Effects of Decomposition Level on the Intrarater Reliability of Multiattribute Alternative Evaluation

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(ABSTRACT)

A common approach for evaluating complex multiattributed choice alternatives is judgment decomposition: the alternatives are decomposed into a number of value-relevant attributes, the decision maker evaluates each alternative with respect to each attribute, and those single-attribute evaluations are aggregated across the attributes by a formal composition rule. One primary assumption behind decomposition is that it would produce a more reliable outcome than direct holistic evaluations. Although there is some empirical evidence that decomposed procedures can improve the reliability of evaluations, the extent of decomposition can have a considerable effect on the resulting evaluations. This research investigated, theoretically and experimentally, the effects of decomposition level on intrarater reliability in multiattribute alternative evaluation.

In a theoretical study, using an additive value composition model with random variables, the composite variance of alternative evaluation was analyzed with respect to the level of decomposition. The composite variance of decomposed evaluation was derived from the variances in the components recomposed using a statistical method of error propagation. By analyzing the composite variance as a function of the number of attributes used, possible effects of decomposition level were predicted and explained. The analysis showed that the variance of an alternative evaluation is a decreasing function with respect to the level of decomposition, in most cases, and that the marginal reduction of variance diminishes as decomposition level increases.

In an experimental study, intrarater test-retest convergence was examined for a job evaluation with different levels of decomposition. Subjects evaluated six hypothetical job alternatives using four levels of decomposition that ranged from a single overall evaluation to evaluations on twelve highly specific attributes. Intrarater convergence was measured by mean absolute deviations and Pearson correlations between the evaluation scores in two identical sessions separated by two weeks. The mean absolute deviations decreased significantly with respect to the decomposition levels while the Pearson correlations were not significant. Further analyses indicated that the mean absolute deviations decreased with a diminishing rate of reduction, as the decomposition level increased.

The research results suggest that decomposition reduces the variability of each alternative evaluation, in most situations. The results, however, also suggest that decomposition may not improve the consistency of preference order of the alternatives that is often important in practical choice decisions.

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1. Introduction

1.1 The Problem

1.1.1 Background

Many practical decision problems require us to evaluate complex alternatives characterized by multiple attributes. For instance, choosing a job requires the decision maker to consider several dimensions such as pay, content of work, working conditions, location, and promotion opportunities. When evaluating facility sites, the decision maker should make tradeoffs among land price, taxes, transportation costs, benefits, environmental impacts, risks, etc. In such instances a direct holistic evaluation may be difficult to produce a reliable[1] outcome, especially if the attributes are in conflict, as is typically the case with difficult choices.

Psychological studies on human judgment and decision making suggest that when a problem is complex people have difficulty making direct overall evaluative judgments. For instance, Shepard (1964) states: ".... although he (decision maker) will probably experience little difficulty in evaluating the alternatives with respect to any one of these subjective attributes, ... his ability

[1] Reliability will be defined more precisely in what follows, but in general, an evaluation can be said reliable if it is relatively free of random variation, or in other words is repeatable or consistent.

to arrive at an over-all evaluation by weighing and combining or 'trading off' all of these separate attributes at the same time is likely to be less impressive" (p.257). Therefore, direct evaluations of such alternatives without decision aids can potentially contain serious errors, consequently resulting in a sub-optimal decision.

One common strategy to overcome such difficulties in complex evaluation is problem decomposition: break down a complex decision problem into simpler problems, solve these simpler problems, and combine the solutions with a mechanical rule. The basic assumption behind the decomposition principle is that decomposition will lead to more accurate solutions than direct or holistic methods, in most situations (Armstrong, Denniston, & Gordon, 1975). Decomposition can reduce the information processing demands of complex judgment problems because the decision maker can isolate and concentrate on selected portions of the problem. Therefore, decomposition should reduce the amount of random errors that can result from imperfect processing of information in holistic evaluations.

The decomposition principle is usefully employed in multiattribute alternative evaluation. Formal procedures of multiattribute utility analysis (MAUA)[2] have been developed as a decision-aiding technology for evaluating such complex alternatives. MAUA is a class of procedures for measuring a decision maker's subjective values expressed on multiattributed, complex tasks. In MAUA procedures, the laborious task of "trading off" can be handled by a formal aggregation model. The decision maker evaluates each alternative with

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[2] Researchers have called the tools of complex value measurement MAUA (multiattribute utility analysis), MAU (multiattribute utility), MAUT (multiattribute utility theory or technique), and MAUM (multiattribute utility measurement). In this dissertation, MAUA was chosen.

respect to each attribute, and the single-attribute evaluations are mechanically aggregated into an overall evaluation by a formal composition model.

Typically these procedures first require the decision maker or analyst to break down the problem into a number of value dimensions or attributes and to rate the alternatives on each attribute separately. Next he or she assigns relative importance weights to the attributes that express the tradeoffs among the attributes. The single-attribute ratings and attribute weights are recomposed by means of an algebraic model that generates an overall evaluation for each alternative.

A primary, if not the only, purpose for using decomposition in evaluation is to obtain a more reliable evaluation. An evaluation can be said reliable if the responses to the same problem are consistent on repeated occasions. Literature on judgment and decision making provides a substantial amount of evidence that decomposed evaluation procedures produce a more reliable outcome than holistic evaluation. However, an arbitrary level of decomposition may not improve evaluation reliability. Decomposed evaluation procedures possess several sources of potential variability. The evaluations on the subproblems can also contain the same kinds of errors that exist in holistic evaluations. If the component evaluations are unreliable in some way, the evaluations derived from the component evaluations may also be unreliable. There are still other sources of error in the decomposed evaluation. One cannot develop a composition model to an arbitrary level of detail without introducing errors, and also cannot measure the model parameters with no error. Therefore, a problem should be carefully decomposed so that total variability in evaluation is minimized.

This issue is related to attribute decomposition in an MAUA application, since the decomposition principle is operationalized through attribute decomposition. For a given problem, an MAUA can use different sets of attributes with different levels of detail and specificity. The alternatives can be evaluated using an all-inclusive attribute that represents the decision maker's overall value, like "overall attractiveness," or "overall effectiveness." In this case the alternatives are evaluated in holistic manner. However, for most problems, the top-most attribute tends to be extremely general, abstract, and broad. People can hardly make reliable evaluations with the overall attribute. For example, a job hunter may not easily evaluate a job offer with a single attribute like "overall attractiveness." Instead, the decision maker may use a number of more detailed attributes such as pay, working conditions, location, benefits, or content of work. In this case the alternative evaluation task is decomposed into the number of attributes specified.

1.1.2 Research Questions

The aim of this research is to predict, explain, and evaluate, analytically and experimentally, how the level of judgment decomposition affects the intrarater reliability of complex choice alternative evaluation. The research question evolved from a primitive question of how far a complex evaluation problem should be decomposed for an optimal outcome, i.e., what will be the optimal level of decomposition in complex alternative evaluation (see Figure 1-1). As a preliminary step to reach an answer to the primitive question, an investigation of the impact of decomposition level on evaluation quality was

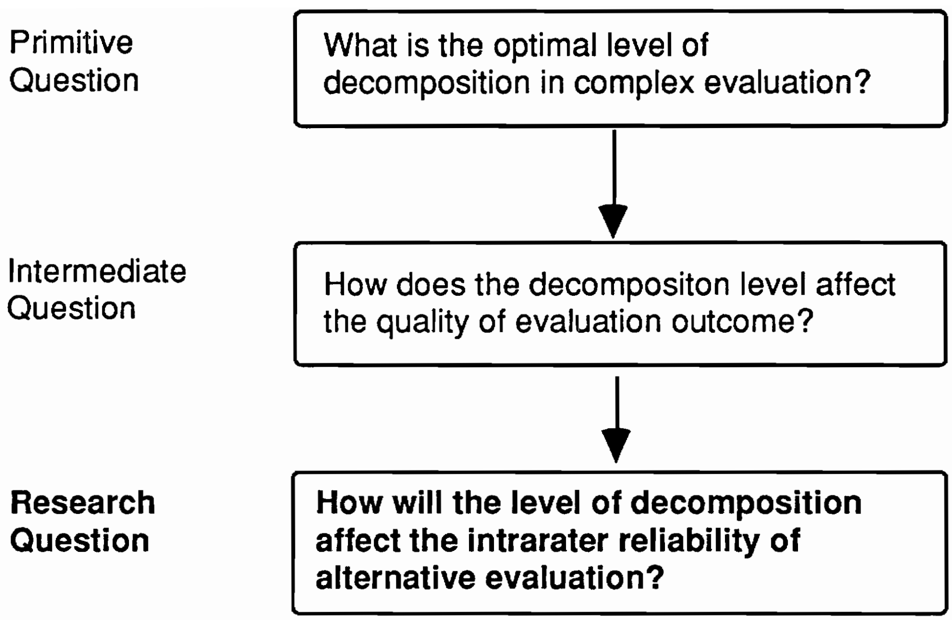

Figure 1-1 Evolution of the Research Question

considered as an intermediate question. Finally a more specific question of how the level of decomposition will affect the intrarater reliability of alternative evaluation was identified as the research problem.

The research question can be clarified by a conceptual diagram, Figure 1-2. Three components are related to the research question. First, the evaluation problem in this research is a choice alternative evaluation. Therefore, the judgments required for the evaluation are preferential judgments. Second, the level of decomposition is the primary factor of decomposition to be investigated. Decomposition can have such characteristics as attribute completeness, dependency, and extent of composition that affect the evaluation outcome. This research is focused only on the level of decomposition. The third component related to this research is outcome quality. An evaluation outcome can be evaluated by several characteristics such as consistency, accuracy, confidence, and regret. This research focuses only on the reliability of outcomes within a decision maker.

Within the main research question, a number of more specific subquestions can be stated as follows.

1. What is the pattern of change in variation as a function of the level of decomposition?

2. How sensitive is the change be to the level of decomposition?

3. Under what conditions does a decomposed evaluation show smaller variation than a holistic evaluation?

4. How can a proper level of attribute decomposition be set for "reliable" evaluation?

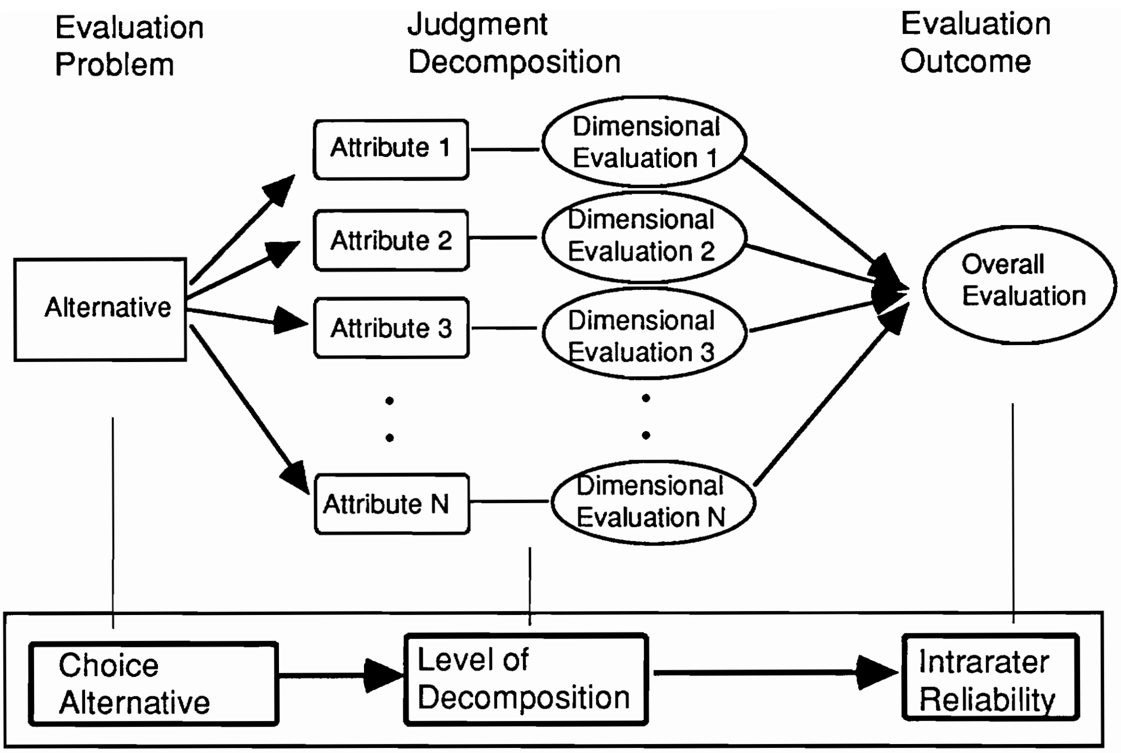

Figure 1-2 Conceptual Model of the Research Question.

1.1.3 Research Objectives

This research examines and describes the effect of decomposition level on the intrarater reliability of multiattribute alternative evaluation. Some more specific objectives are:

• To derive an algebraic expression that estimates the composite variation of the decomposed evaluation from the variations in component assessments.

• To examine the pattern and sensitivity of the change in composite variance as a function of the level of decomposition.

• To identify the conditions under which decomposed evaluations are more reliable than holistic evaluations and the proper level of decomposition.

• To empirically evaluate the primary theoretical results through an illustrative experiment.

6. To suggest some guidelines for attribute decomposition based on the results.

1.2 Research Approaches

Two methods are used for this research: analytical and experimental. The analytical method is useful in developing a general theory giving insights on the research problem for various conditions. That is, this approach is appropriate to predict and explain the possible effect of decomposition on the effectiveness of evaluation outcome. The experimental method is used for the purpose of obtaining an empirical evidence for this issue. The results from the experimental approach can be used to support the theoretical treatment.

This research was performed according to the general procedure depicted in Figure 1-3. First, the variance of value judgment was defined using a statistical measure of variability in random variables. Then, applying a statistical method of error propagation, an expression was derived by which the composite variance of a decomposed evaluation can be calculated from the variances of component evaluations. Next, by examining the behavior of the derived composite variance with respect to the level of decomposition, the effects of decomposition level on the reliability of the evaluation were predicted and explained. An illustrative experiment was conducted in which job alternatives were evaluated with different levels of decomposition, and the results were compared with the results from the theoretical treatment. Finally, based on the theoretical and experimental results, some guidelines were suggested for attribute decomposition in multiattribute evaluation.

1.3 Importance of the Research

MAUA procedures have been applied in such diverse areas as public policy (Anandalingam, 1989; Ulvila and Snider, 1980), energy (Dyer and Lorber, 1982; Allett, 1986; Kirkwood, 1982; Merkhofer and Keeney, 1987), manufacturing and services (Belton, 1985; Brooks and Kirkwood, 1988; Ozernoy, Smith, and Sicherman, 1981), and medicine (Pliskin, Ronen, and

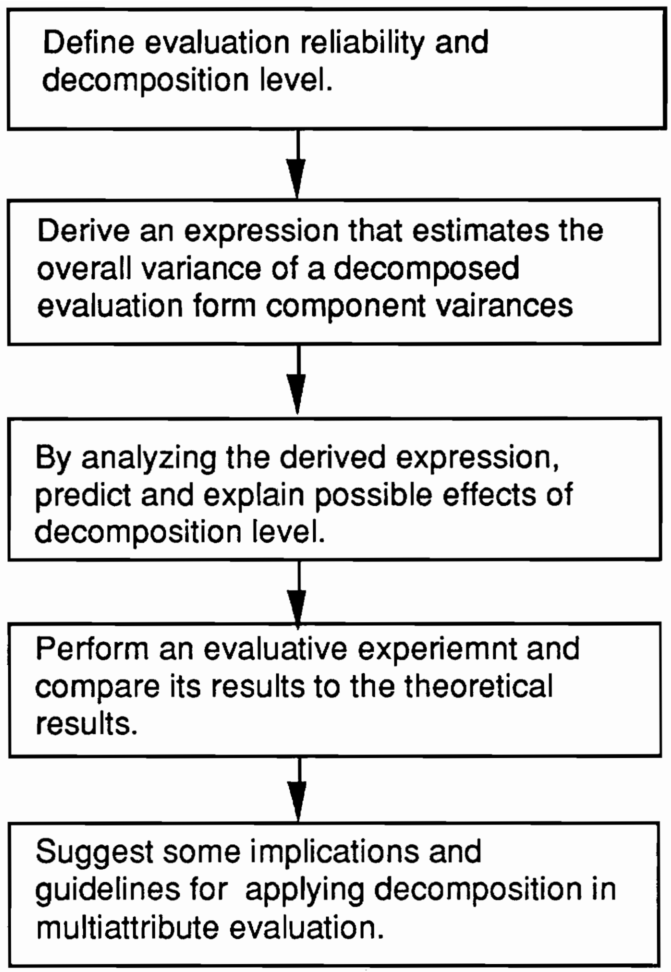

Figure 1-3 Procedure of the Research.

Feldman, 1987; Torrance, Boyle, and Harwood, 1982). No practical decision problems are given pre-formulated. The application of an MAUA procedure to any decision problem requires that the analyst or decision maker first specify the attributes on which the alternatives should be evaluated. Because attribute structuring occurs in the early stages of MAUA, attribute formulation can have a large impact on the outcome of the evaluation procedure (Barron, 1987; von Winterfeldt, 1980). Attribute decomposition should be performed to a degree that can insure the best results when the MAUA is executed.

Practitioners and researchers recognize that attribute structuring is the most important step in the application of MAUA to real-world evaluation problems. For instance, Aschenbrenner (1977) states: "..., one of the main problems in the application of multiattribute utility theory to real world decision problems seems to be the attributes per se" (p. 81). Weber, Eisenführ, and von Winterfeldt (1988) argue: "The structure of objectives not only defines the scope and the detail of evaluative considerations, but it also is likely to shape the numerical inputs that are elicited in later stages of the evaluation" (p.431).

Despite this recognized importance, the present state of knowledge regarding attribute decomposition for evaluation is rather sparse. While decomposition impact has been extensively addressed in the areas of estimation, clinical judgment, and performance appraisal, the topic has rarely been studied in the area of preferential evaluation and choice. That is, most contemporary studies on MAUA have concentrated on developing aggregation models and eliciting the inputs to the models, given a set of attributes decomposed a priori. Contrary to the large number of studies on evaluation model building and parameter elicitation, the attribute structuring phase has been all but ignored. As a result, attribute structuring has been regarded largely as the "art" part of decision analysis.

More systematic studies on this issue are needed with the goal of providing general insights to serve as initial steps toward the development of a more general theory of attribute decomposition. This knowledge can contribute to the advance of decision theory and practice. It can also assist in computerization of the MAUA procedure as a decision support system.

