Risk Attitude Effect in Selecting Decision Criteria Using Decision Tree Analysis: An Empirical Study

BY

Jen-Her Wu

Department of Information Management
National Sun Yat-sen University
Hsi-Tze Wan, Kaohsiung, 80424
Taiwan, Republic of China

Abstract

An approach has recently been proposed to integrate certainty factors (CFs) with probabilities in decision trees to address the effect of ambiguity or vagueness about probabilities. This approach (Involving CFs) has also been psychologically validated in decision tree analysis when probabilities are not precisely known. In this study, an investigation is undertaken regarding the influence of decision analysts' risk attitudes on selecting decision criteria in decision tree analysis, both under risk and under uncertainty. Experimental results indicate that for gain case, people are more risk seeking, and CF as part of decision criteria, is preferable for risk seeking than for risk averse people. On the other hand, for loss case, people are more risk averse, and CF as part of decision criteria, is preferable for risk averse than for risk seeking people.

This empirical evidence suggests that knowledge engineers should be cautious in adopting conventional decision tree approaches, particularly under the circumstances identified in this study. These results provide insights into how decision criteria may be related to risk attitudes under different circumstances, e.g., varying certainty and value magnitudes. Findings obtained in this study enhance our understanding of the psychological validity of extended decision criteria in decision tree approach, which is crucial to knowledge engineer, decision support system (DSS) toolsmiths, and DSS developers.

1. Introduction

Uncertainty is a natural phenomenon which is embedded in all decision problems. This makes decision making both frustrating and intriguing. For instance, the proper course of action for a marketing program that maximizes some utility functions may depend on events that cannot be predicted with certainty. Not all decision makers handle uncertainty in the same manner, i.e., even a single individual may handle uncertainty differently in different situations. A conservative manager may choose to imagine the worst possible scenario, in which demand is lower than expected, and costs are higher than expected. On the other hand, the venturesome manager would tend be optimistic regarding the future of a project and would be willing to take a risk. An alternative is selected when the results appear attractive under the chosen scenario. Thus, different managers may select different alternatives under the same physical environment.

Expected monetary value (EMV) is a common decision criterion in decision analysis, lack of knowledge regarding payoffs for alternative outcomes or events is reflected in probabilities. Well known methods (e.g., decision tree analysis) are currently available for calculating expected payoffs based on probabilities (Raiffa, 1968; Raiffa, 1961).

Decision performance could be affected by ambiguous probabilities, as previously pointed out by various researchers. For instance, Ellsberg (1961) and Raiffa (1961) demonstrated that people do not equally weigh known and ambiguous probabilities in choice situations. In their discussion of prospect theory, Kahneman and Tversky (1979) noted that the decision weight attached to an event could be influenced by such factors as the likelihood of that event, ambiguity, or vagueness. Furthermore, Hogarth and Einhorn (1990) stated that any theory of decision weights must account for the effects of ambiguity or vagueness about probabilities. Although many approaches for coping with uncertainty have been proposed for use in expert systems, the use of certainty factors (CFs) has been widely adopted (Heckerman & Shortliffe, 1992) and is the most prominent approach to model experts' treatment of uncertainty in reasoning process (Tonn & Goeltz, 1990). The purpose here is not to debate CFs versus other approaches, e.g., fuzzy set theory (Zadeh, 1965) or belief networks (Pearl, 1986; Pearl, 1988), but rather to focus on the empirical base for comprehending the efficacy and limitations of CF approaches in descriptively modeling human behavior. Representative viewpoints in this debate are detailed in Kanal and Lemmer (1986).

Certainty factors are defined as numbers that reflect the degree of belief in a hypothesis (Shortliffe, 1976) and are used primarily in the expert system realm. Various methods for combining CFs in the course of inference have been devised, e.g., certainty factor algebra (CFAs) (Tonn & Geoltz, 1990). Empirical evidence indicates psychological validity of some of these CFAs for modeling some experts' treatment of uncertainty (Holsapple & Wu, 1993; Tonn & Geoltz, 1990).

Calantone, et al. (1993) recently proposed an approach that integrates CFs with probabilities in decision trees to address the effects of ambiguity or vagueness about probabilities. Furthermore, Holsapple, et al. (1992) empirically studied the use of CFs in decision tree analysis and confirmed that analysts actually consider CFs when probabilities are not precisely known. However, the relationship of analysts' risk attitudes and decision criteria has not been empirically studied under those conditions. For instance, do decision analysts who are risk seeking tend to combine CFs with probabilities in deciding on an alternative, or do they instead focus on CFs or probabilities alone? An experimental study of decision analysts' risk attitudes for selecting decision criteria can help answer such questions.

