summary of the ease of use results.**

#### 4.4 Level of Confidence

Results summarized in Table 3 show that there is a clear difference in the confidence of the participants for the decisions that can be made based on the three visualizations. Participants showed a low level of confidence in their decisions using the static tornado prototype (2). This level rose noticeably for the interactive tornado prototype (3.7) and rose to (4.3) for UIExplorer. One of the main features of UIExplorer, as most of the participants expressed, is that the risk

associated with each value can be directly seen without the need for further interpretation. It should be noted that although some of the participants responded with incorrect answers, their level of confidence using the interactive tornado prototype was high. This again indicates that the interactive tornado prototype leads to misleading interpretations concerning the risk associated with the decision making.

Visualization	average	sd	min	max
Static Tornado	2	0.8165	1	3
Interactive Tornado	3.7	0.82327	2	5
UIExplorer	4.3	0.94868	2	5

**Table 3: confidence level results.**

#### 4.5 Post-study Questionnaire

Eight of the participants found UIExplorer easier to use, more intuitive, and quicker to understand and learn. They understood the representation of risk by colours. On the other hand, two participants preferred the interactive tornado diagram because they found that moving the sliders to reach the required values was intuitive and lead to more understanding and easier assessment. This is supported by their correct answers when using the interactive tornado prototype.

We didn't notice that participants faced a problem in distinguishing colours/gradients. Participants were able to relate between the degree of colour and the degree of risk. They were also able to understand the relationship between uncertainty and risk through gradations of colours. This is consistent with the results of the experiment which showed that the overall performance of participants was better using UIExplorer.

#### 5 Conclusion and future work

This paper presents the results of an experiment conducted to compare the ability of three visualization prototypes to help people explore the influence of uncertainty in the input variables on the risk associated with the decision making. The first visualization is a static tornado diagram. The second visualization is an interactive tornado diagram, which is a modification of the static tornado diagram. The third visualization is the uncertainty influence explorer.

The results show that most of the participants preferred to use UIExplorer rather than the static or interactive tornado prototypes. The use of UIExplorer leads to more correct answers and a shorter time taken to find those answers. Participants found UIExplorer easier to use and they had greater confidence in their decisions compared with the static tornado and interactive tornado prototypes. This was consistent with the quantitative results. Participants' feedback confirmed that further research is needed to improve the design of the UIExplorer so that the user can explore the risk associated with the decision making models at several levels of detail. It is important for the decision maker to be able to explore the risk associated with each value of each input variable, the risk associated with each input variable regardless of the

current value of that variable, and the risk associated with each scenario.

Although there were only 10 participants in this study and we did not completely get rid of learning effects and bias in the results, we believe that the results clearly indicate that our approach of including the risk of making an acceptable decision as an integral part of the decision-making process has significant merit. However, further evaluation is needed. More extensive user evaluation would include more participants and more tasks. In addition, we intend to develop UIExplorer further and also explore ways of extending the approach to decisions where there are a number of alternative options.

### Acknowledgements

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