1.4 Delimitations of the Research

This research has boundaries as follows.

1. The analysis does not consider modeling errors, which can occur in building a composition model for an evaluation problem. That is, it is assumed that appropriate attributes and a proper composition model can be formulated for the problem.

2. This research is conducted for the most popular value composition rule: the linear additive value composition model. This research does not consider those kinds of decision problems where an additive value model cannot be appropriately defined.

3. Because a large number of parameters can be involved in the analysis of the composite variation, some simplifying assumptions are used.

4. This research focuses only on one criterion of decision quality: the intrarater reliability of evaluation. This research does not concern other issues

of decision quality such as time and effort required, decision maker's subjective satisfaction, future outcome of the decision, etc.

1.5 Clarification of Terms

Decision Analysis: A set of prescriptive methods for analyzing complex decisions to aid people in making better decisions. It provides formal models and procedures with which an individual can make explicit, as much as possible, his or her reasoning on a decision problem.

Attribute: A value dimension on which alternatives are evaluated in decision making. The attributes represent the decision maker's value structure regarding the alternatives to be evaluated. In this document, attribute is used as representative of the terms 'objective,' 'attribute,' 'criterion,' and 'factor' that have been used in the decision analysis literature.

Value: Decision maker's subjective worth or utility of an object on a particular attribute. In the literature on decision analysis, value and utility are often used distinctively: 'value' for riskless situations (when attribute measures are certain) and 'utility' for risky situations (where attribute measures are uncertain). In this document, however, value is used as a neutral term that represents both terms.

Multiattribute Utility Theory: A theory for making multiple value dimensions commensurable in terms of a common scale of value. Multiattribute utility theory frequently represents utility in terms of a functional form and a weight for each value dimension.

Multiattribute Utility Analysis: Multiattribute utility analysis is the name of a class of value integration models and measurement procedures that have been developed based on multiattribute utility theory to aid decision makers in evaluating multiattributed complex alternatives.

Variation in Judgment or Evaluation: Inconsistency or fluctuation of responses to the same problem on independent occasions. The response variation can be caused by unpredictable fluctuations in attention, shifts in information processing strategy, vagueness of information, or inherent indefiniteness of preference.

Reliability: Reliability is a general term that denotes consistency of measurements derived from repeated observations on the same subject under the same circumstance. As such, it is a measure of the "repeatability" of the measurement process, the extent to which we may expect to find that repeated measurements of the same individual or object will give essentially the same results. A classical definition of reliability is the test-retest definition; if the measurement results in the same answer upon retest, then the test is reliable (Lehman, 1991). This form of reliability is established by measuring the same objects twice and correlating the results. A high correlation is evidence of reliability.

Reliability of Evaluation: Reliability of evaluation is defined as the extent to which an evaluation procedure, applied repeatedly to the same problem, would produce the same result each time. That is, an evaluation is regarded as reliable if it is consistent and stable across repetition. In terms of variation, an evaluation is said to be reliable if it is free of random variation. Therefore, a high reliability corresponds to a small variation in evaluation scores across repetition.

1.6 Outline of the Dissertation

This dissertation consists of six chapters that coincide with the flow of the general procedure described in section 1.2.

Chapter 1. Introduces the background for the research and states the research problem and its setting. Also includes approach, importance, and delimitation of the research.

Chapter 2. Provides a review of the literature related to this research, focusing on the theoretical and experimental studies of decomposition effects on judgment and choice outcomes.

Chapter 3. Describes an analytical framework to predict and explain the possible effects of decomposition level on the variability of the alternative evaluation outcomes.

Chapter 4. Describes an experiment for examining the impact of decomposition level on intrarater reliability. Using a test-retest method the intrarater convergence of job alternative evaluations between two sessions are measured and analyzed. The results are compared with the theoretical results from Chapter 3.

Chapter 5. Draws conclusions from the research, based on results from the analytical and experimental investigations. Includes the implications of the study in the application of MAUA. Also describes limitations of the results, and suggestions for further study.

2. Review of the Related Literature

2.1 Overview

Most literature related to this research is found in the areas of behavioral psychology and management science. A decomposed multiattribute evaluation procedure blends a prescriptive value composition model with a decision maker's judgment on model components. Therefore, addressing the present research problem requires one to survey the literature in two areas: psychological characteristics of human value judgment and the technical aspects of value composition models. Numerous psychological studies on human judgment and decision making point out the limitations of value judgments and promote decomposition strategies in evaluation. One of the important contributions of psychological research to multiattribute alternative evaluation is in understanding the problems associated with holistic judgments or dimensional judgments. Regarding the technical aspects of MAUA procedures, a large amount of literature has examined appropriate value composition models and techniques for eliciting numerical scores for the model components. There also exists a growing body of literature on the art of structuring attributes. However, little literature is found on how MAUA outcomes are influenced by varying the structural representation of attributes.

Section 2.2 of this chapter reviews the literature on the reliability of human value judgments, where definitions of reliability in value judgments and sources of unreliability in evaluation are surveyed. In the section 2.3, an overview is provided on the state-of-the-art decomposed evaluation procedures, focusing on the additive value composition procedure. Section 2.4 provides a more detailed review of previous studies on the relationships between decomposition and evaluation reliability. This section includes specific topics on reliability of MAUA results, attribute structuring for MAUA applications, and attribute formulation impact on MAUA results. The final section (§2.5) summarizes the findings, and sets directions for the research, based on the findings.

2.2 Reliability Issues on Evaluative Judgments

The primary purpose of decision aiding procedures is to yield better judgment and choice. However, measuring the quality of evaluative judgments is a difficult task. One major source of difficulty is finding a proper definition for "quality" in evaluative judgments (Johnson and Payne, 1985). Unlike inferential judgments, in which correct answers exist and "accuracy" is the primary criterion, evaluative judgments have few external criteria since evaluations are the result of the decision maker's personal or subjective preference (von Winterfeldt and Edwards, 1986). Therefore, the quality of preferential evaluation is often assessed by the consistency or reliability in responses (Edwards, Kiss, Majone, & Toda, 1984; Johnson and Payne, 1985;

Krzysztofowicz and Duckstein, 1980). That is, reliability is a second-best measure for the quality of evaluation.

Even though reliability is not sufficient for accurate measurement from a psychometric point of view, it is a necessary condition for an evaluation procedure to accurately capture or replace the decision maker's preferential opinion (Balzer, Rohrbaugh, & Murphy, 1983; Miller, Kaplan, & Edwards, 1967,1969). Miller et al., working in a military context, have argued that reliability over time is a minimal requisite of any value measurement procedure. If a subject's value judgments, collected at any time, differ from his value judgments for the same target in the same situation collected at a different time, there would be some doubt about the appropriateness of implementing either set of values.

2.2.1 Definitions of Reliability in Evaluative Judgment

In psychometrics, the term reliability of a measurement refers to the "repeatability" of the measurement process. That is, reliability is the extent to which you may expect to find the same result when you measure the same thing again. Reliability or consistency in evaluative judgment is defined in a number of ways.

Hogarth (1982) suggests two distinctive standards of consistency in judgment: logical consistency and process consistency. One possible standard is consistency with the rules of a normative system (e.g., expect utility rule). This notion of consistency is termed as "logical consistency" by Hogarth, and sometimes used as a measure of accuracy in choice (Johnson and Payne, 1985).

A different notion of consistency can be obtained by comparing behavioral processes across time or situations. Hogarth uses the term “process consistency” to refer to the extent to which an individual applies the same psychological rule or strategy when making judgments. One form of process consistency is the extent to which an individual applies the same underlying process across different problems.

Another form of process consistency involves the consistency of responses to the same problem on two independent occasions (Kleinmuntz, 1990). According to this notion of consistency, an evaluation can be considered reliable if it is free of response variability across occasions, or, in other words, if it produces stable and consistent results for the same problem. Hershey and Schoemaker (1985) and Laskey and Fischer (1987) explain this notion of reliability more theoretically. According to them, a preferential judgment can be thought of as consisting of a systematic component and a random component. The systematic component of responses is commonly assumed to be stable over a “short” period of time, which can be thought of as ranging from a few hours to a few weeks, depending on the alternative in question. Accordingly, variation in responses to the same stimulus at different times is assumed to be due to the random component. This assumption of temporal stability provides a basis for defining the reliability of evaluative judgment responses. If preferences are stable in the short run, reliability can be measured by the convergence between the preference judgments in two preference assessment sessions. Such a between-session convergence of judgments regarding the same stimuli are commonly referred to as “test-retest reliability” (Laskey and Fischer, 1987). This definition of reliability was employed in the present study.

2.2.2 Sources of Variability in Evaluative Judgment

When faced with the same alternatives, under seemingly identical conditions, people do not always make the same evaluation and choice (Coombs, Dawes, & Tversky, 1970). Although the lack of consistent preferences may be attributable to factors such as learning, saturation, or changes over time, inconsistencies exist even when the effects of such factors appear negligible. This variable nature of human choice behavior was recognized earlier by Thurstone (1927). In discussing the process of evaluation and judgment, he wrote:

> An observer is not consistent in his comparative judgments from one occasion to the next. He gives different comparative judgments on successive occasions about the same pair of stimuli. Hence we conclude that the discriminal process corresponding to a give stimulus is not fixed. It fluctuates (p.271).

Fischhoff, Slovic, and Lichtenstein (1980) argue that human value judgments are often unreliable. According to them, people are likely to have unclear opinions regarding the desirability of events and they show a high instability when events are complex and unfamiliar. The authors argue that in such cases any attempt to assess the values is likely to be subject to response error. Fischer (1979) also states that when decision problems are complex, the decision maker may be confused and uncertain about his or her preferences.

These arguments are supported by Nisbet and Wilson (1977), who reviewed evidence from a large number of empirical studies and concluded that individuals have little or no ability to accurately identify their preferences.

Coombs, et al. (1970) suggest that the observed inconsistency is a consequence of an underlying random process. The randomness may reflect uncontrolled momentary fluctuations such as attention shifts, or it may correspond to a choice mechanism that is inherently probabilistic.

Pitz, Heerboth, and Sachs (1980) say that the unreliability in evaluative judgments presumably results from the difficulties in processing complex information rather than real differences in preferences. When people make judgments or decisions on the basis of complex information they appear to use some simplifying heuristics that preclude complete processing of all the relevant information (Payne, 1976; Payne, 1982). That is, they tend to be selective in using that information, ignoring potentially significant information and resulting systematic biases (Slovic & Lichtenstein, 1971). In addition, holistic judgments are characterized by a substantial degree of random error, with the amount of error increasing with the number of relevant dimensions that the person attempts to consider (Larichev & Moshkovich, 1988; Shepard, 1964). Such biases and errors can be an important source of sub-optimality in decision making (Fischer, 1977: von Winterfeldt & Fischer, 1975).

In summary, the variability in evaluative judgments is caused largely by two sources: human inherent indefiniteness in preference and imperfect processing of information.

2.3 Decomposition in Evaluation

As the unreliability of value judgments is apparent, one common strategy in evaluating a complex choice alternative is to decompose the task into component judgments and combine the judgments. Polya (1948) provided a general discussion on the use of decomposition in problem solving, and Raiffa (1968) states: "The spirit of decision analysis is divide and conquer: Decompose a complex problem into simpler problems, get one's thinking straight in these simpler problems, paste these analyses together with a logical glue, and come out with a program for action for the complex problem,"(p. 271).

There is a reason that the use of the decomposition principle can improve the quality of complex evaluation. With decomposition, one can consider more factors than one can consider holistically (Armstrong, Denniston, & Gordon, 1975; Fischer, 1977). In addition, decomposition should improve the accuracy of a decision by reducing the information processing burden on the decision maker (Fischer, 1977; Ravinder, Kleinmuntz, & Dyer, 1988). It is also expected that decomposition will improve accuracy since errors from the parts should tend to compensate for one another (Armstrong, et al., 1975).

However, the evidence on the benefits of the decomposition strategy is not conclusive. For example, Pitz, et al. (1980) point out some reasons for not trusting decomposed evaluations. According to them, every decomposed evaluation procedure requires some judgments as raw material for obtaining an overall evaluation. The component judgments, although being easier, may employ the same processes used in holistic judgments, and contain the same kinds of errors. If the component judgments are flawed in some way, then the evaluations derived from the component evaluations may also be flawed. Mosleh and Bier (1991) describe several possible sources of error in the use of decomposition, such as errors in modeling and errors in parameter assessments. According to them, one can hardly develop a model to an arbitrary level of detail without introducing any errors, and also one can not propagate information through the resulting model without any loss or contamination.

2.3.1 Decomposed Multiattribute Evaluation Procedures

Multiattribute utility analysis (MAUA) is a class of evaluation procedures, based on the decomposition principle, to facilitate value measurement of multiattributed options. An MAUA combines a mathematical value composition model and scaling methods that are based on multiattribute utility theory. Multiattribute utility theory prescribes the conditions under which an alternative's value can be expressed as an algebraic combination of its separate components. Multiattribute utility theory has been well discussed in several books (e.g., Keeney and Raiffa 1976; von Winterfeldt and Edwards, 1986) and articles (e.g., Fischer, 1979; Huber, 1974; MacCrimmon, 1973; von Winterfeldt & Fischer, 1975).

Von Winterfeldt and Edwards (1986) identify the common steps of all MAUA procedures:

1. Define alternatives and value-relevant attributes.
2. Evaluate each alternative separately on each attribute.
3. Assign relative weights to the attributes.

4. Aggregate the weights of attributes and the single-attribute evaluations of alternatives to obtain an overall evaluation of alternatives.

5. Perform sensitivity analyses and make recommendations.

MAUA has a variety of versions according to the type of value composition model (step 4) and the techniques for single-attribute value assessment (step 2) and attribute weighting (step 3). Table 2-1 lists the main models and techniques (for a comprehensive and detailed review, see Keeney and Raiffa 1976; von Winterfeldt and Edwards, 1986). However, only a few of these models and techniques are commonly applied to real-world situations (von Winterfeldt and Edwards, 1986; Zeleny, 1982).

2.3.2 Linear Aggregation Rule

A typical model in combining components into a composite is the additive model. In this model it is assumed that each dimension (e.g. pay, location, etc.) can be measured on a scale (implicitly at least !) and given a weight reflecting its relative importance. The overall value of each alternative is then the sum of the weighted values on the dimensions. Formally, the additive value aggregation model is expressed as

$$V(A_i) = w_1v_1(A_i) + w_2v_2(A_i) + ...+ w_jv_j(A_i) + ... + w_nv_n(A_i)$$

where $V(A_i)$ is the overall value of alternative A_i, $v_j(A_i)$ is the single-attribute value of the alternative for the j-th attribute, and w_j is an appropriate scaling factor reflecting the relative importance of attribute j. The $V(A_i)$ and $v_j(A_i)$ are, though not necessary, often scaled between 0 and 1, and the w_j are appropriate

Table 2-1 Value Composition Models and Techniques for Single-attribute Value and Weight Elicitation. (summarized from von Winterfeldt & Edwards, 1986 and Zeleny, 1982)

Composition Models	Techniques for single-attribute value elicitation	Techniques for weight elicitation
• Additive • Multiplicative • Quasi additive • Multi-linear	• Direct rating • Ratio estimation • Curve drawing • Difference standard sequence • Sequential trade-off	• Ranking • Direct rating • Ratio estimation • Swing weights • Cross-attribute indifference

numbers satisfying $0<w_j<1$ and $\Sigma w_j = 1$. An important aspect of the additive model is that it is compensatory. That is, the additive model implies that a decision maker will trade-off between a high value on one dimension of an alternative and a low value on another dimension. The additive model requires that attributes be preferentially independent (Keeney and Raiffa, 1976). Less formally, this means that the contribution of an individual attribute to total value is independent of other attribute values.

Studies (Farmer, 1987; Edwards, 1977; von Winterfeldt and Fischer, 1975) have found that the linear model yields an extremely close approximation to the "true" utility function even when preferential independence does not exactly hold. In practice, many analysts simply use an additive model without verifying the necessary independence conditions (Zeleny, 1982). Dawes and Corrigan (1974) argue that linear models are successful in a variety of contexts, because these contexts have common structural characteristics: (a) each input variable has a conditionally monotone relationship with the output; (b) there is error of measurement; and (c) deviations from optimal weighting do not make much practical difference.

The additive models require two types of inputs: value scores of each alternative with respect to each attribute, and weights for each attribute that reflect the relative contribution each attribute makes to the overall value. The input numbers are usually obtained judgmentally - sometimes requiring rather difficult judgments. However, Barron, von Winterfeldt, and Fischer (1984) argue that, in most applied contexts, the inputs can be obtained by relatively simple techniques. According to them, to construct the v_j scales simple anchored rating scale techniques are appropriate, and to elicit the weighting factors, w_j, relatively simple two-attribute ratings or tradeoffs can be used. In many instances the SMART (simple multiattribute rating technique) procedure (Edwards, 1977) or equal-weighting scheme (Dawes & Corrigan, 1974; Einhorn & Hogarth, 1975) can be successfully used to assess V and v_j (Hogarth, 1987).

In practice, additive value models are most commonly used, largely because they are easiest to work with, but also because they seem adequate for a broad range of decision problems (Fischer, 1979; Yoon and Kim, 1989; Stillwell, Seaver, and Edwards, 1981). It is frequently assumed that an additive model is adequate for describing the relationship between a composite and its components (Einhorn & Hogarth, 1975). Furthermore, many studies have shown that the linear model will approximate nonlinear functions quite well (e.g., Yntema & Torgerson, 1961; Slovic & Lichtenstein, 1971).

2.3.3 Attribute Structuring for MAUA Application

The decomposition of judgments is implemented in evaluation by way of attribute formulation. That is, the level of decomposition depends on the specificity of the attributes on which individual evaluations are made. Studies for attribute structuring are rare but growing. (For a general discussion, see Buede, 1986; von Winterfeldt, 1980.) The major technological discussion in the literature at the moment concerns whether attribute structuring should be top-down or bottom-up. The top-down approach (Keeney and Raiffa, 1976; Mannheim and Hall, 1968; Miller, 1970) means that abstract attributes should be defined first, and more concrete attributes inferred from them, until a level sufficiently concrete to be susceptible to measurement and/or judgment is reached. The bottom-up approach (Humphreys and Humphreys, 1975) means that specific value attributes that discriminate among options should be identified and classified into a tree structure if necessary. Although existing evidence is not sufficient to determine which approaches are preferable (Adelman, Sticha, and Donnell, 1986), top-down approaches are more common than bottom-up approaches (von Winterfeldt and Edwards, 1986).