Knowing of potential human risk attitude effect could facilitate builders of development tools, developers of decision support systems (DSSs), and knowledge engineers. For instance, subjects could be categorized in some manner by their risk attitudes and the kind of decision criteria they use. Better choice could be made in modeling a decision analyst if patterns could be established so that (1) a toolsmith could offer such an option to a tool; (2) a DSS developer could have the flexibility in tool selection or selecting decision criteria offered by a tool; and (3) a knowledge engineer could categorize a decision analyst as fitting a pattern based on his/her risk attitude. Consequences of failing to closely model a decision analyst can be significant, not only in terms of constructing a DSS that will be used, but also in terms of the impact of ultimate decisions based on that system's advice.

An empirical study is conducted in this study which addresses the foregoing types of questions. Experimental data are presented and analyzed in terms of the relative frequencies of subject responses in selecting decision criteria using decision tree approach. The presentation is organized as follows. The research background is provided in Section 2 to outline the purpose and contribution of this study. The experimental design is provided in Section 3. Experimental data are analyzed in Section 4. Finally, a summary of observed findings, together with a brief discussion of their applications, are provided in Section 5.

2. Background

Decision tree analysis is one of the most common analytic tool employed for selecting the "best" alternative or course of action. The approach is used in an extensive variety of production and operations management situations, e.g., new product analysis, location planning, capacity planning, equipment selection, scheduling, maintenance planning (Heizer & Render, 1991). Decision trees provide mathematical analysis of decision options when states of nature are uncertain; however further information can be obtained by experimentation.

The analysis of a decision problem under uncertainty typically requires that a decision maker (a) list the possible options available for gathering information, for experimentation, and for action, (b) list the events that may occur, (c) arrange the order of information that may be acquired and choices that may be made as time goes on, and (d) select the "best" consequence from the various courses of action based on a set criteria. The objective of such an analysis lies in identifying a course of action (which may or may not include experimentation) that is logically consistent with the decision maker's own preferences for outcomes, as expressed via quantitative utilities and reflecting probabilistic weights attached to possible states of the nature (Raiffa, 1968; Raiffa, 1961).

As noted earlier, various researchers have pointed out that decision performance could be affected by ambiguous probabilities. In traditional decision analysis, however, probabilities are treated as if they are certain and suitable. Therefore, decisions based on computations of EMV and/or expected value of perfect information are questionable.

Calantone, et al. (1993) proposed an approach that integrates CFs with probabilities in decision trees to address the effects of ambiguity or vagueness about probabilities. This approach is an extension of the conventional decision tree approach. Three decision criteria for decision tree analysis are identified, i.e., CF, expected payoff, and a combination of CF and expected payoff. These criteria classify decision makers into three categories, i.e., certainty sensitive, certainty tolerant, and certainty insensitive (see Table 1). Subjects who select CF only, expected payoff only, or both certainty and expected payoff as a decision criteria, are classified as certainty sensitive, certainty insensitive, or certainty tolerant, respectively.

For decision makers who are certainty sensitive, certainty factor maximization is the major decision criterion. In contrast, for the certainty insensitive decision makers, maximizing expected payoff (i.e., utility value) is the major decision criterion. Certainty tolerant decision makers are positioned between these two extremes: the certainty factor and the expected payoff are both key factors in their decision criterion. In each category, decision makers are grouped into three categories according to their risk attitudes, i.e., optimistic (or venturesome), realistic (or compromising), and pessimistic (or conservative) (Calantone, et al., 1993).

Table 1: Decision criteria vs. characteristics

Certainty Approach	Certainty Sensitive (C-S)	Certainty Tolerant	Certainty Insensitive (C-IS)
Decision Criterion	Max(CF)	Max(CF*Utility)	Max(Utility)
Optimistic	Tend to select CFA that yields higher CF	Combinations of C-S and C-IS	Tend to set higher outcomes or higher probability to higher outcomes
Realistic	Tend to select CFA that yields CF between optimistic and the pessimistic	Combinations of C-S and C-IS	Tend to set outcomes and probabilities between the optimistic and the pessimistic
Pessimistic	Tend to select CFA that yields lower CF	Combinations of C-S and C-IS	Tend to set lower outcomes or lower probability to lower outcomes

Furthermore, Holsapple, et al. (1992) verified the psychological validity of considering CFs in decision tree analysis (Calantone, et al., 1993). This study provides an empirical base for understanding which decision criteria various analysts use under circumstances such as varying certainty magnitudes and value magnitudes. More specifically, they show that: (1) most analysts consider CF as being a part of the decision criteria; (2) more analysts combine probability with CF in decision criteria than considering probability or CF only; (3) as CF difference increases, more analysts switch from non-consideration of CFs to consideration of CFs than vice versa; (4) as payoff difference increases, more people switch from non-consideration of CFs to consideration of CFs than vice versa. Their empirical results clearly imply the potential value of theoretically extending conventional decision tree analysis to encompass CFs.

Beyond the above findings, Calantone, et al. (1993) and Holsapple, et al.(1992) also suggest the requirement for further empirical research to understand how analysts' risk attitudes relate to their decision criteria selection in decision tree analysis. Knowing whether decision analysts select decision criteria in approaches suggested by previous literature is critical from a knowledge acquisition perspective. Also, this suggests that subsequent empirical studies should be taken one step further to explore the relationship between analyst's risk attitude and the decision criteria used. Do venturesome decision analysts tend to combine CFs with probabilities in deciding on an alternative? Or do they instead focus on CFs rather than probabilities? Or do they ignore CFs entirely and simply focus on the probabilities?

In addition, how can a knowledge engineer be aided in ascertaining which decision criterion should model a certain type of uncertainty? What guidelines can a knowledge engineer follow in selecting a decision criterion? The answers are potentially crucial to knowledge engineers who are confronted with the issue of acquiring knowledge regarding a specific analyst's treatment of uncertainty within a specific problem domain. However, the relationship of decision analysts' risk attitudes and decision criteria has not yet been empirically studied. The remainder of this study provides an experiment that begins to address these issues.

3. Experimental Design

This experiment, as conducted in a laboratory environment, used a computer and a questionnaire to elicit and capture the subjects' behavior and treatment of certainties in a decision tree analysis. Several preliminary versions of the experimental software and questionnaire were tested prior to the experiment to ensure clarity of the task descriptions presented, proper functioning of the software, adequacy of the user interface, correspondence between data collected and hypotheses to be tested, and sufficient time required to complete the experiment. This feedback served as a basis for correcting, refining, enhancing, and extending the experimental instruments. This testing continued interactively, thereby resulting in progressively better instruments until significant criticisms were no longer encountered.

Two questions were provided to assess the subject's risk perspective. These questions followed a scenario from Schoemaker (1989). For example, for a gain on the interval [$0, $200], subjects were asked if they would prefer a certain $100 to a gamble offering even chances of $0 or $200. Based on the response to this question, subjects were classified as either risk-averse, risk-neutral, or risk- seeking with respect to a gain. A similar scenario was applied to classify a subject's risk attitude with respect to a loss.

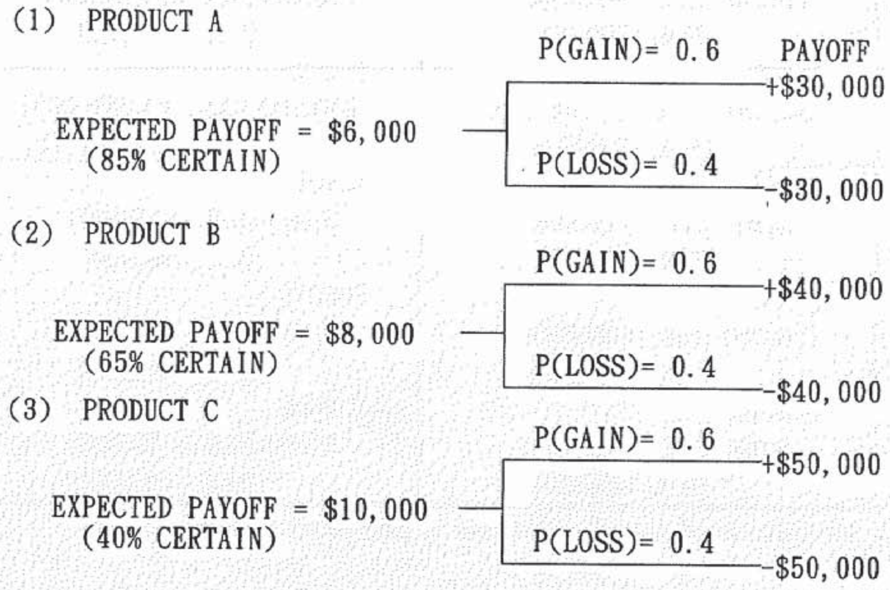
Four different decision scenarios were furnished in the questionnaire. There was no time constraint in this experiment. Out of three alternatives for each scenario, a subject had to select one and only one. Various payoffs were associated with these alternatives. A payoff could be a gain (+) or a loss (-), and a probability was associated with each payoff.