Both the top-down and bottom-up approaches are based on the hierarchical nature of value attributes. How far should one disaggregate the attributes to carry out an evaluation? Keeney and Raiffa (1976) point out a number of desirable properties for a set of attributes: completeness, operability, decomposability, nonredundancy, and minimum size. A set of attributes is considered complete when it includes all concerns relevant to the problem and when the set completely represents the overall attribute. Attributes are operational when they are meaningful enough to allow the decision maker to assess the alternatives. Attributes are decomposable when they are judgmentally independent and analyzed one at a time. Nonredundancy means the attributes should not overlap, that is, no two attributes should mean the same thing. The size of the attribute set should be small enough to manage. The "operability" and "minimum size" criteria are more closely related to the question of proper level of decomposition. But, they do not provide an explicit answer. Further, there is a contradiction between the criteria. Operability requires further decomposition, thus increasing the number of attributes. Edwards(1977) states that when first starting an analysis one should be careful not to include too many dimensions; specifically, 'As a rule of thumb, eight dimensions is plenty, and fifteen is too many,' (p. 328).

These arguments, however, do not provide a satisfactory answer to the question about when the analyst should stop disaggregating the attributes to carry out the evaluation. The usual answer is: when the dimensions at the lowest level are measurable, operationalizable, or easy to assess. Actually, the determination of the attribute decomposition level is left to the analyst's or decision maker's intuition.

2.4 Decomposed Evaluation and Reliability

Despite the existence of extensive research on other issues related to decomposed multiattribute alternative evaluation, few studies were reported about the impact of attribute decomposition on the final outcome of MAUA procedures.

2.4.1 Variability in Decomposed Evaluation

Mosleh and Bier (1991) describe two kinds of error in decomposed estimation: modeling error and parameter error. Modeling errors arise during the process of value composition model building, such as omitting important components, specifying an incorrect functional form of the model, or ignoring dependencies among elements of the model. Parameter errors are the errors in assessing the model components. They can arise from inaccuracy of the information, fallibility of judgments, or assessment techniques.

The notions of errors described by Mosleh and Bier are equally applicable to the context of alternative evaluation. In building a value integration model for a problem, one can misspecify or omit some attributes, ignore the independence conditions among the attributes, and determine an inappropriate functional form. Although some guidelines for reducing modeling errors are suggested in a number of MAUA references (e.g., Keeney & Raiffa, 1976; von Winterfeldt and Edwards, 1986), they are difficult to identify or analyze.

Parameter errors can occur even after a correct model has been formulated. Because model components are measured from the decision maker's judgmental responses, they can contain serious errors (Badinelli & Baker, 1990; Johnson & Schkade, 1989; Krzysztofowicz and Duckstein, 1980; Laskey & Fischer, 1987). Psychological evidence on the unreliability of human judgment indicates that any methods used to assess parameter values are likely to be subject to response errors (Fischhoff et al., 1980). In the case of additive composition models, the assessments of single-attribute values and weights are subject to such errors. These errors are propagated through the linear function into the overall error of an alternative. This research deals with these parameter errors for estimating the reliability of decomposed evaluations.

2.4.2 Experimental Studies

There exists a considerable amount of empirical evidence for the effectiveness of decomposed strategies in complex judgments. Research on clinical judgment (e.g., Brown, 1970, Einhorn, 1972) and on judgment on known quantities (e.g., Armstrong, Denniston, & Gordon, 1975; MacGregor, Lichtenstein, & Slovic, 1988) has demonstrated that decomposition of complex judgments into a series of simpler judgments results in more reliable and accurate judgments. Similar decomposition effects have been shown in the contexts of performance appraisal and job analysis (e.g., Lyness and Cornelius, 1980, 1982; Butler and Harvey, 1988; Jako & Murphy, 1990).

However, decomposition effects have rarely been studied in the context of preferential judgments. Balzer, Rohrbaugh, and Murphy (1983) reported a higher temporal reliability in the evaluations derived from decomposed judgments by regression models than unaided direct evaluations. Two experiments conducted by Pitz (1980) and Pitz et al. (1980) also demonstrated the usefulness of decomposed evaluation procedures. In evaluating hypothetical job offers and apartments, analytically derived judgments using an expected utility model showed higher sensitivity to relevant information than direct evaluations (Pitz, 1980). By comparing holistic evaluations and analytically derived evaluations of hypothetical apartments, Pitz et al. (1980) found that the direct evaluations were less sensitive to differences among alternative apartments than the analytically derived evaluations using the additive multiattribute utility model. The investigators suggest that, as people integrate successively more complex levels of information, sensitivity to relevant information diminishes.

There are also a number of experimental studies that investigated the effects of attribute structuring on multiattribute utility or value models (Aschenbrenner, 1977; Barron, 1987; Barron and Kleinmuntz, 1986; Fischer, Damodaran, Laskey, and Lincoln, 1987; Kleinmuntz, 1983). The general finding was that the structure and formulation of attributes can make a substantial difference in the quantification of elicited multiattribute values

(Weber, et al., 1988). However, studies on the specific issue of attribute decomposition impact are very limited. Two recent studies examined how weights in multiattribute utility measurement change when attributes are split into more detailed levels. Weber (1983) asked subjects to evaluate cars using four or five attributes. The five-attribute set was created by splitting one attribute (cost per mile) into two more specific attributes (depreciation per mile and yearly operating costs). Subjects could choose whether they would like to carry out a multiattribute analysis with the four or five attribute set. Both groups had identical weight ratios for the attributes they shared, but the sum of the weights on the split attributes was significantly higher than the weight attached to the split attribute. This study suggests that people over-estimate those parts of a value tree that are presented in detail relative to those that are more general.

Weber, et al. (1988) asked subjects to weight attributes in value trees containing three attributes (objectives in their term) which were specified by three, four, or six attributes. They found that when attributes are split into more detailed attributes, the sum of the attribute weights was significantly larger than the weight directly attached to the attribute: that is, the subjects overweighted the parts of the value tree that were specified in detail relative to those that were not. They suggested that overweighting detailed parts of a value structure is robust regardless of response modes, types of objectives, or different subjects.

The two studies, however, investigated attribute decomposition impact on a very limited part of MAUA, i.e., attribute weighting.

2.4.3 Theoretical Studies

While most studies on the decomposition impact on evaluation have been experimental, some attempts have been recently made to set up a more general theory of decomposition. A number of studies provide useful analytical frameworks for estimating the overall variances of a linear composition model from model component variances. Armstrong (1985) provides a theoretical argument on the value of decomposition in estimation. He considered the problem of minimizing the variance in the total estimate of phenomenon M, where M is a positive number. If M is broken down into two segments, X_1 and X_2., and the standard errors of X_1 and X_2 can be estimated, the errors in an estimate done by the segments can be calculated as follows. Given that $M = X_1 + X_2$, with both X_1 and X_2 being positive, the composite variance is, in general, $\sigma^2_{\overline{M}} = \sigma^2_{X_1} + \sigma^2_{X_2} + 2\operatorname{cov}(X_1, X_2)$. After an algebraic analysis of the composite variance, he argues that decomposition will improve the accuracy of estimation under the following conditions:

- the segments are relatively independent,
- the segments tend to be of equal importance, and
- the information on each of the segments is "valid and reliable."

Ravinder et. al. (1988) discussed the value of decomposition as a procedure for improving the consistency of probability judgments. Although carried out in a different context (probability estimation rather than evaluation), the structural similarities of the study make it relevant for the present investigation. They examined the reliabilities of subjective probability encoding obtained through a decomposition procedure. Using a psychometric measurement model, they mathematically expressed the random error of the probability estimates obtained by a Bayesian probability decomposition procedure as a function of the measurement errors of the component estimates. They used the following approach. In the law of probability, the probability of the target event, denoted A, is assessed conditionally upon each of a set of background events, denoted $B_1, \ldots, B_n$, as follows:

$$\Pr(A) = \sum_{i=1}^{n} \Pr(A|B_i)\Pr(B_i)$$

Let the marginal probabilities of the background events be expressed as

$$\Pr(B_i) = \beta_i + \delta_i$$

where β_i is the true score and δ_i is the random error, with its standard error of measurement (SEM) denoted by σ_i. Similarly, let the conditional probabilities of the background events be expressed as

$$\Pr(A|B_i) = \gamma_i + \varepsilon_i$$

with its SEM denoted τ_i. In addition, the correlation between δ_i and δ_j is denoted ϕ_{ij}, and the correlation between ε_i and ε_j is denoted by ρ_{ij}. When errors in the two types of components are assumed to be unrelated, the variance of the Pr(A), denoted by σ_d^2, is expressed as:

$$\sigma_d^2 = \sum_{i=1}^{n}\sum_{j=1}^{n}(\gamma_i\sigma_i)(\gamma_j\sigma_j)\phi_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{n}(\beta_i\tau_i)(\beta_j\tau_i)\rho_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{n}(\sigma_i\tau_i)(\sigma_j\tau_j)\phi_{ij}\rho_{ij}$$

Using this expression, they evaluated overall errors according to the characteristics of the component assessments. Their conclusion is that potential error reduction due to decomposition can be considerable, particularly when the component probabilities can be assessed more precisely than the direct assessment of the target event. They also suggest that as the number of decomposed components increases, error reduction will occur only up to a point. While this study was intended to deal only with probability assessment, which are not proper tasks for MAUA application, its framework of error analysis can be appropriately applied to almost any linear composition that can be formulated as a weighted average (Kleinmuntz, 1990). By generalizing the framework of Ravinder et al.(1988), Kleinmuntz argues that linear composition models are particularly useful for the control of random response errors in component judgments.

Yoon and Kim (1989) presented an analytical procedure to accommodate imprecise attribute ratings and weights for the purpose of making more precise discriminations among competing alternatives. They applied the technique of propagation of errors to measure the composite utility error of the linear additive utility model due to individual attribute rating errors and/or attribute weight errors. They expressed the uncertain scores using a bounded interval measure: ($r_{ij} \pm \Delta r_{ij}$) for single-attribute rating, where r_{ij} is the rating of alternative i on attribute j and Δr_{ij} is the maximum estimation error of r_{ij}; ($w_j \pm \Delta w_j$) for weight. Two approaches were considered to obtain the composite error in utility due to individual errors of attribute rating and weight, i.e., Δr_{ij} and Δw_j. One is the approximation approach by the total differential; the other is the statistical approach by the propagation of errors (Pugh & Winslow, 1966). Yoon and Kim recommended the propagation of error method. In this method, by considering errors of attribute ratings and weights to be their standard deviations, they obtained a composite error of the additive utility function to be

$$\sigma_i^2 = \sum_{j=1}^{n} \left(w_j^2 \sigma_{r_{ij}}^2 + r_{ij}^2 \sigma_{w_j}^2 \right)$$

This composite error function can be applied to the present research as a useful tool for examining the attribute decomposition impact on composite error.

2.5 Summary of Findings and Directions for Research

Research on the decomposition in evaluation is insufficient to draw a conclusion about the decomposition effects on multiattribute evaluations. This section summarizes the general findings from the literature review and sets research directions.

1. For many situations, with the proper choice of attributes, decomposed procedures may produce reduced errors associated with alternative evaluations in comparison to direct and holistic methods.

2. Most studies on decomposition are limited to a simple comparison of a holistic versus a decomposition method, given that alternatives were described by a number of prespecified attributes. This fact makes us unable to draw any conclusion regarding the effects of the extent of decomposition on evaluation. More research is therefore needed on the impact of decomposition level on evaluation results, with varying levels of decomposition.

3. The impact of attribute decomposition on an MAUA outcome does not seem so simple. It may be a function of the characteristics of the decision problem. Therefore, more investigations are needed on the role of task characteristics in determining the impact of attribute decomposition. This issue is, however, not addressed in the present research.

4. Most studies on the decomposition effects were performed experimentally. Experimental studies can not provide a general theory of decomposition impact, since individual experiments focus only a specific case or specific context of evaluation. Therefore, more theoretical studies should be conducted for the purpose of developing a more general theory on the issue.

3. An Analytical Evaluation of Decomposition Effects

3.1 Overview

This chapter provides a theoretical treatment of the effect of decomposition on the variances of evaluation outcomes. An analytical framework is described that is used to predict the possible effects of decomposition level on the variance of choice alternative evaluation. For the case of the additive linear value composition rule, the variation in the overall value of an alternative is expressed as a function of the variations in the component evaluations, using the statistical technique of error propagation. The behavior of the composite variation is analyzed algebraically, with respect to the changes in decomposition level.

3.2 Notation and Assumptions

3.2.1 Linear Additive Value Composition Model

Suppose a decision maker must choose one alternative from a set. When each alternative is evaluated with respect to N attributes and the overall evaluation of the alternative is derived by a weighted sum of the single-attribute evaluations, the overall value V can be written as

$$V = \sum_{j=1}^{N} W_j X_j \tag{3-1}$$

where X_j is the decision maker's evaluation of the alternative on the j-th attribute and W_j is the importance weight for the attribute. The single-attribute evaluations are scaled as $0 \le X_j \le 1$, and the weights are scaled as $0 \le W_j \le 1$ and $\sum W_j = 1$.

Under expression (3-1), a holistic evaluation corresponds to the case when the alternative is evaluated with one overall attribute, i.e., N=1 and $W_1=1$. In this case, the overall evaluation V, which equals X_1, is especially denoted V_h.

3.2.2 Variations in Evaluation

The subjective value of the same alternative rated by the same subject on several different occasions appears to have a different score each time it is rated. If the same situations were replicated a large number of times, and if the person had no memory of his or her previous judgments, the elicited scores would give rise to a distribution for that particular person. The expected value of the distribution is a systematic component of the judgment, and the variance of the hypothetical distribution is due to a random component. As discussed in the literature review chapter, the variance of the distribution can be a combination of the inherent indefiniteness in preference and unpredictable fluctuations in attention or shifts in information processing.

A convenient way to represent the variation in a person's evaluation of an alternative is to consider the evaluation as a random variable. It is assumed that the random variable follows a normal distribution, as is often assumed in the measurements of a psychological construct (Dunn, 1989).

The concept of a random variable is applied to both holistic evaluation and decomposed evaluation. That is, it is assumed that the indefinite holistic evaluation V_h is a random variable with a normal distribution. Under this assumption, a specific holistic evaluation score of V_h on some particular trial can be represented by a random sample from the normal distribution. Likewise, the single-attribute evaluation X_j and attribute weight W_j are also regarded as random variables with normal distributions. If the scores of X_j and W_j are governed by independent normal distributions, then the composite evaluation V, derived by equation (3-1), is also a random variable with a normal distribution (Taylor, 1982).

Within this framework, the variation of the random variable is related to reliability: small variation is equivalent to high reliability. In this research, the standard deviation (STD) of a random variable is used as a measure of variation.

σ_h = standard deviation of the holistic evaluation V_h.

σ_{x_j} = standard deviation of the evaluation X_j

σ_{w_j} = standard deviation of the attribute weight W_j

σ_v = standard deviation of the composite evaluation V.

3.3 Derivation of Composite Variation

When the component measurements of a prescribed composition model have their own variations, the variation in the derived composite value can be computed by the statistical method of error propagation. The propagation of errors is a statistical method that estimates the uncertainty or error in some prescribed function involving a number of quantities with their uncertainties or errors (Pugh and Winslow, 1966; Taylor, 1982). If various quantities x, . . ., z are measured with errors δ_x, . . ., δ_z, and the measured values are used to compute some quantity q, then the errors in x, . . ., z cause an uncertainty in q as follows. If q is any function of the variables x, . . ., z, and the errors in x, . . ., z are independent and random, then the error in q is

$$\delta_q^2 = \left(\frac{\partial q}{\partial x}\delta_x\right)^2 +,\cdots,+ \left(\frac{\partial q}{\partial z}\delta_z\right)^2,$$

i.e.,

$$\delta_q = \sqrt{\left(\frac{\partial q}{\partial x}\delta_x\right)^2 +,\cdots\cdots,+ \left(\frac{\partial q}{\partial z}\delta_z\right)^2}.$$

A good measure of the uncertainty δ_x in a measurement is given by the standard deviation σ_x . If the measurements of x, . . ., z are governed by normal distributions, with standard deviations σ_x, . . ., σ_z, then the standard deviation of q can be expressed as

$$\sigma_q = \sqrt{\left(\frac{\partial q}{\partial x}\sigma_x\right)^2 +,\cdots\cdots,+ \left(\frac{\partial q}{\partial z}\sigma_z\right)^2}.$$

In the linear additive value composition, the variations of the assessed model components (single-attribute evaluations and weights) are propagated into the overall evaluation through function (3-1). When the propagation of errors method is applied to equation (3-1), the variation in the overall evaluation is derived as follows (Yoon & Kim, 1989):

$$\sigma_v^2 = \sum_{j=1}^{N}\left(\frac{\partial V}{\partial X_j}\sigma_{X_j}\right)^2 + \sum_{j=1}^{N}\left(\frac{\partial V}{\partial W_j}\sigma_{W_j}\right)^2 = \sum_{j=1}^{N} W_j^2\sigma_{X_j}^2 + \sum_{j=1}^{N} X_j^2\sigma_{W_j}^2$$

i.e.,

$$\sigma_v = \sqrt{\sum_{j=1}^{N} W_j^2\sigma_{X_j}^2 + \sum_{j=1}^{N} X_j^2\sigma_{W_j}^2} \quad . \tag{3-2}$$

In the expression 3-2, a note should be made. The X_j and W_j express the "true" single-attribute evaluations and weights. In this subjective evaluation, the "true" values are defined by the means of the distributions of single-attribute evaluations and weights, for a particular decision maker.

3.4. Analysis of Composite Variation in Relation to Decomposition Level

How can the effect of decomposition level be predicted using equation (3-2)? One approach is to see the possible changes in the model components, and the resulting change in the composite evaluation, with respect to the level of decomposition. The extent of decomposition alters the number of component evaluations to be aggregated. In structuring a hierarchy of attributes, the level of decomposition is closely related to the number of attributes chosen to characterize choice alternatives. As an evaluation problem is decomposed further, the number of attributes increases. It is, possible, therefore to analyze the composite variation as a function of the number of attributes used.

However, it is not simple to analyze the composite variation with respect to the number of attributes because the number of attributes is expressed as the number of terms in the summation. Conventional sensitivity analysis techniques deal with possible changes in the parameter values, within a given function. In the present case, an algebraic analysis of the composite variation can be extremely difficult, because the inclusion of additional attributes changes the number of terms in the linear function.