However, the probability distributions were not precisely known. Thus, the subjects were not entirely certain about the exact nature of each alternative. For instance, one might be 90% certain about the nature of one alternative and only 50% certain about another. Nevertheless, one alternative had to be select.

As a specific example, three alternative products were assumed to be available, i.e., A, B, and C, of which one was to be introduced to the market.

(1) We are 85% sure that alternative Product A has a 0.6 probability of yielding $30,000 and has a 0.4 probability of losing $30,000;
(2) We are 65% sure that alternative Product B has a 0.6 probability of yielding $40,000 and has a 0.4 probability of losing $40,000;
(3) We are 40% sure that alternative Product C has a 0.6 probability of yielding $50,000 and has a 0.4 probability of losing $50,000.

Which alternative product should we choose to produce? This problem can be graphically represented in decision tree form as follows:



Subjects were asked to imagine that they are the decision makers in a medium-sized firm (i.e., sales of $30 million and net profit of $4 million last year). For each scenario, what decision a subject would make and what decision criterion would be used were primary concern. The expected payoff for each alternative was calculated for the subjects and the associated certainty was shown beneath the expected payoff in parentheses.

The magnitude of CF differences and payoff differences are investigated in four scenarios, i.e., High and low CF differences coupled with high and low payoff differences, a 2 x 2 design. The CFs levels in the two high CF difference scenarios are 90, 60, and 30, respectively; meanwhile the CFs levels in the two low level CF difference scenarios are 40, 30, 20, respectively. The payoff levels considered in the two high payoff difference scenarios are 300,000, 700,000, and 1,000,000, respectively; meanwhile the payoff levels in the two low payoff difference scenarios are 15,000, 30,000, and 40,000, respectively. These cases are summarized in Table 2.

There are forty-eight subjects, from an upper division undergraduates in the college of business and economics who volunteered for the experiment. The number of subjects was constrained by the available budget. They formed a fairly homogeneous group, for all were schooled in the basics of probability theory and had studied decision tree analysis in the same course. Thus, all were comparably trained as decision analysts in terms of having a common, sound base of quantitative/analytical skills. None of them were familiar with either expert systems or CFs, and so were not biased by prior knowledge of decision criteria choices in varying situations.

4. Experimental Results

Tables 4 and 5 summarize subjects' decision criteria behavior for different risk attitudes in gain and loss situations, respectively. The first column displays the different risk attitudes, e.g., risk averse, risk neutral, and risk seeking. The next column shows decision criteria: P denotes payoff and expect-

Table 2: Four experimental scenarios

	Magnitude of CF difference	
	High	Low
High	A:90% 60,000 (0.6, +300,000) (0.4, -300,000) B:60% 140,000 (0.6, +700,000) (0.4, -700,000) C:30% 200,000 (0.6, +1,000,000) (0.4, -1,000,000)	A:40% 60,000 (0.6, +300,000) (0.4, -300,000) B:30% 140,000 (0.6, +700,000) (0.4, -700,000) C:20% 200,000 (0.6, +1,000,000) (0.4, -1,000,000)
Low	A:90% 3,000 (0.6, +15,000) (0.4, -15,000) B:60% 6,000 (0.6, +30,000) (0.4, -30,000) C:30% 8,000 (0.6, +40,000) (0.4, -40,000)	A:90% 3,000 (0.6, +15,000) (0.4, -15,000) B:60% 6,000 (0.6, +30,000) (0.4, -30,000) C:30% 8,000 (0.6, +40,000) (0.4, -40,000)

Note: Magnitude of payoff difference is presented in vertical axis

Table 3: Risk attitude for gain and loss

GAIN	LOSS			
	SURE LOSS	INDIFFERENT	PLAYING THE GAME	TOTAL
SURE GAIN	12.5%(6)	2.1%(1)	56.2%(27)	70.8%(34)
INDIFFERENT		2.1%(1)		2.1%(1)
PLAYING THE GAME			27.1%(13)	27.1%(13)
TOTAL	12.5%(6)	4.2%(2)	83.3%(40)	100%(48)

ed payoff only, CF denotes certainty factor only; PCF denotes the use of both P and CF as a decision criterion; CF+PCF denotes the use of CF as part of the decision criteria. The next four columns show the treatment of differences in payoffs and certainties.

4.1 Risk Attitude for Gain and Loss

Three attitudes with respect to risk are traditionally defined as follows:

(1) Risk averse:
A subject is risk averse if his or her certainty equivalent is smaller than the mathematical expectation of that prospect (Cohen, et al., 1985);

(2) Risk seeking:
A subject is risk seeking if his or her certainty equivalent is greater than the mathematical expectation of that prospect; and

(3) Risk neutral:
A subject is risk neutral if his or her certainty equivalent is equal to the mathematical expectation of that prospect.

Each subject's risk attitude was elicited in this study with respect to gain and loss situations. Observations are summarized in Table 3. Prior research has pointed out that more people tend to be risk averse for gain situations (Cohen, et al., 1985; Kahneman & Tversky, 1979). Our data support this argument, as 71% of our subjects preferred a sure gain, and only 27% of the subjects preferred playing the game. Prior researchers also point out that people are more risk seeking for loss situation (Cohen, et al., 1985; Kahneman & Tversky, 1979). Observed data also support this argument, as only 13% of our subjects preferred sure loss, while 83% of the subjects preferred playing the game.

4.2 Risk Attitude (for Gain) and Decision Criteria

Table 4 summarizes subjects' decision criteria behavior for the risk averse, neutral, and seeking attitudes in the gain situation. This table presents the relative frequencies for using the alternative criteria under various circumstances. The disparities in numbers of subjects in these attitude categories present straightforward statistical tests. Also, patterns can be identified in the observed relative frequencies. The following observations are made:

(1) The majority of subjects generally used a combined payoff and CF decision criterion, regardless of the risk attitude category. This is also true on a case-by-case basis for each of the four treatments. These results are consistent with Holsapple, et al. (1992).

(2) On average, a higher percentage of risk seeking subjects (71%) than risk averse subjects (60%) used both payoff and CF in their decision criteria. On the other hand, a lower average percentage of risk seekers than risk averse subjects used payoff-only or certainty-only as decision criteria. Risk averse subjects had more than twice the average percentage for the payoff-only decision criterion, relative to risk seekers. For both the risk averse and risk seeking groups, the (L,L) treatment's payoff-only percentage was more than double the next highest of any treatment. For both groups, the (H,L) treatment had a higher percentage of subjects selecting the certainty-only criterion than any other treatment. The proportion of risk seeking subjects who chose CF as part

Table 4: Risk attitude (for gain) vs. decision criteria.

RISK ATTITUDE	CRITERIA P:PAYOFF PCF:P+CF	CASES (PAYOFF, CERTAINTY): DIFFERENCE: H = HIGH, L = LOW (H,H)	(L,H)	(H,L)	(L,L)	AVERAGE %
RISK AVERSE (70.8%) (34)	P		11.8%(4)	11.8%(4)	26.5%(9)	12.5%(17)
	CF	26.5%(9)	14.7%(5)	38.2%(13)	29.4%(10)	27.2%(37)
	PCF	73.5%(25)	73.5%(25)	50.0%(17)	44.1%(15)	60.3%(82)
	CF+PCF	100%(34)	88.2%(30)	88.2%(30)	73.5%(25)	87.5%(119)
RISK NEUTRAL (2.1%) (1)	P					
	CF					
	PCF	100%(1)	100%(1)	100%(1)	100%(1)	100%(4)
	CF+PCF	100%(1)	100%(1)	100%(1)	100%(1)	100%(4)
RISK SEEKING (27.1%) (13)	P		7.7%(1)		15.4%(2)	5.8%(3)
	CF	23.1%(3)	23.1%(3)	30.8%(4)	15.4%(2)	23.1%(12)
	PCF	76.9%(10)	69.2%(8)	69.2%(9)	69.2%(9)	71.1%(36)
	CF+PCF	100%(13)	92.3%(11)	100%(13)	84.6%(11)	94.2%(48)

of decision criteria is generally greater than that of risk averse (e.g., 94.2% vs. 87.5%).