Another point makes the analysis more complex. As the level of decomposition changes, all other components of equation (3-2) can vary simultaneously. The means and variances in the single-attribute evaluations can change because a different set attributes is used in evaluation with a different level of decomposition. Also, attribute weights can change with the level of decomposition. It is, however, difficult to predict the possible changes in these model component characteristics with the level of decomposition. As a problem is decomposed more deeply, the attributes tend to be more specific and simpler. The size of variations in the component evaluations may become smaller. For the attribute weights, it is somewhat harder to predict the decomposition impact. Attribute weights may become less variable as decomposition increases, because each attribute tends to be simpler. But an opposite change is also conceivable: weights could be more variable due to the cognitive burden of comparing a larger number of attributes. It is even harder to predict the means of single-attribute evaluations and weights. They are largely dependent on the attributes used in the different level of decomposition. That is, as a different set of attributes is used, different single-attribute evaluations and weights will be assigned.

Considering the large number of components involved and the simultaneous changes in those components, several simplifying assumptions regarding the characteristics of components are made in the following analysis, when necessary for a manageable analysis. A common assumption used throughout the analysis is that all the variances in the single-attribute evaluations and attribute weights at a particular level of decomposition are of equal size. This assumption was adopted for convenience of analysis, and is, however, a reasonable one, considering that all the attributes at a particular level of decomposition are formulated with a similar degree of specificity by an analyst or decision maker. Other specific assumptions for analysis are described in the corresponding analysis steps.

3.4.1 Changing Pattern of Composite Variation due to Decomposition Level

In this section, the general pattern of change in the composite variation is examined with respect to the level of decomposition. The analysis is divided into two categories: when the attribute weights are constant and when weights are variable. This division was considered according to the two modes of weight assignment in linear composition model applications. While single-attribute evaluations are always elicited from the decision maker's judgments, the attribute weights are not always elicited in this manner. In one case, the attribute weights are elicited from the decision maker's judgments, as well as single-attribute evaluations. This case is familiar, since it is probably the most widely used technique in evaluation practice. In another case, attribute weights are given as constant and the decision maker rates the single-attribute values only. This constant weighting scheme again can be divided into two cases: equal, or unit, weighting and constant but unequal weighting. The analysis is performed for the constant weighting case first and then proceeds to the variable weighting case.

(a) When Weights are Constant

Equal (or Unit) Weighting

This is the simplest case of weighting, when the attribute weights are equal, or unit. This is a non-weighting scheme, where the overall evaluation is the unweighted mean of single-attribute evaluations. The equal, or unit, weighting scheme is often successfully used in practical evaluations (Einhorn, 1987).

This case specifies $W_j = \frac{1}{N}$ and $\sigma_{W_j} = 0$, for all j. The composite variation for this case becomes:

$$\sigma_V^2 = \sum_{j=1}^{N} W_j^2 \sigma_{X_j}^2 + \sum_{j=1}^{N} X_j^2 \sigma_{W_j}^2 = \sum_{j=1}^{N} \left(\frac{1}{N}\right)^2 \sigma_{X_j}^2 = \left(\frac{1}{N}\right)^2 \sum_{J=1}^{N} \sigma_{X_j}^2$$

i.e.,

$$\sigma_V = \frac{1}{N}\sqrt{\sum_{J=1}^{N} \sigma_{X_j}^2} \qquad (3\text{-}3)$$

Let's assume all the single-attribute evaluations have a same size of variation and equal the variation of holistic evaluation have a same size of variation, i.e., $\sigma_{x_j} = \sigma_h$, for all j. This assumption is a reasonable one because the single-attribute evaluations and the holistic evaluation use the same value scale. Under this assumption, the composite STD becomes

$$\sigma_v = \frac{1}{N}\sqrt{\sum_{j=1}^{N}\sigma_h^2} = \frac{1}{N}\sqrt{N\sigma_h^2} = \frac{\sigma_h}{\sqrt{N}} \tag{3-4}$$

and decreases as the number of attributes N increases, approaching a value of zero at infinity (See Figure 3-1). For example, if an alternative is decomposed into two, three, and four attributes, the composite STDs become $0.71\sigma_h$, $0.58\sigma_h$, and $0.5\sigma_h$, respectively. According to equation 3-4, the composite variance approaches a zero value as the number of attributes increases to infinity.

The change of σ_V can be re-plotted against a more practically defined level of decomposition in an attribute hierarchy, instead of the number of attributes as a proxy measure of decomposition level, L. Suppose every attribute in a level is split into two subattributes with one more level of decomposition. Then, the level of decomposition can be conveniently expressed by a log value of the number of attributes, i.e., $L = \log_2 N$. Then, the composite STD is expressed as $\sigma_V = \frac{1}{\sqrt{2^L}}\sigma_h$. When an alternative is evaluated with the first level of decomposition (i.e., L = 1 and N = 2), the composite STD equals $0.71\sigma_h$. In case of the second, third, and fourth levels of decomposition, the composite STD becomes $0.5\sigma_h$, $0.35\sigma_h$, and $0.25\sigma_h$, respectively.

If the STDs of each single-attribute evaluation are smaller than the STD of holistic evaluation, the composite STD will be smaller than the values plotted in Figure 3-1.

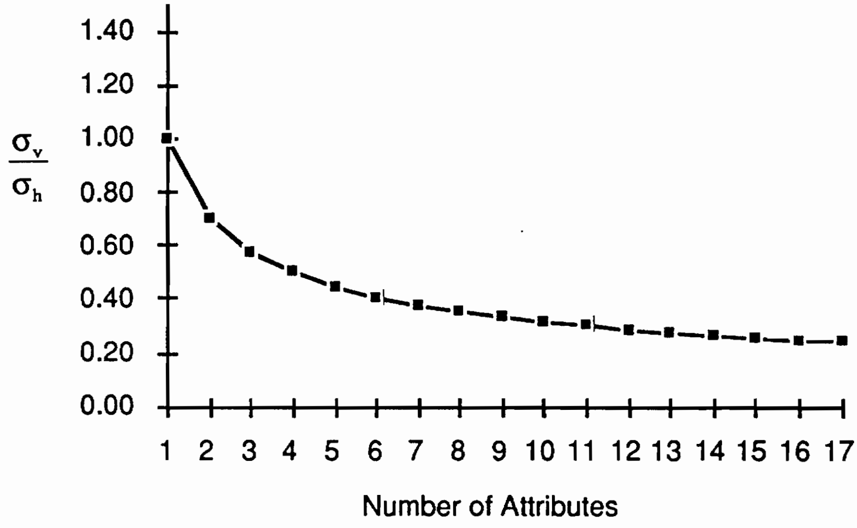

Figure 3-1 Plot of Composite STD in the Equal Weighting Scheme.

The above results mean that when the attributes of an alternative are decomposed so as to allow equal weighting, the variation of an alternative evaluation obtained through decomposition greatly decreases (equivalently, the reliability increases) as the attributes are further decomposed.

Unequal Weighting

This is the case when unequal but predetermined constant weights are used in combining the single-attribute evaluations; the attribute weights have no variation, i.e., $\sigma_{W_j} = 0$. One example of this is when a particular set of weights, predetermined by expert groups on the problem or through a regression analysis of previous evaluations, are used for current evaluations.

In this weighting scheme, the composite STD becomes as:

$$\sigma_V = \sqrt{\sum_{j=1}^{N} W_j^2 \sigma_{X_j}^2}$$

If we again assume all the single-attribute value scores and the holistic evaluation score have equal variations, i.e., $\sigma_{X_j} = \sigma_h$, for all j, the composite STD becomes:

$$\sigma_V = \sigma_h \sqrt{\sum_{j=1}^{N} W_j^2} \ .$$

Here, the size of σ_V is determined by the allocation of weights W_j, satisfying $\Sigma W_j = 1$. Although it is not easy to appraise σ_V, we can identify the range of values that σ_V can take by calculating its bounds. σ_V reaches a minimum value of $\frac{1}{\sqrt{N}}\sigma_h$, when all weights are equal, i.e., $W_j = \frac{1}{N}$, for all j. Actually this best case is equivalent to the Case a-1 above. σ_V reaches a maximum value of σ_h, when only one of the weights is 1 and all the rest are 0 (essentially a holistic evaluation). In this worst case, the variation remains constant with decomposition, i.e., $\sigma_v = \sigma_h$. For other weight allocations, σ_v has a value between the two extreme values, i.e., $\frac{1}{\sqrt{N}}\sigma_h \le \sigma_v \le \sigma_h$ (See Figure 3-2). When a decomposition level L is used, the minimum and maximum values of σ_v are $\frac{1}{\sqrt{2^L}}\sigma_h$ and σ_h, i.e., the range of composite STD becomes $\frac{1}{\sqrt{2^L}}\sigma_h \le \sigma_v \le \sigma_h$.

In summary, the constant weighting scheme exhibits considerable potential for variation reduction with decomposition. That is, if a set of constant weights can be used, an additive decomposition procedure can reduce the variability in evaluations.

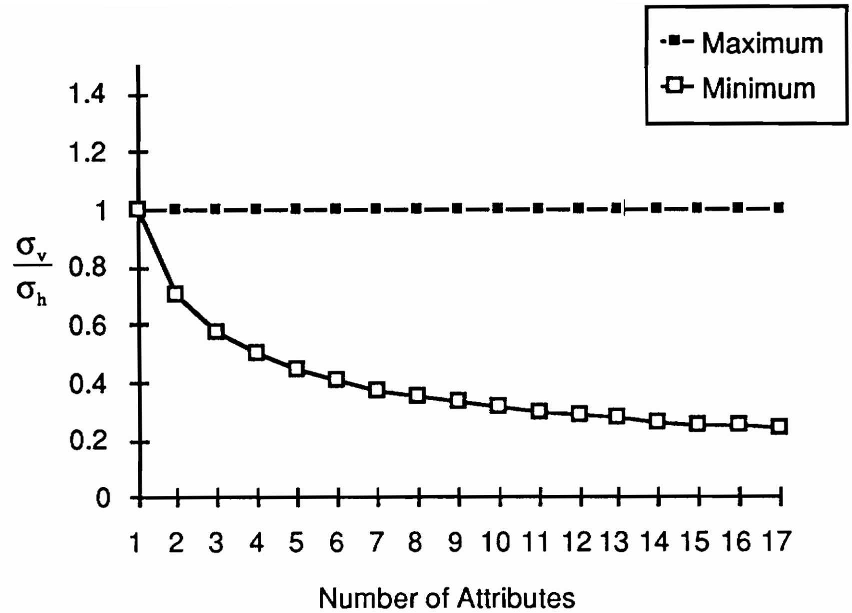

Figure 3-2 Plot of Composite STD in the Constant Weighting Scheme.

(b) When Weights are Variable

This case is when both the single-attribute evaluations and attribute weights are variable, occurring when attribute weights are also assessed by the decision maker. This mode of weighting is common in practical multiattribute evaluation.

In this case, the general expression of composite STD is

$$\sigma_V = \sqrt{\sum_{j=1}^{N} W_j^2 \sigma_{X_j}^2 + \sum_{j=1}^{N} X_j^2 \sigma_{W_j}^2} \ . \tag{3-5}$$

Let's again assume all the variations in the single-attribute evaluations are the same and equal the variation of holistic evaluation, i.e., $\sigma_{X_j} = \sigma_h$, for all j. One reasonable assumption about the variations of attribute weights is that they are one N-th of the variation of holistic evaluation, i.e., $\sigma_{W_j} = \frac{\sigma_h}{N}$, because the attribute weights are scaled down so that their sum to be 1. With these assumptions, equation (3-5) then becomes

$$\sigma_V = \sigma_h \sqrt{\sum_{j=1}^{N} W_j^2 + \frac{1}{N^2} \sum_{J=1}^{N} X_j^2} \ . \tag{3-6}$$

Here, the size of σ_V depends on the scores X_j and W_j. σ_V reaches a minimum value of $\sigma_h \sqrt{\frac{1}{N}}$ when $X_j = 0$ and $W_j = \frac{1}{N}$, for all j. σ_V reaches a maximum value of $\sigma_h \sqrt{\frac{1}{N} + 1}$ when all X_j's equal 1, one of the W_j's is 1, and all other W_j's are 0. For other values of X_j and W_j, σ_V attains a value between the two bounds, i.e., $\sigma_h \sqrt{\frac{1}{N}} \leq \sigma_V \leq \sigma_h \sqrt{\frac{1}{N} + 1}$ (See Figure 3-3).

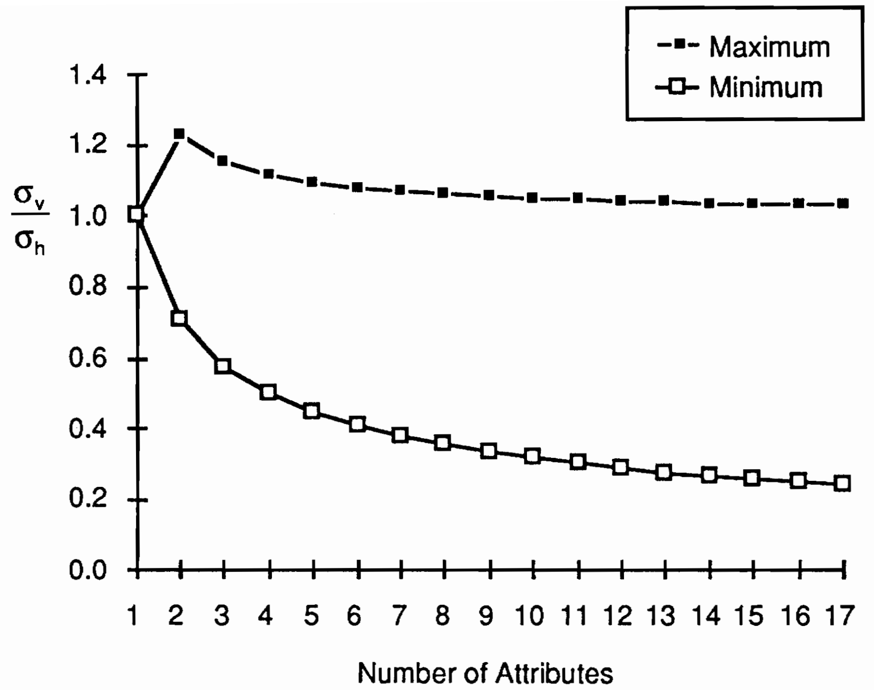

Figure 3-3 Plot of Composite STD in the Variable Weighting Scheme.

If we use a decomposition level L, the lower and upper bounds become $\frac{1}{\sqrt{2^L}}\sigma_h$ and $\sqrt{2^L+1}\ \sigma_h$, respectively.

The results mean that when both single-attribute values and attribute weights are rated by the decision maker, the effects of decomposition level on the reliability of evaluation outcomes are uncertain, i.e., the reliability can be improved or degraded. The magnitude of composite variation is largely dependent on the characteristics of the single-attribute values and weights. For instance, when the means of single-attribute values are approximately the same and the means of attribute weights are equally distributed across the attributes, the potential for variation reduction is large. On the other hand, if the single-attribute values and weights are unevenly distributed, the composite variation can increase. However, as shown by Figure 3-3, the potential of variation reduction is still considerable, in the variable weighting scheme.

3.4.2 Sensitivity of Composite Variation to Decomposition Level

The sensitivity of the composite variation to decomposition level can be examined by analyzing the marginal changes in the composite error as decomposition level changes. Here, an analysis of the marginal change of composite variation is provided for the variable weighting scheme.

In the best case, the marginal reduction in the composite variation can be analyzed as follows:

$$\nabla\sigma_v(N) = \frac{\sigma_v(N+1) - \sigma_v(N)}{\sigma_v(N)} = \frac{\frac{\sigma_h}{\sqrt{N+1}} - \frac{\sigma_h}{\sqrt{N}}}{\frac{\sigma_h}{\sqrt{N}}} = \sqrt{\frac{N}{N+1}} - 1 \qquad (3\text{-}7)$$

where $\sigma_v(N)$ and $\nabla\sigma_v(N)$ denote the composite STD and its marginal change when the number of attributes is N.

For N = 1, adding one more attribute results in a 29% marginal reduction in composite STD. For N = 2, 3, 4, adding one more attribute results in 18%, 13%, 10% marginal reductions, respectively. For N larger than four, the addition of one more attribute yields less than 10% reduction in composite variation.

If the decomposition level L is used, the marginal reduction in STD is

$$\nabla\sigma_v(L) = \frac{\frac{\sigma_h}{\sqrt{2^{L+1}}} - \frac{\sigma_h}{\sqrt{2^L}}}{\frac{\sigma_h}{\sqrt{2^L}}} = \sqrt{\frac{2^L}{2^{L+1}}} - 1 = \sqrt{\frac{1}{2}} - 1 = -0.29. \qquad (3\text{-}8)$$

Equation (3-8) means that if the attributes are decomposed in dichotomy, every one level increase in decomposition can reduce STD by 29%, in the best case.

In the worst case, the marginal change ratio becomes as:

$$\nabla\sigma_v(N) = \frac{\sigma_h\sqrt{\frac{1}{N+1}+1} - \sigma_h\sqrt{\frac{1}{N}+1}}{\sigma_h\sqrt{\frac{1}{N}+1}} = \frac{\sqrt{N(N+2)}}{N+1} - 1, \qquad \text{for } N \geq 2.$$

$$= \frac{\sigma_h\sqrt{1.5} - \sigma_h}{\sigma_h} = 0.22, \qquad \text{for } N = 1.$$

For N=1, adding one more attribute increases the variation by 22%, That is, evaluating an alternative with two attributes will increase the variation by 22%, in the worst case. For N=2, 3, 4, with an extra attribute, the composite STD decreases by 6%, 3%, 2%, respectively.

In general, the rate of change in the composite variation diminishes as the number of attributes increases. That is, the composite variation is more sensitive to decomposition level in early steps of decomposition than in late steps. These results imply that the impact of additional decomposition on the variability of the resulting evaluation is larger for low levels of decomposition and is smaller for high levels of decomposition.

3.4.3 Other Analyses

Analysis on the composite variation can be extended to other research subquestions: what are the conditions required for decomposed evaluation to be more reliable than holistic evaluation, and what is the optimal level of decomposition for reliable evaluation. Though these questions can not be appropriately answered by an algebraic analysis, some preliminary thoughts are provided below.

3.4.3.1 Conditions Required for Decomposed Evaluation To Be More Reliable Than Holistic Evaluation

It is important to examine the conditions under which a decomposed evaluation is "better" than holistic evaluation. One approach is to compare the standard deviation of the decomposed evaluation to the standard deviation of the holistic evaluation.