(3) When the CF difference moved from L to H, the proportion of subjects who considered CF as part of the decision criteria (CF and PCF) increased for both low and high payoff differences. At both levels of payoff difference, the increase for risk averse subjects was greater than that for risk seekers. At the high level, the increase for risk averse subjects was 12% (from 88% to 100%) versus no increase for risk seekers (remains at 100%). At the low payoff difference level, the risk averse increase was 14% (from 74% to 88%) versus only half as large an increase for risk seekers (from 85% to 92%). These results indicate that in the high CF difference situation, CF as part of decision criteria in the high CF situation is more preferable than in the low CF difference situation, regardless of risk attitude. In addition, this tendency is stronger for risk seeking subjects than for risk averse subjects.

(4) When the payoff difference increases, the proportion of subjects who considered CF as part of a decision criterion is also increased. For a high CF difference, the increase for risk averse subjects is greater than that for risk seekers. For the risk averse case, the increase was 12% (from 88% to 100%). The risk seekers' difference is only two-thirds that of risk averse subjects (from 92% to 100%). As payoff difference increases while the CF difference remains low, the increases for risk averse and risk seeking subjects are approximately the same. These results indicate that CF, as part of the decision criteria, is preferable in the high payoff difference situation than in the low payoff difference situation.

4.3 Risk Attitude (for Loss) and Decision Criteria

Table 5 summarizes subjects' decision criteria behavior for risk averse, neutral, and seeking attitudes in the loss situation. This table presents the relative frequencies for using the alternative criteria under various circumstances. The disparity in numbers of subjects in the attitude categories presents straightforward statistical tests. Also, patterns can be identified in the observed relative frequencies.

The following observations are made:

(1) An even smaller percentage of subjects are in the risk averse category. As in the gain situation, most of the subjects used a combined payoff and CF decision criterion in both the risk averse and risk seeking categories. However, a nearly even split occurred in the risk averse category between those who

Table 5: Risk attitude (for loss) vs. decision criteria.

RISK ATTITUDE	CRITERIA P:PAYOFF PCF:P+CF	CASES (PAYOFF, CERTAINTY): DIFFERENCE: H = HIGH, L = LOW				AVERAGE %
		(H,H)	(L,H)	(H,L)	(L,L)	
RISK	P					
AVERSE	CF	50%(3)	33.3%(2)	50%(3)	50%(3)	45.8%
(12.5%)	PCF	50%(3)	66.7%(4)	50%(3)	50%(3)	54.2%
(6)	CF+PCF	100%(6)	100%(6)	100%(6)	100%(6)	100%
RISK	P			50%(1)	50%(1)	25%
NEUTRAL	CF					
(4.2%)	PCF	100%(2)	100%(2)	50%(1)	50%(1)	75%
(2)	CF+PCF	100%(2)	100%(2)	50%(1)	50%(1)	75%
RISK	P		12.5%(5)	7.5%(3)	22.5%(9)	10.6%
SEEKING	CF	22.5%(9)	15.0%(6)	35.0%(14)	25.0%(10)	24.4%
(83.3%)	PCF	77.5%(31)	72.5%(29)	57.5%(23)	52.5%(21)	65.0%
(40)	CF+PCF	100%(40)	87.5%(35)	92.5%(37)	77.5%(31)	89.4%

used CF only and those who used a combined CF and payoff criterion. No subject who was risk averse in loss situations used only payoff magnitudes as a decision criterion. In general, the proportion of risk averse subjects who chose CF as part of decision criteria is greater than that of risk seeking (e.g., 100% vs. 94.2%).

(2) As in the gain situation, a higher average percentage of risk seeking subjects than risk averse subjects (65% vs. 54%) used both payoff and CF in their decision criteria. On the other hand, only about half the percentage of risk seekers compared to risk avoiders relied on CF only. Also, a greater percentage of risk seekers used the combined payoff and CF criteria for high certainty differences than for low ones. As in the gain situation, the highest percentage of risk seekers chose CF only decision criterion in the case of high payoff difference and low certainty factor difference. However, unlike the gain situation, this was not the case for risk averse subjects.

(3) As the CF difference increased from L to H, the proportion of subjects who considered CF as part of a decision criterion (CF or PCF) increased. This is true for both low and high payoff differences. For the low payoff difference, the increase for risk averse subjects (remains at 100%) is less than that for risk seekers (from 77% to 87%). This increase is also less for the high payoff difference, where there was no increase for risk avoiders (remains at 100%) compared to an 8% increase (from 92% to 100%) for risk seekers. Thus, this is opposite to what was observed in the gain situation. For risk seeking subjects, CF as part of decision criteria was generally preferable in a high CF difference situation than in a low CF difference situation.

(4) When the payoff difference increased from L to H, the proportion of subjects who considered CF as part of a decision criterion also increased. In contrast to the gain situation, the increase for risk averse subjects is less than that for risk seekers. Where the CF difference is high, risk averse subjects considered CF regardless of the payoff difference. When the payoff difference was low, 87% of risk seekers considered CF as part of the decision criteria, as compared to 100% when the payoff difference was high (an increase of 13%). A similar result occurs for a low CF difference, where the risk averse increase

was 0 (remaining at 100%) as compared to a 15% increase among risk seekers (from 77% to 92%). For risk seeking subjects, CF as part of decision criteria was generally preferable in a high payoff difference situation than in a low payoff difference situation.

5. Conclusion

Calantone, et al. (1993) integrated certainty factors with probabilities in decision trees to address the effects of ambiguity or vagueness about probabilities. Holsapple, et al. (1992) confirmed that analysts actually consider CFs when probabilities are not precisely known. This study has gone an step further in exploring the analyst's risk attitude effect in selecting decision criteria. Empirical evidence indicates that, for gain case, people are more risk seeking, and CF as part of decision criteria, is preferable for risk seeking people than for risk averse. On the other hand, for loss case, people are more risk averse, and CF as part of decision criteria, is preferable for risk averse than for risk seeking people. These observations are summarized as follows:

(1) The proportion of subjects who considered CFs in their decision criteria was greater for risk seeking than for risk averse attitudes for gain case. However, the results are inverse for loss case. These are consistent with Holsapple, et al. (1992).

(2) On average, as payoff differences increased, the proportion of subjects who considered CFs as part of the decision criteria increased more for gain risk averse persons than for gain risk seekers. In contrast, the proportion increased more for loss risk seekers than for loss risk avoiders. For loss risk seeking subjects, CF as part of decision criteria is generally preferable in a high payoff difference situation than in a low payoff difference situation.

(3) On average, as CF differences innoindent creased, the proportion of subjects who considered CFs as part of the decision criteria increased more for gain risk averse persons than for those who were gain risk seeking. For gain case, the proportion of risk seeking subjects who chose CF as part of decision criteria was generally greater than that of risk averse. In contrast, the proportion increased more for loss risk seekers than for loss risk avoiders. For loss risk seeking subjects, CF as part of decision criteria is generally preferable in a high CF difference situation than in a low CF difference situation.

The foregoing results provide a descriptive characterization of how decision analysts behave when selecting decision criteria, using decision tree approach, under circumstances such as varying certainty and value magnitudes. This study indicates that psychological uniformity cannot be expected among decision analysts. These results substantially extend the empirical base for knowledge engineers in understanding how people manipulate uncertainties. Also, these same results may be viewed as guidelines for knowledge engineers, indicating general tendencies of various decision criteria for modeling decision analyst behaviors with respect to their risk attitudes in treating uncertainty for gain and loss.

This empirical base is also a valuable complement to theoretical prescriptions for knowledge engineers. As the understanding of decision analysts' treatment of uncertainty increases, knowledge engineers will have a better understanding of how decision analysts' risk attitudes relate to decision criteria in decision tree analysis. However, this evidence does not tell a knowledge engineer which particular decision criterion is "right" or "better" than others for a specific analyst and a given situation.

The bulk of knowledge acquisition literature has concentrated on the acquisition of data, rules, or procedures which guide the decision process. Little explicit attention has been devoted to the issue of acquiring knowledge regarding decision analysts' risk attitudes related to their treatment of certainties for decision criteria. Experimental results have been presented in this study which shed some light on the psychological validity of how a decision analyst's decision criteria are related to the risk attitude under different circumstances, e.g., varying certainty and value magnitudes. It is a step in the direction of addressing concerns of Hogarth, Einhorn, and others, about accounting for effects of ambiguity or vagueness about probabilities. This should result in a significant improvement in our understanding of the psychological validity of extended decision criteria in decision tree approach, therefore benefiting knowledge engineer, DSS developers (e.g., in tool selection or selecting decision criteria offered by a tool), and DSS toolsmiths (e.g., in offering such an option).