A general condition for which a decomposed evaluation can produce a more reliable result than a holistic evaluation can be expressed as:

$$\sigma_V = \sqrt{\sum_{j=1}^{N} W_j^2 \sigma_{X_j}^2 + \sum_{j=1}^{N} X_j^2 \sigma_{W_j}^2} \leq \sigma_h \tag{3-9}$$

Because formula (3-9) is too general, it is hard to interpret. However, as shown in the previous section, a decomposed evaluation can yield reduced variation when a constant set of weights is used. Thus, if the attributes of a problem have been appropriately formulated to use a fixed set of weights, a decomposed evaluation can produce a more consistent outcome than a holistic evaluation. In particular, if attributes are formulated with equal importance, decomposition always can reduce the variations in evaluations.

For the variable weighting case, Figure 3-3 appears to suggest that variation reduction can not be achieved in many situations. However, this conclusion may be too conservative, because the extreme situations are not expected to occur in practice. The worst case bound is based on the theoretical assumption that all attributes except one have no importance weights. This situation is, however, unlikely in practice because no decision maker or analyst would formulate such a set of attributes. A practical range of the composite STD may be narrower than the boundary in Figure 3-3 and the lower part of the region would be the more probable area.

3.4.3.2 Choosing the Proper Level of Decomposition

The proper level of decomposition is identified as the level at which the variation of the resulting evaluation is minimized, or the level at which the size of marginal STD reduction begins to be less than some specified value. For example, the smallest number N that satisfies the following condition can be a suggested number of attributes.

$$\frac{\sigma_V}{\sigma_h} \leq \alpha \tag{3-10}$$

For the best case discussed in the previous section, if α is set to 0.5, expression (3-10) becomes

$$\frac{1}{\sqrt{N}} \leq 0.5 \tag{3-11}$$

Then, the minimum number of attributes N that satisfies expression (3-11) is 4.

For another example, let the appropriate number of attributes be the minimum number of attributes that makes the marginal reduction in STD smaller than a specified value of α.

$$\frac{\sigma_V(N=\mathbf{n})-\sigma_V(N=\mathbf{n}+1)}{\sigma_V(N=\mathbf{n})} \leq \alpha \tag{3-12}$$

For the best case discussed in the previous section, this condition becomes $1-\sqrt{\frac{\mathbf{n}}{\mathbf{n}+1}} \leq \alpha$. If α = 0.1 (i.e., 10%), the smallest number n that meets the condition is 5. If α = 0.05 (i.e., 5%), the required number of attributes becomes 10.

3.5 Discussion of the Analytical Results

The results of the theoretical analysis are summarized as follows.

• When attribute weights are constant, the variance of an alternative evaluation through decomposition is much smaller than holistic evaluation and decreases as the level of decomposition increases.

• In the variable weighting case, the effect of decomposition level is not uni-directional. Composite variance can be improved or degraded, depending on the characteristics of the component evaluations and attribute weights. However, the potential for variation reduction through decomposition is still considerable.

• In all situations, the rate of change in variation decreases as the level of decomposition increases.

A possible explanation for the results can be sought from the characteristics of a linear function. The additive composition model is a weighted average where single-attribute evaluations are weighted using attribute weights. Because the weights cause a smoothing effect, the larger number of attributes can induce smaller aggregated variation. Each extra attribute included in the average results in lower variation for the average as a whole. But this benefit is obtained at the cost of the variation present in the extra weight that has to be assessed. Adding attributes can cause increased variation in the composite evaluation. However, the effect of additional weights will be relatively small because the sizes of variation in individual attribute weights will be smaller as the number of attributes increases, due to the normalization process. Thus, the overall composite variation tends to decrease as the decomposition level increases, even in the variable weighting case.

As with any analysis of this type, the usefulness of the results depends on the appropriateness of the assumptions. All the above results are obtained under a pre-assumption that modeling of the evaluation problem is perfect. That is, for every case, attribute formulation is assumed to cover all the relevant value dimensions and meet the requirements for additive linear composition model application. However, in practice it may be impossible to formulate attributes perfectly. A decision maker or analyst will probably not be able to decompose a problem without introducing errors such as incompleteness, redundancy, and irrelevancy. Imperfect modeling will cause extra errors in decomposed evaluations. Therefore, the overall error of an alternative evaluation using MAUA can be a sum of errors through the linear composition function and the errors from modeling. The modeling error can be an increasing function with decomposition level. A conceivable pattern of the overall error of an alternative evaluation is expected to exhibit a parabolic relationship (Koelling & Cho, 1991) to the attribute decomposition level, as depicted in Figure 3-4. There would be a particular level of decomposition at which the total error is minimized. The present analytical study focused on the errors of evaluation under correct modeling (the decreasing curve in Figure 3-4).

Another assumption used for the convenience of analysis was that the sizes of variations of single-attribute evaluations equal the variation of a holistic evaluation. This assumption, however, is somewhat conservative in assessing the benefit of decomposition. Actual variation in each single attribute evaluation may be smaller than that of the holistic evaluation, because the judgment on a single attribute will be simpler and easier than the holistic judgment. Therefore, the reduction in composite variation through decomposition may be larger than shown in the analyses above.

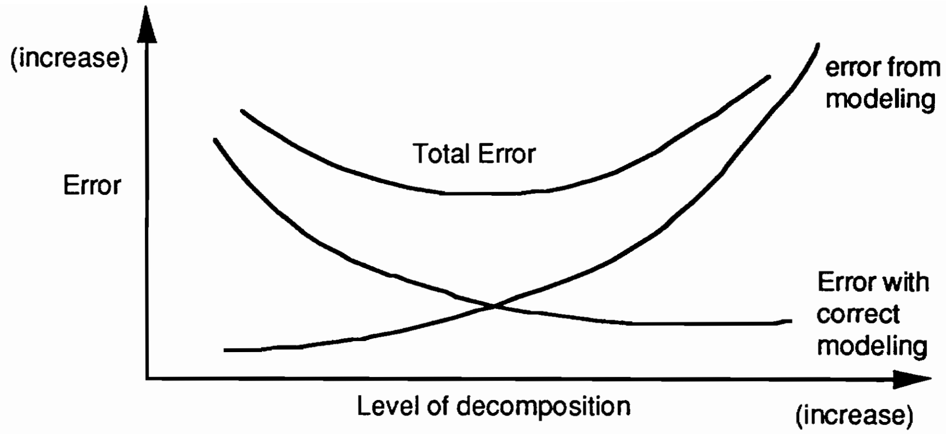

Figure 3-4 Errors of Evaluation through Decomposition.

4. An Experimental Evaluation of Decomposition Effects

4.1 Overview

An experiment was performed for the purpose of empirically examining the effects of decomposition level on the intrarater reliability of multiattribute alternative evaluation. Subjects evaluated hypothetical job alternatives, with four different levels of judgment decomposition. Using the test-retest method, the convergence between the outcomes of two identical evaluation sessions was examined with respect to the decomposition levels. The results of this experiment are compared with the theoretical results obtained in the preceding chapter.

4.2 Subjects and Experimental Design

Twenty-four students from Virginia Polytechnic Institute and State University, including sixteen males and eight females, served as the subjects for this experiment. Eleven subjects were undergraduate students and thirteen subjects were graduate students. They were recruited by an advertisement and were paid $12.50 at the completion of the experiment. All the subjects had given consideration to the problem of finding a job following their graduation, but did not have experience with the evaluation procedure used in this experiment.

The experiment used a single-factor, within-subjects design, with the level of decomposition as the experimental factor. The level of decomposition was manipulated in terms of the number of attributes and their specificity, ranging from a single overall rating (level 0) to ratings on 12 highly-specific attributes (level 3). Each subject was assigned to one of the 24 counterbalanced sequences of the four decomposition levels (See Table 4-1) to control possible order and/or carry-over effects. Assignment of subjects to the treatment sequences depended upon the date the subjects signed up to participate in the experiment, and thus was assumed to be unbiased. To assess the test-retest reliability of evaluations, all the subjects participated in two sessions separated by two weeks. All four levels of decomposition were experienced in each session and the experimental procedures for the two sessions were identical. A fixed-effects model was assumed. Subjects were random-effects.

4.3 Task Construction

4.3.1 Job Alternatives

Six hypothetical job alternatives were constructed that were described by the information on 12 job-relevant attributes. The attributes for the job

Table 4-1 The Orders of Decomposition Levels Presented

		Decomposition Level			
		First	Second	Third	Fourth
	S1	level 0	level 1	level 2	level 3
	S2	level 0	level 1	level 3	level 2
	S3	level 0	level 2	level 1	level 3
Subject	S4	level 0	level 2	level 3	level 1
	•	•	•	•	•
	•	•	•	•	•
	•	•	•	•	•
	S24	level 3	level 2	level 1	level 0

alternative descriptions were formulated by referring to the attributes appearing in the literature on job or career evaluation (See Appendix A), considering their clarity, relevance, and mutual independence. The information on the attributes was specified by the experimenter arbitrarily by referring to several job guidebooks (Krantz, 1988; Norback, 1980). A sample job alternative is shown in Table 4-2, and descriptions of all six alternatives can be found in Appendix B. Six job alternatives were used as a proper number of alternatives on the basis of the subjects' cognitive burden and the time spent in evaluation sessions of a pilot study (Appendix C).

4.3.2 Attribute Formulation

An attribute hierarchy (Figure 4-1) for evaluating the job alternatives was constructed by combining the attributes that were used for the job alternative descriptions. From this attribute hierarchy, four sets of attributes were selected on which the job alternatives were evaluated. The four attribute sets represented four different levels of decomposition as shown in Table 4-3. The attributes were finalized after a modification based on the results from the pilot study.

Table 4-2 A Sample Job Alternative used in the Experiment

Content of Work: Plans for optimum use of facilities, equipment, and personnel to improve industrial efficiency.

Stress: Quotas & deadline: None, Competition: none.

Physical Demand: Low.

Working Hours: 45 hrs/week.

Travel: 10 trips per year, 20 days away per year.

Location of Employment: New York City, New York.

Salary: $31,000.

Benefits: Semi-private office, company car, health insurance.

Promotion Level: Experienced workers can advance to the positions of supervisors or managers.

Job Growth: 46% (faster than average).

Firm Security: No risk of bankruptcy.

Personal Security: Cannot be fired.

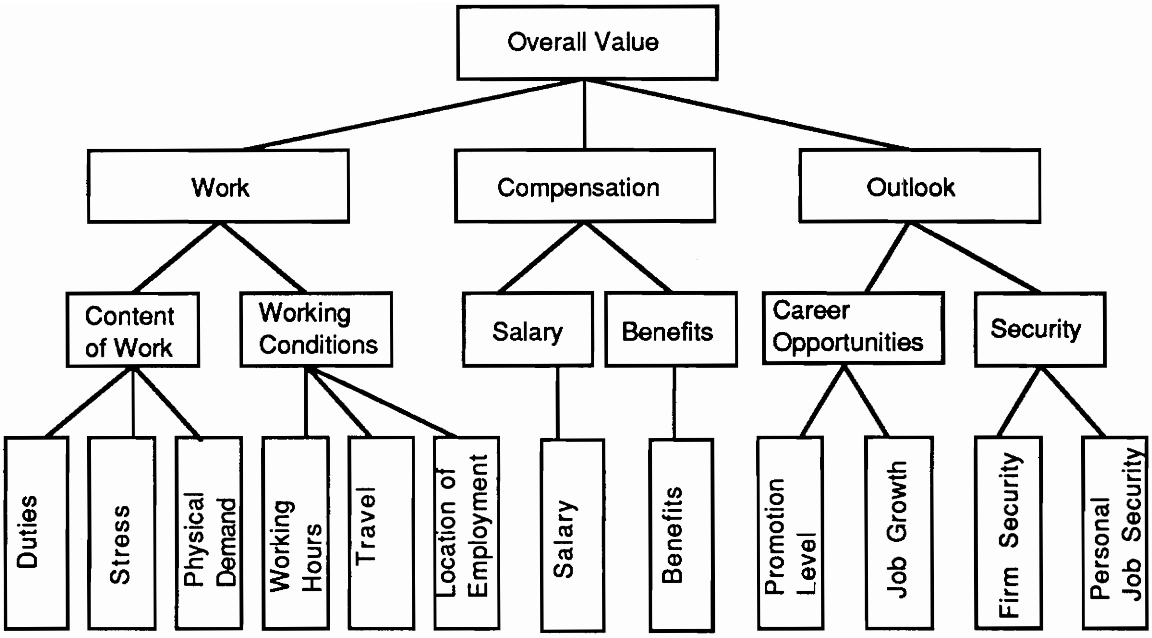

Figure 4-1 An Attribute Hierarchy for Job Evaluation.

Table 4-3 The Four Attribute Sets used in the Job Alternative Evaluation.

Decomposition Level		Attributes
Decomposition Level	0	Overall Value
	1	Work; Compensation; Outlook
	2	Content of Work; Working Conditions; Salary; Benefits; Career Opportunities; Security
	3	Duties; Stress; Physical Demand; Working hours; Travel; Location of Employment; Salary; Benefits; Promotion Level; Job Growth; Firm Security; Personal Job Security

4.3.3 Experimental Materials

A packet of experimental materials (See Appendix B) was prepared that included the following materials.

• An overview of the experiment: The purpose and nature of the experiment were briefly described.

• Scoring Instructions: Specific instructions that subjects should follow were described.

• Job Alternatives: Each of the six hypothetical job alternatives was described on a separate 5x8 inch card. A hierarchical heading was attached to all the job alternative descriptions to help subjects easily categorize the job information according to the attributes to be used.

• Evaluation Scoring Sheets: Four scoring sheets were designed that were used to record the single-attribute value scores and weighting scores by subjects. Each scoring sheet corresponded to a particular level of decomposition. Every scoring sheet contained the attributes at the corresponding level of decomposition.

4.4 Procedure

Subjects were given the experimental packet. Before reading the experimental instructions, the subjects were given a brief explanation of the purpose and nature of the experiment. After the subjects read the experimental instructions, the experimenter answered questions from the subjects.

The subjects evaluated the job alternatives according to the evaluation procedure described on the "Scoring Instructions" in the experimental packet (Appendix C). They evaluated the alternatives using the four scoring sheets in the provided order.

For the holistic evaluation case (i.e., decomposition level 0), subjects rated the overall attractiveness of each alternative directly on a 0-100 value scale, where 0 is defined as the minimum plausible value and 100 defined as the maximum plausible.

For the other three decomposition levels, subjects evaluated the alternatives following a decomposed evaluation procedure described below. The evaluation procedure was adapted from a multiattribute utility measurement procedure, called SMART (simple multiattribute rating technique), that was proposed by Edwards (1977). The evaluation procedure adopted a direct rating method for single-attribute value assessments and a ratio estimation method for attribute weight assessments, as described in the following paragraphs.

Rating alternatives on each attribute

Subjects determined the relative value of each alternative on each attribute on a 0-100 scale, where 0 is defined as the minimum plausible value and 100 defined as the maximum plausible.

Assessing attribute weights

To determine the importance weights for each attribute used, a three step procedure was adopted. Subjects were first asked to rank the attributes in order of importance. Subjects then made ratio estimates of the importance of each attribute relative to the one ranked lowest in importance. To do this, subjects were asked to assign the value 10 to the least important attribute. Subjects were then requested to rate the importance of remaining attributes relative to the least important attribute. For example, if an attribute was thought two times as important as the least important attribute, subjects assigned a weight of 20. These attribute weights were normalized for each subject, by summing the importance weights and dividing each attribute weight by the sum. The normalization was performed by the experimenter.

Calculating the overall value of each alternative

The overall value of each alternative was calculated by summing its single-attribute values weighted by the weights determined in the attribute weighting step. This calculation was performed by the experimenter.

The entire procedure was repeated about two weeks later. The actual intervals ranged from twelve days to sixteen days according to individual subjects. A two-week interval has been considered an appropriate period for this kind of experiment, because preferential judgment responses are commonly assumed to show no systematic change over such an interval (Laskey & Fischer, 1987). Actually, a two-week interval was often used in the studies on temporal stability of judgments (for example, Laskey & Fischer, 1987). Subject were requested not to try to match their responses on the second session to their original responses, but rather to make judgments as they felt at the time.

4.5 Data Collection and Reduction

The raw data of the single-attribute ratings and attribute weightings from each subject were collected on the evaluation scoring sheets included in the experimental packet. Using the raw data, the weight normalization and overall value calculation were performed by the experimenter. The raw data and calculated overall values are given in Appendix D.

The reliability of evaluations across session was operationalized in two ways: in terms of a mean absolute deviation (MABS) measure and a Pearson's correlation coefficient. The mean absolute deviation (MABS) was chosen because it is an appropriate measure to examine the size of variation in the evaluation and is proportional to the standard deviation. The MABS values were calculated for each level of decomposition, for each subject. The MABS was defined for each individual subject as follows:

$$\text{MABS} = \sum_{i=1}^{6} \left| V_{i1} - V_{i2} \right| / 6,$$

where

V_{i1} = overall value of alternative i on session 1,

V_{i2} = overall value of alternative i on session 2.

Pearson's **r** values were also calculated for each subject by correlating the overall evaluations for the six alternatives between session 1 and session 2. Although Pearson's **r** is a less sensitive measure than the MABS to the size of variation, it was included in this study because it is one of the most common measures of interval scale convergence across occasions, methods, and multiple raters (Lyness & Cornelius, 1982). Pearson's **r** may also have a more practical meaning than MABS, because in real decision making situations, the order of alternatives could be more important than the actual size of variation.

4.6 Results

Table 4-4 shows the computed MABS and Pearson's **r** values for each subject and decomposition level, including their averages across the subjects. Using the two measures, three kinds of analyses were performed. First, to examine the overall effects of decomposition level on the dependent measures a one-way analysis of variance was performed. This analysis was done by two sub-steps: first performing a multivariate analysis of variance (MANOVA) for the two measures as a group and then conducting an individual analysis of variance (ANOVA) for the measures that showed a significant effect in the MANOVA. Second, a post-hoc multiple comparison test was performed for the measure to test the significance of differences for all possible pairs of the decomposition levels. Finally, a trend analysis was conducted for the measures

Table 4-4 The MABS and Pearson's **r** Values of the Job Evaluation Experiment.

Subject	MABS				Pearson's **r**			
	Decomposition Level				Decomposition Level			
	0	1	2	3	0	1	2	4
1	16.667	13.667	6.676	7.459	0.448	0.669	0.683	0.621
2	12.500	13.715	6.344	10.149	0.790	0.475	0.861	0.780
3	19.167	8.105	7.879	6.752	0.508	0.968	0.792	0.882
4	7.500	4.788	3.588	5.048	0.869	0.929	0.951	0.903
5	16.167	2.762	7.836	5.174	0.704	0.935	0.901	0.933
6	24.167	16.946	3.734	6.542	0.740	0.772	0.955	0.709
7	4.667	9.954	6.232	2.975	0.623	0.765	0.672	0.803
8	9.667	4.119	4.416	11.109	0.061	0.356	0.722	0.947
9	25.833	17.568	14.591	5.429	0.598	0.640	0.785	0.875
10	17.167	5.765	4.715	6.490	0.416	0.962	0.958	0.862
11	10.000	13.102	7.811	4.357	0.894	0.961	0.833	0.931
12	8.333	8.135	11.344	7.474	0.918	0.801	0.922	0.813
13	13.333	3.333	7.252	3.654	0.545	0.947	0.412	0.682
14	9.167	9.286	8.027	6.975	0.096	0.387	0.519	0.945
15	4.167	12.576	5.053	5.071	0.981	0.788	0.814	0.878
16	4.167	3.820	3.747	7.305	0.831	0.653	0.733	0.503
17	10.000	6.667	6.486	2.896	0.690	0.667	0.576	0.924
18	19.000	8.619	8.192	6.835	0.727	0.511	0.800	0.752
19	5.833	5.992	3.158	5.125	0.781	0.491	0.844	0.650
20	10.000	6.354	4.540	6.156	0.291	0.241	0.863	0.720
21	16.667	11.508	10.232	7.032	0.646	0.182	0.433	0.333
22	12.500	8.631	8.145	6.144	0.619	0.657	0.954	0.906
23	6.500	4.612	3.058	4.499	0.916	0.771	0.323	0.384
24	6.667	12.154	8.097	3.145	0.694	0.898	0.935	0.992
Mean	12.076	8.841	6.715	5.991	0.641	0.684	0.760	0.780

to examine the pattern of change in the dependent measures with respect to the level of decomposition.

For all the statistical analyses, a log transformation was applied to the MABS measure and the Fisher **r**-to-z transformation was applied to the Pearson's **r** as follows:

$$MABS' = Log_{10}MABS$$

and

$$z = \frac{1}{2}\log_e\left(\frac{1+r}{1-r}\right).$$

These transformations were applied so the measures would more closely approximate the normality assumption required for the ANOVA and trend analysis.

The test results were compared with the results from the analytical steps with respect to the general trend and sensitivity of the reliability to the level of attribute decomposition.

4.6.1 Multivariate Analysis of Variance

For the purpose of examining if the two dependent measures as a whole were sensitive to changes in the independent variable, a multiattribute analysis of variance (MANOVA) was performed. The data were analyzed using the "GLM" procedure of the Statistical Analysis System (SAS) computer package (SAS Institute, 1990, pp. 891-996). The GLM procedure calculated four criterion values and their transformed F values for the test.

Table 4-5 summarizes the results of MANOVA for the decomposition level effect. The MANOVA results showed the MABS and Pearson's **r** measures, as a group, were statistically significant for the level of decomposition, with $F(6,136) = 4.41$, $p = 0.0004$ for the Wilk's criterion. These results mean that at least one of the two dependent measures is significantly sensitive to the level of decomposition. The correlation between the MABS and Pearson's **r** measures was -0.33.

4.6.2 Univariate F tests

Subsequent to the MANOVA, a single analysis of variance (ANOVA) was performed on each individual dependent measure. These individual ANOVAs were also computed by the GLM procedure of the SAS computer package. Tables 4-6 and 4-7 present the results of the univariate ANOVAs for each of the two dependent variables.

The level of decomposition showed a significant effect on the MABS ($F(3,69) = 9.50$, $p = 0.0001$), while it did not show a significant effect on the Pearson's **r** ($F(3,69) = 2.30$, $p = 0.08$). As an aid in interpretation, plots of the means across subjects for the two dependent measures appear in Figures 4-2 and 4-3. Both plots show a trend in the direction of increasing reliability, i.e., a decrease in MABS and an increase in Pearson's **r**, as decomposition level increases. However, the change in Pearson's **r** is not large enough to show statistical significance.

Table 4-5 Summary of MANOVA Results

Statistic	Value	F	Num df	Den df	p
Wilks' Lambda	0.7008	4.410	6	136	0.0004
Pillai's Trace	0.2995	4.052	6	138	0.0009
Hotelling-Lawley Trace	0.4264	4.762	6	134	0.0002
Roy's Greatest Root	0.4252	9.780	3	69	0.0001

Note. The analysis was performed using the log-transformed values for MABS and Fisher's z values for Pearson's **r**.

Table 4-6 Summary of ANOVA Results for MABS Measure

Source	df	MS	F	p
Subjects	23	0.0767		
Decomposition	3	0.3311	9.50	0.0001
Error	69	0.0348		
Total	95			

Note. The analysis was performed using the log-transformed values.

Table 4-7 Summary of ANOVA Results for Pearson's **r** Measure

Source	df	MS	F	p
Subjects	23	0.4458		
Decomposition	3	0.5086	2.30	0.0849
Error	69	0.2211		
Total	95			

Note. The analysis was performed using Fischer's **z** statistic.

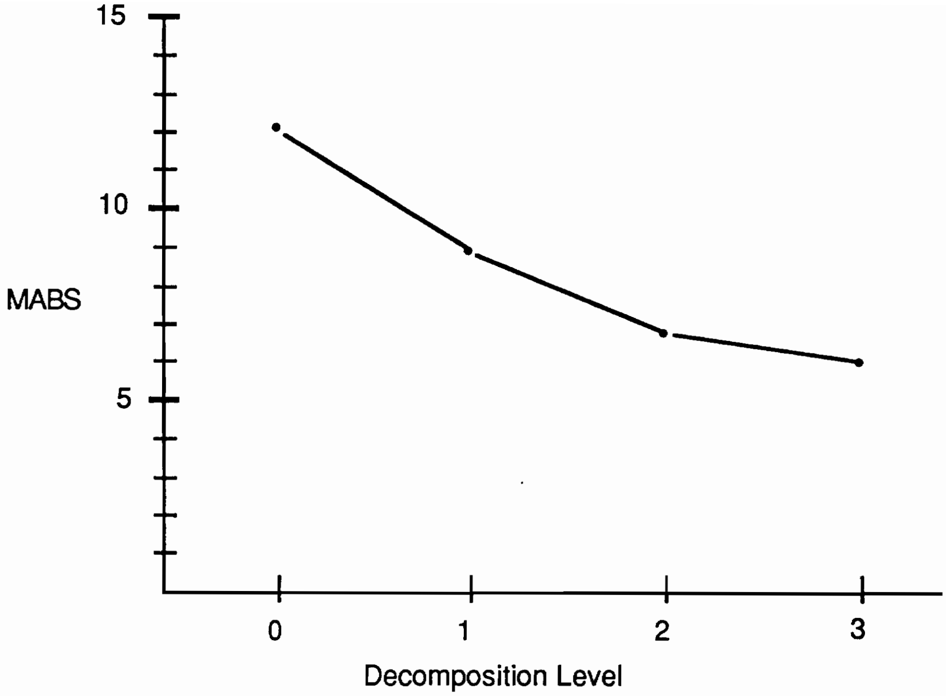

Figure 4-2 Plot of Means for MABS Measure

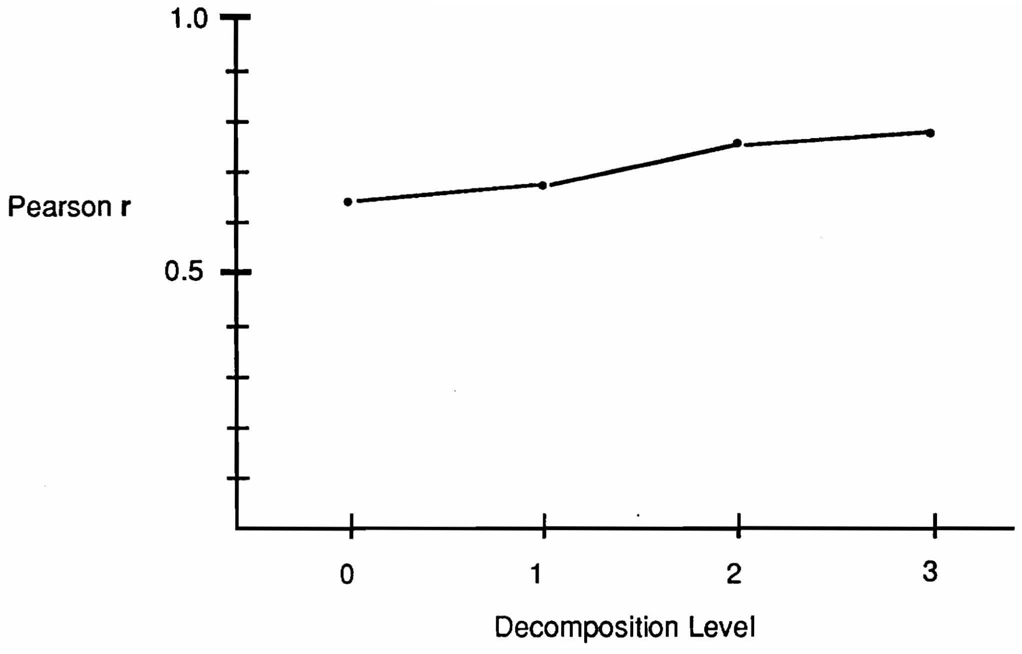

Figure 4-3. Plot of Means for Pearson's **r** Measure

4.6.3 Individual Comparisons among Means

Since the ANOVA for MABS measure showed a significant effect, a Newman-Keuls post hoc analysis was subsequently performed to determine between which conditions the significant difference existed for the MABS measure (Table 4-8). The test indicated that decomposition level 1 resulted in significantly more reliable evaluations than decomposition level 0 (holistic evaluation). However, the test showed that the reliabilities between levels 1 and 2, and between levels 2 and 3 did not differ significantly from each other. The results indicate that a larger improvement in reliability would be achieved in the early stage of decomposition than in the late stages.

4.6.4 Trend Analysis

To examine the shape of change in the MABS measures with respect to decomposition level, a trend analysis was performed using the GLM procedure of the SAS package. As shown in Table 4-9, the change of MABS showed a linear trend with respect to the level of decomposition. It can be inferred that the changing pattern would follow a quadratic trend, if the level of decomposition is represented by the number of attributes, because the number of attributes tends to increase exponentially with the hierarchical level of decomposition.

Table 4-8 Results of Student-Newman-Keuls Test for MABS Measure

Decomposition			
Level 0	Level 1	Level 2	Level 3
12.076	8.841	6.715	5.991

Note. A Log-transformation was applied to the measures for analysis. Means sharing a common double-underline are not significantly different, at Alpha = 0.05.

Table 4-9 Summary of Trend Analysis Results for MABS Measure

Contrast	df	Contrast SS	MS	F Value	p
Linear	1	0.9616	0.9616	27.60	0.0001
Quadratic	1	0.0301	0.0301	0.86	0.3559
Cubic	1	0.0016	0.0016	0.05	0.8325

Note. This analysis was performed using the Log-transformed values from the MABS values.

4.7 Discussion of Experimental Results

Different conclusions were reached depending on the way reliability was operationalized. When reliability was measured by a mean absolute deviation measure, decomposition resulted in improved intrarater reliability. However, when reliability was measured by a correlation coefficient, the level of decomposition did not appear to be significant. A possible reason for the disagreement using Pearson's **r** as compared to the MABS in operationalizing intrarater reliability can be explained as follows. At first it would appear that the two measures would overlap quite a bit, resulting in similar conclusions. However, the two measures can be shown to be relatively independent. That is, it is possible to have two sets of evaluation scores that exhibit low variation (or low absolute deviation) but are uncorrelated. Likewise, it is possible to have two sets of scores that are highly correlated, and yet quite divergent in the scores. In this study, the empirical correlation between the MABS and Pearson's **r** was -0.33. The major conceptual difference between Pearson's correlation measure and the MABS measure lies in the importance attached to the units involved. Pearson's correlation coefficient is more sensitive to the rank order agreement between two variables than the actual deviations in values. The MABS measures, on the other hand, indicate the actual size by which two sets of scores differ. This measure does not, however, reflect the pattern similarity between two sets of evaluation scores. It would appear, therefore, that each of these measures provides unique information.

Pearson's correlation coefficient was used in this experiment because it is a commonly used measure for test-retest reliability. Pearson's **r** is based on differences between scores and their means. However, from a practical point of view those differences may not be really meaningful in choosing the best alternative. Therefore, a correlation measure that indicates the degree of order agreement would be more appropriate to be used in this type of experiment. Possible candidate measures include the two commonly used measures of relationship for ordinal data: Spearman's rank-order correlation, often called Spearman's rho, and Kendall's tau. The rankings recorded by the subjects can be used for calculating those correlation coefficients.

The experimental data also can be used for obtaining some insights for using a different weighting scheme. In this experiment, the overall evaluation of each alternative was derived summing the individual single-attribute evaluations scaled by the attribute weights that were assessed by the subjects. However, we consider an alternative weighting scheme: equal or unit weighting. This unit scheme is the case where the overall evaluations are the unweighted average of the single-attribute evaluations. The equal weights are successfully employed in a wide range of typical prediction problems (Dawes & Corrigan, 1974; Einhorn & Hogarth, 1975). According to Einhorn and Hogarth (1975), equal (or unit) weighting is a viable alternative for weights determination because equal weights: (1) are not estimated from the given information and therefore do not "consume" degrees of freedom; (2) are "estimated" without error (i.e., they have no standard errors); (3) cannot reverse the "true" relative weights of the components.

For the same reason, equal weights can also be considered in decision models. Weights for MAUA are usually obtained judgmentally, often requiring rather difficult judgments. Therefore, the equal weights could be used for MAUA to the extent that difficult judgments are eliminated while decisions are little changed (Stillwell, Seaver, & Edwards).

The experimental data were analyzed with the equal weighting scheme to acquire insights on the reliability when using the equal weighting scheme. The overall evaluations of each job alternative were calculated by the simple average of the single-attribute evaluations. For these overall evaluations the same analyses were performed as the weighted additive evaluations. The results of statistical analyses using the equal weighting scheme are summarized in Appendix E. The results showed that the MABS measures decreased faster than in the differential weighting case, and Pearson's **r** decreased significantly, with respect to the level of decomposition. This outcome means the equal weighting scheme can reduce the random variability in evaluations with decomposition more easily than the judgmental weighting. On the other hand, the results also mean that the reliability decreases when it is measured by the correlation. This may be the result of the systematic biases caused by considering the attributes are equally important where they are not, for the experimental task. Therefore, the use of equal weighting should be determined with a trade-off between increased precision and degraded order agreement.

The degree of impact for each successive level of decomposition appeared to diminish when the reliability was measured by MABS. Based on this a non-linear shape, such as a convex function, in the MABS was expected.

However, the trend analysis results did not show a non-linear trend in the data. The failure in finding non-linearity might be due to the small number of levels used. For a more dependable conclusion on the shape of the change, empirical studies with a larger number of decomposition levels are needed.

4.8 Comparison to Theoretical Results

The analytical study and the experimental study examined the effects of decomposition level using different measures of reliability: STD, MABS, and Pearson's **r**. Therefore, the results from the two studies cannot be compared directly. A reasonable comparison can be achieved by addressing the relationships between the measures.

The reliability measured by MABS indicated results similar to the analytical results. Both the STD and MABS suggested a significant impact of decomposition level on reliability. They also showed a decreasing rate of change in reliabilities with respect to level of decomposition. This agreement can be expected from the similarity of the two measures. The two measures are proportional and interchangeable for the case of relatively small variation of the scores (Yoon & Kim, 1989). The actual values of the MABS measures look "reasonable." The average ratios of the MABS values in the four decomposition levels to the MABS of decomposition level 0 are 1, 0.732, 0.556, and 0.496, at decomposition levels of 0, 1, 2, and 3, respectively. Figure 4-4 depicts a plot of the ratios. The shape of the plot looks similar to that of the best-case plot in Figure 3-3.

However, the reliability measured by Pearson's **r** does not completely match the analytical results. While the composite variance in each alternative evaluation was found to decrease in the theoretical study, Pearson's **r** did not show statistical significance with the level of decomposition. This lack of agreement is mainly due to the same reason as that discussed in comparing the reliabilities measured by the MABS and Pearson's **r** in the preceding section. A correlation coefficient is not sensitive to the size of variance in each alternative evaluation. No change in correlations occur even when decomposition significantly reduces the variance in alternative evaluation. This has an important practical implication. Even though decomposition can make each alternative evaluation more precise, the priority order of the alternatives may not change. This phenomenon seems to occur in the cases when alternatives are relatively "distant" from each other.

However, the lack of agreement can be alleviated if the characteristics of choice alternatives are considered. When alternatives are very close in value, the precision in each alternative evaluation may have a substantial impact on the priority order of the alternatives.

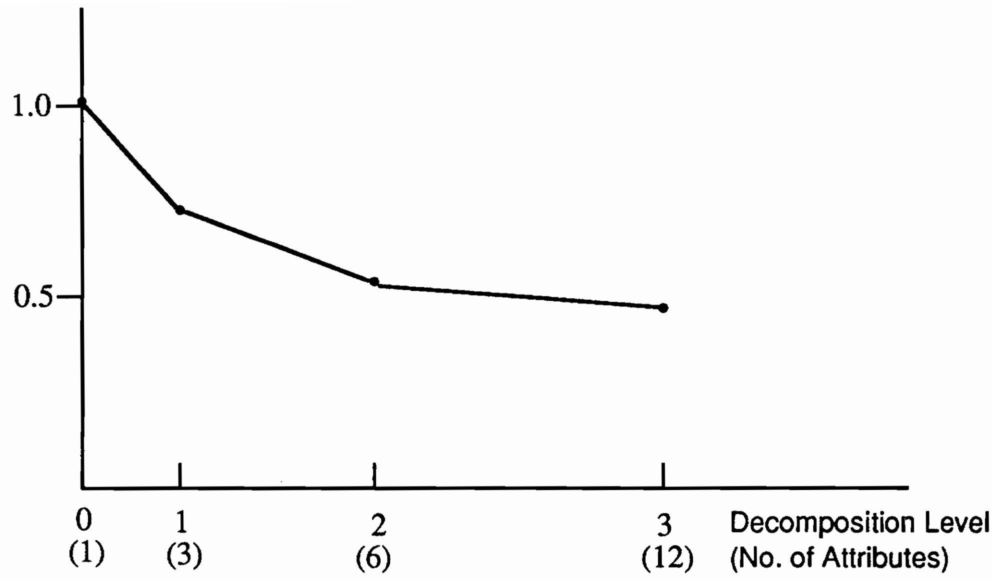

Figure 4-4 Plot of the Ratio of MABS at each Decomposition Level to the MABS at Decomposition Level 0

In summary, the experimental results generally support the theoretical results but the practical utility of the theoretical results are somewhat inconclusive. The results from both the theoretical and experimental parts suggest that decomposition yields more reliable (in terms of intrarater convergence) evaluations of choice alternatives. However, the precise nature of the impact differed, depending on the measures used for reliability. While the MABS measures supported the change in variance due to decomposition predicted in the theoretical study, Pearson's correlation measures did not show a complete agreement with the theoretical results, suggesting a practical utility issue.