This is an exploratory research aimed at exploring the behavior of decision makers. Statistical inferences could not be made due to the small number of subjects. The sample hypotheses can be as follows:

H1: For gain case, the proportion of people who consider CFs as part of decision criteria is greater for risk seeking than for risk averse attitudes.

H2: For loss case, the proportion of people who consider CF as part of decision criteria is greater for risk averse than for risk seeking attitudes.

Thus, further empirical work is required to substantiate and broaden these findings, as well as sharpen and develop an understanding of the risk attitude effect that this study has revealed.

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Reference

1. Calantone, R. J., Holsapple, C. W., Rayens, W. S., and Wu, J., "Decision Under Uncertainty: Integrating Certainty Factors with Probabilities in Decision Trees," Decision and Decision Support Systems, Vol. 3, No. 3, 1993.
2. Cohen, M., Jaffray, J. Y., and Said, T., "Individual Behavior Under Risk and Under Uncertainty: An Experimental Study," Theory and Decision, Vol. 18, No. 2, 1985.
3. Ellsberg, D., "Risk, Ambiguity, and the Savage Axioms," Quarterly Journal of Economics, Vol. 75, No. 4, 1961.
4. Heckerman, D., "Probabilistic Interpretations for MYCIN's Certainty Factor," in Kanal, L. N. and Lemmer, J. F. (eds), Uncertainty in Artificial Intelligence, New York: North-Holland, New York, 1986.
5. Heckerman, D. and Shortliffe, E., "From Certainty Factors to Belief Networks'," Artificial Intelligence in Medicine, Vol. 4, pp. 35-52, 1992.
6. Heizer, J. and Render, B., Production and Operations Management, 2nd edition, Allyn and Bacon, Boston, 1991.
7. Hogarth, R. M. and Einhorn, H. J., "Venture Theory: A Model of Decision Weights," Management Science, Vol. 36, No. 7, 1990.
8. Holsapple, C. W., Rayens, W. S., and Wu, J., "Decision Tree Analysis with Certainty Factors: Empirical Evidence about Decision Criteria," Kentucky Initiative for Knowledge Management, Research Paper No. 43, College of Business and Economics, University of Kentucky, Lexington, KY, 1992.
9. Holsapple, C. W. and Wu, J., "Psychological Validity of Certainty Factor Algebras: An Empirical Study," Expert Systems, Vol. 10, No. 2, May 1993.
10. Kahneman, D. and Tversky, A., "Prospect Theory: An Analysis of Decision Under Risk," Econometrica, Vol. 47, No. 2, 1979.
11. Kanal, L. N. and Lemmer, J. F. (eds), Uncertainty in Artificial Intelligence, New York: North-Holland, New York, 1986.
12. Pearl, J., "Fusion, Propagation, and Structuring in Belief Networks," Artificial Intelligence, Vol. 29, pp. 241-288, 1986.
13. Pearl, J., Probabilistic Reasoning in Intelligent Systems, San Mateo, CA: Morgan Kaufman, 1988.
14. Raiffa, H., "Risk, Ambiguity, and the Savage Axioms," Quarterly Journal of Economics, Vol. 75, No. 4, 1961.
15. Raiffa, H., Decision Analysis: Introductory Lectures on Choice Under Uncertainty, Addison-Wesley, Reading, Massachusetts, 1968.
16. Raiffa, H. and Schlaifer, R., Applied Statistical Decision Theory, Harvard

University, Boston, 1961.
17. Schoemaker, P. J., "Preferences for Information on Probabilities Versus Prizes: The Role of Risk-Taking Attitudes," Journal of Risk and Uncertainty, Vol. 2, No. 4, 1989.
18. Shortliffe, E. H., Computer-Based Medical Consultations: MYCIN, American Elsevier, New York, 1976.
19. Tonn, B. E. and Goeltz, R. T., "Psychological Validity of Uncertainty Combining Rules in Expert Systems," Expert Systems, Vol. 7, No. 2, 1990.
20. Zadeh, L. A., "Fuzzy Sets," Information and Control, Vol. 8, No. 3, 1965.