5. Conclusion

5.1 Primary Findings

In this research the effects of decomposition level on the intrarater reliability in multiattribute alternative evaluation were investigated theoretically and empirically using an analytical method of error propagation and an experiment of job alternative evaluation. The primary results of the research are described below.

1. Decomposition yields more reliable (in terms of intrarater convergence) evaluations of multiattributed choice alternatives, as long as the attributes can be decomposed so that an additive composition rule can be applied. In most cases, the variances in the alternative evaluations theoretically follow a decreasing function with respect to the level of decomposition.

2. The marginal effect of decomposition level decreases as the decomposition level increases. That is, the reliability improvement from an additional decomposition is smaller in high decomposition than in low decomposition.

3. The impact of decomposition level is largely contingent on the characteristics of the attributes and component assessments. The means and variances of single attribute ratings and weightings can be a determinant of the

decomposition level impact. The more precise the single-attribute values and weights are, the larger the improvement in reliability achieved by decomposition. When the single-attribute values and weights are equally distributed, reliability can be greatly improved through decomposition.

4. The correlation between repeated evaluations is not sensitive to the level of decomposition. Therefore, decomposition may not improve the consistency of preference ordering of the alternatives, that is often more important in practical choice decision.

5.2 Implications for MAUA Application

While there are many open issues in implementing decomposition, an important issue is how much detail to decompose the problem. In multiattribute evaluation practice, the extent of decomposition is left to the discretion of the analyst. What are the implications of the results of this study for determining the appropriate level of decomposition in the practice of multiattribute alternative evaluations? The results suggest that considerations of random variance in alternative evaluation alone will generally favor highly disaggregated analyses. That is, for the purpose of precision in alternative value assessments, the judgment should be decomposed in as much detail as possible.

However, it can not be presumed that a high degree of decomposition would always be preferred. Common sense dictates that overly disaggregate models may introduce errors of their own due to the omissions of relevant attributes or the lack of highly disaggregate data. Therefore, high levels of decomposition can be preferred only when the decomposed parts are non-redundant and comprehensive of all relevant value dimensions. If these conditions are violated, the overall variation of a decomposed evaluation can be aggravated. Achieving both completeness and non-redundancy, however, is a difficult task.

In addition, the level of decomposition used in practice will often be constrained by other factors such as time and effort. A decomposed evaluation procedure requires more time and effort than a holistic evaluation. The effort in attribute structuring and multiple judgments should be a factor to be considered in determining the appropriate level of decomposition.

A high degree of decomposition may not always be desirable for other reasons. In practical choice problems, excessive precision will not be needed. If the objective of an evaluation is to choose the best alternatives, precision beyond a certain level may not be helpful because it will have no effect in altering the order of alternatives. Therefore, a lower level of decomposition will be accepted when the alternatives are non-competitive, while high decomposition is beneficial when the alternatives are close in value.

To practitioners, this research suggests a careful analysis of the appropriate level of attribute decomposition before a decomposed evaluation procedure is applied. Following are some concrete guidelines for practitioners interested in structuring multiattribute decision tasks to improve consistency.

1. When the alternatives in consideration are competitive, a high decomposition would be useful for the purpose of increasing power to discriminate the close alternatives. On the other hand, when the alternatives are

relatively distant in value from each other, a lower decomposition can be acceptable.

2. The attributes should be formulated to be equally important for a decomposition to attain a larger reduction in variance.

3. The analyst should try to verify and maintain the independence of the component evaluations. Dependencies among the single-attribute evaluations could undermine the worth of decomposition.

4. It may be worthwhile to carry out an analysis with alternative sets of attributes, if there is doubt about the appropriate level of detail.

5.3 Contribution of the Research

Most researchers and practitioners have recognized the importance of attribute structuring on the effectiveness of decomposed MAUA. This research is an early, if not the only, attempt to more systematically investigate the problem decomposition issue in MAUA, which has been largely regarded as an "art".

This research has expanded the current knowledge on the impact of decomposition in preferential judgment for choice. While several issues related to decomposition have been addressed in recent studies (e.g., Kleinmuntz, 1990; Mosleh & Bier, 1991), the specific issue of decomposition level impact has not been extensively investigated in the area of decision analysis. This research has provided some knowledge on the specific issue of decomposition level impact, which has been considered as an important factor in implementing a decomposition strategy.

This research provides an initial step toward the development of a more general theory of decomposition. The analytical framework can provide general insights into the decomposition effects, on which experimental studies are prevalent.

5.4 Recommendations for Future Research

Several possible topics for future research, stemming from the present research, include the following.

1. In predicting the possible effect of decomposition level on the variances of alternative evaluations, the analytical study has derived theoretical bounds for the variances. In practice, however, actual variances are less likely to fall in the regions near the boundaries. A study is needed that provides additional insights about the practical region of the variance through decomposition. Simulations may be needed for such research.

2. Similar studies for other value composition models are recommended. This research addressed the decomposition level effect using the linear additive composition model. Although nonlinear composition models may require extremely complex analysis and their practical usefulness is uncertain, the quasi-additive model and multilinear model (Fischer, 1979), at least, are researchable.

3. This research addressed only the random component of the variability in evaluation. Studies on the impact of decomposition on systematic variation are recommended. There may be systematic variation associated with choosing a different level of detail. For example, there are problems with models that incorporate too few attributes (Aschenbrenner, 1977; Barron and Kleinmuntz, 1986). An analytical framework that can deal with systematic variation is needed.

4. More empirical studies are needed with different decomposed evaluation procedures. This research used a simple and popular multiattribute evaluation procedure. As mentioned in Chapter 2, there exist several methods and approaches for decomposition. To extend the usefulness of the theoretical results much empirical work needs to be done using the different decomposed evaluation procedures.

5. Studies are recommended on the interaction effects of decomposition level and problem characteristics on evaluation outcomes. The role of task characteristics in determining the impact of attribute decomposition should be investigated. Attribute decomposition effects may be contingent on the task to be performed. Decomposing may not provide equal benefits to every decision problem. This fact presents an important research problem. The problem is to identify the conditions under which attribute decomposition becomes beneficial. Decomposition impact should be studied over systematic variations in task characteristics such as complexity, familiarity, attributes' properties, and the purposes of the task.

6. Decomposition effects should be evaluated with respect to the multiple criteria of decision effectiveness. Because an MAUA application serves many purposes other than simply deriving an aggregate value measure, it is necessary to examine the attribute decomposition effects using other criteria, including increased understanding of the complexities of the problem, as well as reliability and validity.

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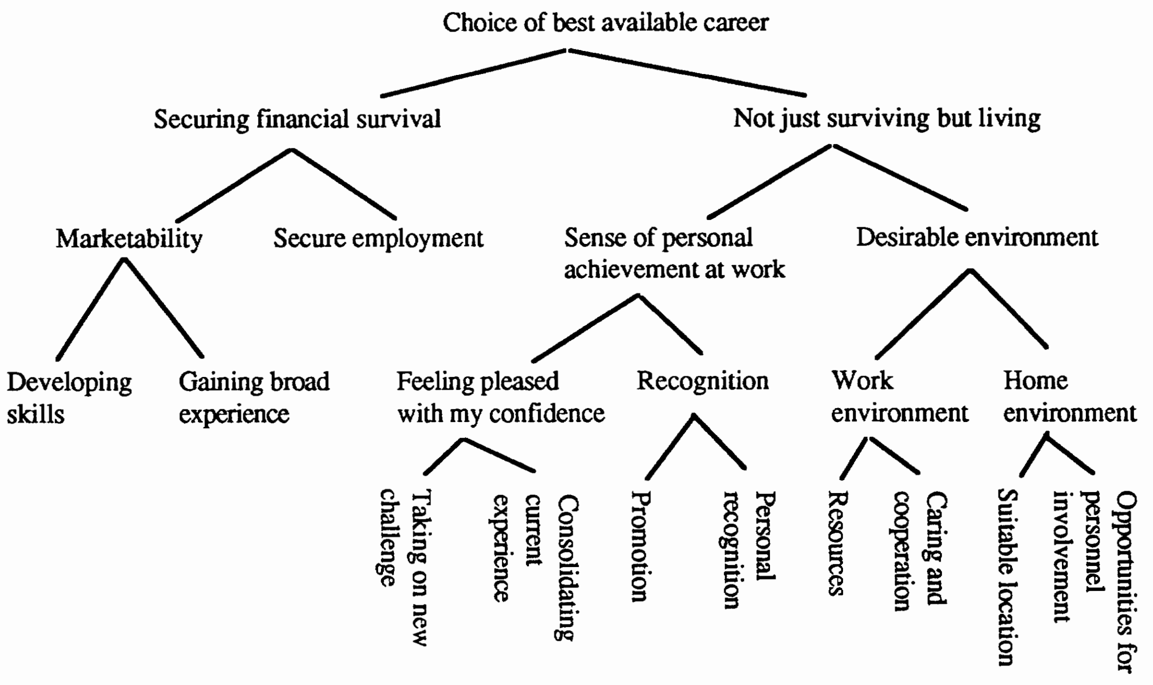
Appendix A. The Attributes for Career or Job Evaluation in the Literature

1. Wooler (1982): Attributes Hierarchy for Evaluating Career Choice Options



2. Weber, Eisenführ, and von Winterfeldt (1988): Value Tree for Job Evaluation

- Job security
  - Stability of the firm
  - Personal job security
- Income
  - Annual starting salary
  - Future salary increase
- Career opportunities
  - Educational opportunities
  - Image of the firm

3. Fischer (1977) : Attributes for Evaluating Job Offers

- City
- Salary
- Type of work

4. Krantz (1988) : Criteria for Job Rating

- Environment
- Income
- Outlook
- Stress
- Travel Opportunities
- Physical Demands
- Extras
- Security

Appendix B. Experimental Packet

- Overview of the Experiment
- Informed Consent Form
- Scoring Instructions
- Job Alternatives
- Evaluation Scoring Sheets

Overview of the Experiment

One common strategy in evaluating complex alternatives is to decompose the problem into a number of simpler judgments and then combine the judgments into an overall evaluation. In a typical decomposed evaluation procedure, an alternative is expressed on a number of value-relevant attributes (criteria or dimensions), and is evaluated with respect to each attributes. Then an overall evaluation is derived by a weighted sum of the dimensional evaluations.

The purpose of this experiment is to examine the effects of level of decomposition on the alternative evaluations by such a decomposed evaluation procedure. The experiment will examine the intrarater reliability (consistency) of a job alternative evaluation with different levels of decomposition.

In this experiment, you are requested to evaluate six hypothetical job alternatives using four different scoring sheets, according to the procedure described in the "Scoring Instructions." The four scoring sheets represent four different levels of decomposition. Your task is to rate the values (attractiveness or worth) of the alternatives on the individual attributes and determine the importance weights of the individual attributes. Combining your scores into an overall value will be done by the experimenter.

INFORMED CONSENT FORM

This constitutes informed consent by you to participate in this study. Please read it carefully, and then sign it below.

As a participant in this experiment, you have the following rights.

1) You have the right to withdraw from the study at any time and for any reason by simply notifying the researcher.

2) You have the right to inspect your data and withdraw them from the study if you wish. The data will be used only for scientific or educational purposes. Your data will be handled confidentially by the researcher. No one else will see your individual data with your name.

3) You have the right to be informed of any risks or discomforts associated with this experiment. There will be minimal risk in this study. That is, the risks of harm anticipated in this experiment are not greater than those encountered in daily life or during performance of routine psychological examinations or tests.

4) You may ask questions of the researcher at any time prior to data collection. All questions will be answered to your satisfaction subject only to the constraint that an answer will not pre-bias the outcome of the study. If bias would occur, with your permission an answer will be delayed until after the data collection, at which time a full answer will be given.

5) If you have any further questions about your rights as a participant, you may contact the chairman of the Institutional Review Board at VPI & SU, at 231-9359.

Before you sign this form, please make sure that you understand, to your complete satisfaction, the nature of the experiment and your rights as a participant. If you have any questions, please ask them of the experimenter at this time. Your signature below indicates that you have read this document in its entirety, that your questions have been answered, and that you consent to participate in this study.

Signature: ______________________________ Date: ____________________

Printed Name: ____________________________ Phone: ____________________

Address: ____

____

The research team for this study consists of Young Cho, Ph.D. Student, and Dr. C. P. Koelling, Associate Professor in the Department of Industrial and Systems Engineering. Your participation is appreciated and we hope that you will find the study a pleasant and interesting experience. The research team may be reached at the following phone numbers.

Young Cho	Office: 231-7822	Home: 951-4941
Dr. Koelling	Office: 231-6656	

Scoring Instructions

There are six job alternatives that are described on the included 5x8 inch cards. Please, assume you are offered the job alternatives and going to evaluate the alternatives based on your preferences. You are provided four evaluation scoring sheets. Using each of the scoring sheets, please evaluate the job alternatives according to the procedure described below.

1. Assessing Single-attribute Values

Rate the value of each alternative with respect to each attribute on a 0-100 scale, where 0 is defined as the minimum plausible value and 100 defined as the maximum plausible value. For each attribute, consider all the information under the attribute, and determine your subjective value score of the alternative. Note "minimum and maximum plausible" rather than "minimum and maximum." The minimum plausible value often is not total absence of the attribute. It is also not necessary that the worst of the given alternatives gets 0 score and the best alternative gets 100 score. That is, assign 100 to an alternative when its attribute level is fully satisfactory or desirable, and assign 0 to an alternative when its attribute level is not satisfactory at all. Assign in-between scores to the alternatives of which attribute levels are intermediate. Write the scores in the "Single-attribute Value" columns on the scoring sheets.

2. Assessing Attribute Weights (Skip this step when you evaluate the alternatives using the scoring sheet with one attribute "Overall Value".)

2-1. Rank the attributes in order of importance. Write the rankings in the "Rank" column on the scoring sheet.

2-2. Assign a score of 10 to the least important attribute. Determine the weight scores of the remaining attributes relative to the least important attribute. Consider these ratings as ratios, for example, if the next-least-important attribute is two times as important as the least important attribute, assign a score of "20" to reflect the ratio. Continue this ratio estimation for the next important attributes successively, up to the most important attribute. You can revise previous judgments during the process. Write the weight scores in the "Weights" column on the scoring sheet.

You can perform the step 1 and step 2 with no strict order. That is, you can revise your scores if you wish to do so during the process. However, you must use the scoring sheets in the provided order. Do not proceed to the next scoring sheet before completing the current scoring sheet.

Job Alternative 1

Work	**Content of Work**	**Duties:**	*Plans for optimum use of facilities, equipment, and personnel to improve industrial efficiency.*
		Stress:	*Quotas & deadlines: None, Competition: None.*
		Physical Demand:	*Low.*
	Working Conditions	**Working Hours:**	*45 hours/week.*
		Travel:	*10 trips per year, 20 days away per year.*
		Location of Employment:	*New York City, New York.*
Compensation	**Salary**	**Salary:**	*$31,000.*
	Benefits	**Benefits:**	*Semi-private office, company car, and health insurance.*
Outlook	**Career Opportunities**	**Promotion Level:**	*Experienced workers can advance to the positions of supervisors or managers.*
		Job Growth:	*46% (fast).*
	Security	**Firm Security:**	*No risk of bankruptcy.*
		Personal Security:	*Can not be fired.*

Job Alternative 2

- **Work**
  - **Content of Work**
    - **Duties:** *Plans and develops computer systems for businesses, scientific institutions, and other establishments.*
    - **Stress:** *Quotas & deadline: Moderate, Competition: None.*
    - **Physical Demand:** *Moderate*
  - **Working Conditions**
    - **Working Hours:** *48 hours/week.*
    - **Travel:** *8 trips per year, 8 days away per year.*
    - **Location of Employment:** *Houston, Texas.*
- **Compensation**
  - **Salary**
    - **Salary:** *$35,000.*
  - **Benefits**
    - **Benefits:** *Health insurance, free housing and meal, company car.*
- **Outlook**
  - **Career Opportunities**
    - **Promotion Level:** *Can advance to positions as senior programmer or data processing manager.*
    - **Job Growth:** *69% (very fast).*
  - **Security**
    - **Firm Security:** *Low risk (5%) of bankruptcy.*
    - **Personal Security:** *Low risk (2%) to be fired.*

Job Alternative 3

Work	Content of Work	**Duties:**	*Coordinates the activities of production departments of manufacturing firms.*
		Stress:	*Quotas & deadline: Moderate, Competition: Moderate.*
		Physical Demand:	*Heavy.*
	Working Conditions	**Working Hours:**	*56 hours/week.*
		Travel:	*24 trips per year, 47 days away per year.*
		Location of Employment:	*Detroit, Michigan.*
Compensation	Salary	**Salary:**	*$43,000.*
	Benefits	**Benefits:**	*Free housing and meal, company car, secretary, bonuses, health insurance.*
Outlook	Career Opportunities	**Promotion Level:**	*Can advance to positions as executive or top manager.*
		Job Growth:	*5% (very slow).*
	Security	**Firm Security:**	*Low risk (8%) of bankruptcy.*
		Personal Security:	*High risk (20%) to be fired.*

Job Alternative 4

Work	Content of Work	**Duties:**	*Prepares and analyzes financial reports to assist managers in businesses, industry, and government.*
		Stress:	*Quotas & deadlines: Moderate, Competition: Moderate.*
		Physical Demand:	*Low.*
	Working Conditions	**Working Hours:**	*40 hours/week.*
		Travel:	*12 trips, 20 days away per year.*
		Location of Employment:	*San Francisco, California.*
Compensation	Salary	**Salary:**	*$38,000.*
	Benefits	**Benefits:**	*None*
Outlook	Career Opportunities	**Promotion Level:**	*Can advance to positions as budget director, controller, or treasurer.*
		Job Growth:	35% (average).
	Security	**Firm Security:**	*Some risk (15%) of bankruptcy.*
		Personal Security:	*Low risk (4%) to be fired.*

Job Alternative 5

Work	Content of Work	Duties:	*Negotiates contracts with clients for advertising in publications on radio and television.*
		Stress:	*Quotas & deadlines: Moderate, Competition: High.*
		Physical Demand:	*Moderate.*
	Working Conditions	Working Hours:	*50 hours/week.*
		Travel:	*85 trips per year, 140 days away per year.*
		Location of Employment:	*Washington, D. C.*
Compensation	Salary	Salary:	*$44,000.*
	Benefits	Benefits:	*Bonuses, company car.*
Outlook	Career Opportunities	Promotion Level:	*Can advance to positions as advertising manager or director.*
		Job Growth:	*15% (slow).*
	Security	Firm Security:	*High risk (40%) of bankruptcy.*
		Personal Security:	*High risk (30%) to be fired.*

Job Alternative 6

Work	**Content of Work**	**Duties:**	*Collects and evaluates data to make recommendations to businesses concerning trends in consumer and business purchasing.*
		Stress:	*Quotas & deadlines: Heavy, Competition: High.*
		Physical Demand:	*Low.*
	Working Conditions	**Working Hours:**	*46 hours/week.*
		Travel:	*30 trips per year, 85 days away per year.*
		Location of Employment:	*Atlanta, Georgia.*
Compensation	**Salary**	**Salary:**	*$41,000.*
	Benefits	**Benefits:**	*Company car, bonuses, life insurance*
Outlook	**Career Opportunities**	**Promotion Level:**	*Experienced workers can advance to the positions of market research director and administrator.*
		Job Growth:	*0 %.*
	Security	**Firm Security:**	*Low risk (8%) of bankruptcy.*
		Personal Security:	*Some risk (12%) to be fired.*

Evaluation Scoring Sheet # 1

Value Scores

Attribute	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6
Overall Value						

Evaluation Scoring Sheet # 2

Single-attribute Values

Attributes	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6
Work						
Compensation						
Outlook						

Attribute Weights

Ranking	Weight

Evaluation Scoring Sheet # 3

Single-attribute Values

Attributes	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6
Content of Work						
Working Conditions						
Salary						
Benefits						
Career Opportunities						
Security						

Attribute Weights

Ranking	Weight

Evaluation Scoring Sheet # 4

Single-attribute Values

Attributes	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6
Duties						
Stress						
Physical Demand						
Working Hours						
Travel						
Location of Employment						
Salary						
Benefits						
Promotion Level						
Job Growth						
Firm Security						
Personal Job Security						

Attribute Weights

Ranking	Weight

Appendix C. Pilot Test of the Experiment

A pilot test was conducted, using a preliminary design of the experiment, for the purpose of acquiring information on the appropriateness of the task design. Although the experimental materials used in this pilot study were a little different from those used in the main experiment, the basic structures were the same.

Subjects

Six graduate students served as subjects of the pilot test. All the subjects had no previous knowledge or experience in the multiattribute evaluation procedure. Each subject was assigned to a randomly ordered sequence of decomposition levels (Table A-1).

Procedure

The pilot test was conducted at the office of the experimenter. Subjects were told that the purpose of the study was to compare the consistencies in the evaluations using different types of evaluation scoring forms. However, they were not told that identical job alternatives were used in both sessions until the end of second session. Different numberings on the alternatives were used in the second session. The time spent in evaluation was not controlled, but the starting and ending times were recorded in order to estimate a proper time in the main experiment. After the second evaluation session, the experimenter had a free discussion with individual subjects.

Results

Dependent Measures

The experimental data were analyzed less formally because the experiment was not controlled sufficiently and the number of subjects was not enough to apply a statistical analysis.

The MABS appeared to decrease as the level of decomposition increased (See Table A-2 and Figure A-1). However, for Pearson **r**, a noticeable trend did not appear (See Table A-3 and Figure A-2). The results showed that different conclusions might be reached in the main experiment depending on the way reliability was operationalized. The mixed results seemed to be caused by a conceptual difference between absolute deviation measures and correlation measures in the importance attached to the units involved. The Pearson correlation coefficient is more sensitive to the rank order agreement between two sets of scores than to the actual size of difference. Therefore, MABS is a more sensitive measure for the magnitude of variability in evaluations.

Table A-1 The Sequences of Decomposition Levels presented to the Subjects.

Subject	Order of Decomposition Levels			
K. L.	3	1	0	2
G. C.	1	0	2	3
B. C.	3	0	2	1
C. K.	3	2	1	0
S. A.	2	3	0	1
Y. K.	0	1	2	3

Table A-2 MABS Measures for Individual Subjects and Their Average

Subject	Decomposition Level			
	0	1	2	3
K. L.	0.05	0.044	0.045	0.07
G. C.	0.12	0.122	0.067	0.057
B. C.	0.106	0.029	0.025	0.015
C. K.	0.05	0.035	0.067	0.05
S. A.	0.24	0.096	0.082	0.047
Y. K.	0.05	0.036	0.032	0.021
Mean	0.103	0.06	0.053	0.043

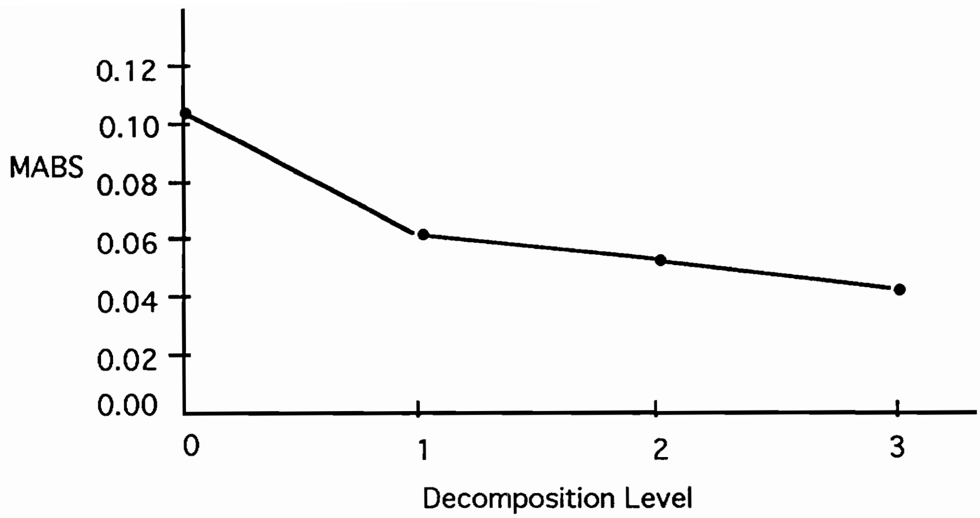


Figure A-1 The Plot of the Average MABS with respect to the Level of Decomposition.

Table A-3 Pearson r Measures for Individual Subjects and Their Mean

Subject	Decomposition Level			
	0	1	2	3
K. L.	0.958	0.688	0.767	0.752
G. C.	0.941	0.979	0.856	0.954
B. C.	0.807	0.999	0.957	0.999
C. K.	0.910	0.892	0.881	0.910
S. A.	0.869	-0.665*	0.863	0.654
Y. K.	0.869	0.578	0.277	0.702
Mean	**0.893**	**0.578**	**0.767**	**0.828**
		0.827 **		

* An extraordinary datum.
** A mean after excluding the extraordinary datum.

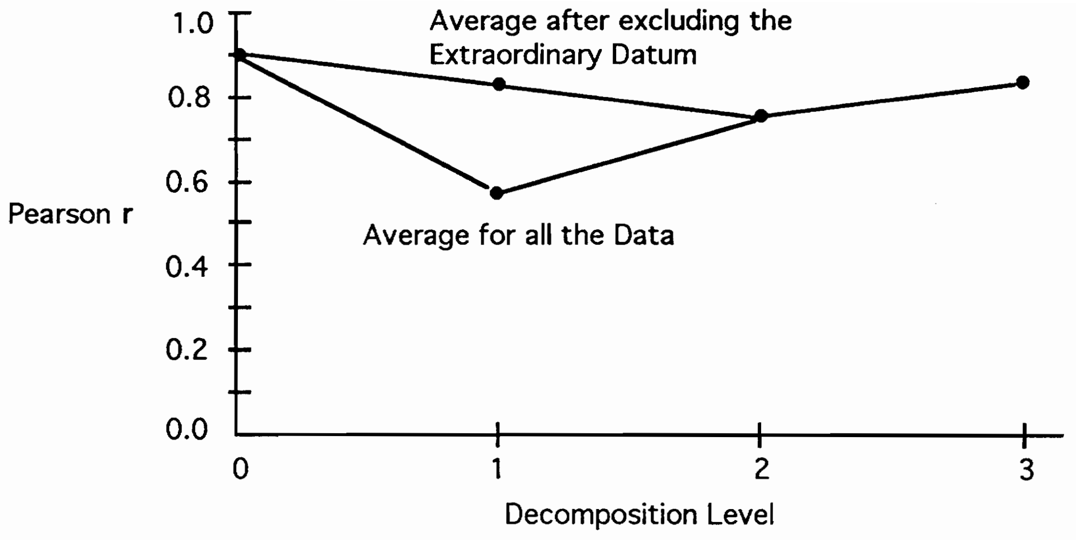


Figure A-2 The Plot of Pearson **r** with respect to the Level of Decomposition.

Design Related Findings

Amount of Task Load

The net time spent in one evaluation session, excluding the introduction time, varied from 30 minutes to 53 minutes, with an average of 40.4 minutes. Therefore, considering the average time, one more job alternative could be added in the evaluation task, and about one hour would be an appropriate time to be allowed for each evaluation session.

Between-session Interval

The interval between the test and re-test sessions should be as short as possible to avoid a systematic shift in preference over time. However, there must also be sufficient time before retesting, to avoid a memory effect. In this pilot test, the between-session intervals ranged from 10 days to 17 days with an average of 13.5 days. All the subjects stated that they could not remember the scores they gave on the first session, at the time of the second session. Therefore, an interval of about 2 weeks was regarded as an appropriate interval for the experiment.

Scoring Instructions

Some parts of the instructions were found unnecessary and could cause confusion for the subjects. Attribute weight normalizing (step 2-3) and single-attribute value combining (step 3) were unnecessary components of the scoring instruction because those steps were done by the experimenter.

Job Alternative Descriptions

During attribute rating and weighting, the subjects repeatedly compared the alternatives on the level of attributes. In this pilot study, the job descriptions were printed on normal letter size paper. To aid subjects in handling the alternatives more conveniently, a device (e.g., a paper card) was needed.

Scoring Sheets

The scoring sheets also contained two unnecessary parts. The "Normalized Weights" column and "Overall Value" row should have been deleted form the scoring sheets.

Materials Used in the Pilot Study

Overview of the Experiment

One common strategy in evaluating complex alternatives is to decompose the problem into a number of simpler judgments and then combine the judgments into an overall evaluation. The purpose of this experiment is to examine the effects of the level of decomposition on the final outcome of alternative evaluations through such a decomposed evaluation strategy. The experiment will examine the intrarater reliabilities (consistency) of job alternative evaluations when using different sets of attributes (evaluation criteria) in the level of detail through a decomposed evaluation procedure called SMART (simple multiattribute rating technique).

In the SMART procedure, a decision maker evaluates each alternative with respect to each attribute and assesses the relative importance weight of each attribute used. Then the single-attributed ratings and weights are combined into an overall evaluation.

In this experiment, you will be given five hypothetical job alternatives and four attribute sets. You will be requested to evaluate the job alternatives using each of the attribute sets according to the procedure described in the "Experimental Instructions" on the next pages.

The experiment involves two sessions separated by two weeks. The experimental procedures in the two sessions will be the same. However, you will be requested not to try to match your responses on the second session to your original responses, but rather to make judgments as you feel at the current time.

Experimental Instructions

There are six job alternatives that are described on 12 attributes. Please assume that you are provided with the job alternatives and going to evaluate the attractiveness (or value) of them based on your personal preferences.

You are provided four evaluation scoring sheets. Using each of the job evaluation scoring sheets, please evaluate the job alternatives according to the procedure described below.

1. Assessing Single-attribute Values

Rate the value of each alternative with respect to each attribute on a 0-100 scale, where 0 is defined as the minimum plausible value and 100 defined as the maximum plausible value. For each attribute, consider all the information under the attribute, and determine your subjective value score of the alternative. The least favorable alternative does not necessarily get 0 score, and the most attractive alternative does not necessarily get 100 score. That is, assign 100 to the alternative when its attribute level is fully satisfactory or desirable, and assign 0 to the alternative when its attribute level is not satisfactory at all. Assign an in-between score to the alternatives of which attribute levels are intermediate.

2. Assessing Attribute Importance Weights (Skip this step when you evaluate the alternatives using the attribute set composed of one attribute "Overall Attractiveness".)

2-1. After reviewing the information under each attribute, rank the attributes in order of importance. Write the rankings in the "rank" column on the "Job Evaluation Scoring Sheet."

2-2. Make ratio estimates of the relative importance of each attribute relative to the one ranked lowest in importance. To do this, start by assigning the least important attribute an importance of 10. To the next-least-important attribute, assign a score that reflects the ratio. For example, if an attribute is thought two times as important as the least important attribute, assign a weight of 20. Write the estimates in the "weight" column in the "Job Evaluation Scoring Sheet."

2-3. Sum the importance weights, and normalize the attribute weights by dividing each by the sum. This step will be performed by the experimenter after the session.

3. Combining the single-attribute values

Sum the single-attribute values using a weighted additive function. You don't need to perform this step. This will be done by the experimenter after the experimental session.

You must use the scoring sheets according to the provided order. Do not proceed to the next scoring sheet before completing one scoring sheet. However, within the evaluation with a scoring sheet you can perform the step 1 and step 2 with no strict order. That is, you can change your scores if you wish to do so during the process.

Job Alternative # 1

- **Duties & Working conditions**
  - **Duties**
    - **Content of Work**: Plans for optimum use of facilities, equipment, and personal to improve industrial efficiency.
    - **Stress**: Quotas & deadline: None, Competition:None
    - **Physical Demand**: Low
  - **Working Conditions**
    - **Workhours**: 45 hours/week
    - **Travel**: 10 trips per year, 20 days away per year
    - **Location of Employment**: New York
- **Compensation**
  - **Salary**
    - **Salary**: $ 31,000
  - **Benefits**
    - **Benefits**: Semi-private office, company car, personal secretary, and life insurance.
- **Outlook**
  - **Career Opportunities**
    - **Promotion Level**: Experienced workers can advance to the positions of supervisors or managers.
    - **Job Growth**: 46% (faster than average).
  - **Security**
    - **Firm Security**: No risk of bankruptcy.
    - **Personal Security**: Can not be fired.

Job Alternative # 2

Duties & Working conditions	Duties	Content of Work	Plans and develops computer systems for business, scientific institutions, and other establishment.
		Stress	Quotas & deadline: Moderate, Competition: None.
		Physical Demand	Moderate.
	Working Conditions	Workhours	48 hours/week.
		Travel	8 trips per year, 8 days away per year.
		Location of Employment	Houston, Texas.
Compensation	Salary	Salary	$ 35,000.
	Benefits	Benefits	Free housing and meal, Company car.
Outlook	Career Opportunities	Promotion Level	Can advance to positions as senior or lead programmer, data processing manager.
		Job Growth	69% (very fast).
	Security	Firm Security	Low risk of bankruptcy.
		Personal Security	Low risk to be fired.

Job Alternative # 3

Duties & Working conditions	**Duties**	**Content of Work**	Coordinates the activities of production departments of manufacturing firms.
		Stress	Quotas & deadline: Moderate, Competition: Moderate.
		Physical Demand	Heavy.
	Working Conditions	**Workhours**	56 hours/week.
		Travel	24 trips per year, 47 days away per year.
		Location of Employment	Detroit, Michigan.
Compensation	**Salary**	**Salary**	$ 43,000.
	Benefits	**Benefits**	Free housing and meal, Company car, Secretary, Bonuses, Life.
Outlook	**Career Opportunities**	**Promotion Level**	Can advance to positions as executive or top manager.
		Job Growth	5% (very slow).
	Security	**Firm Security**	Low risk of bankruptcy.
		Personal Security	High risk to be fired.

Job Alternative #4

Duties & Working conditions	Duties	Content of Work	Prepares and analyzes financial reports to assist managers in business, industry, and government.
		Stress	Quotas & deadline: Moderate, Competition: Moderate.
		Physical Demand	Low.
	Working Conditions	Workhours	40 hours/week.
		Travel	12 trips per year, 20 days away per year.
		Location of Employment	Sanfrancisco.
Compensation	Salary	Salary	$ 38,000.
	Benefits	Benefits	None.
Outlook	Career Opportunities	Promotion Level	Can advance to positions as budget director, controller, or treasurer.
		Job Growth	35% (average).
	Security	Firm Security	Some risk of bankruptcy.
		Personal Security	Low risk to be fired.

Job Alternative #5

Category	Subcategory	Attribute	Description
Duties & Working conditions	Duties	Content of Work	Negotiates contracts with clients for advertising in publications on radio and television.
		Stress	Quotas & deadline: Moderate, Competition: High.
		Physical Demand	Moderate.
	Working Conditions	Workhours	50 hours/week.
		Travel	85 trips per year, 140 days away per year.
		Location of Employment	Washington.
Compensation	Salary	Salary	$ 44,000.
	Benefits	Benefits	Bonuses, Company car
Outlook	Career Opportunities	Promotion Level	Can advance to positions as advertising manager or director.advertising.
		Job Growth	15% (slow).
	Security	Firm Security	High risk of bankruptcy.
		Personal Security	High risk to be fired.

Evaluation Scoring Sheet # 1

Value Scores

Attribute	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
Overall Attractiveness					

Evaluation Scoring Sheet # 2

Value Scores

Attributes	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
Duties & Working Conditions					
Compensation					
Outlook					

Attribute Weights

Ranking	Weights	Normalized Weights

Overall Value					

Evaluation Scoring Sheet # 3

Value Scores

Attributes	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
Duties					
Working Conditions					
Salary					
Benefits					
Career Opportunities					
Securities					

Attribute Weights

Ranking	Weights	Normalized Weights

Overall Value					

Evaluation Scoring Sheet #4

Value Scores / **Attribute Weights**

Attributes	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Ranking	Weights	Normalized Weights
Content of Work								
Stress								
Physical Demand								
Work Hours								
Travel								
Location of Employment								
Salary								
Benefits								
Promotion Level								
Job Growth								
Firm Security								
Personal Job Security								

Overall Value					

Appendix D. Experimental Data

Subject 1

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	80	90	70	90	70	65

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	50	90	40	70	60	75

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	100	90	60	90	70	20	1	40
Compensation	70	95	100	60	80	70	2	25
Outlook	100	90	60	70	0	40	3	10
Overall Value	90	91.7	73.3	77.3	64	39.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	80	40	90	60	50	2	30
Compensation	45	85	100	50	90	87	3	10
Outlook	70	90	55	100	40	50	1	50
Overall Value	72.2	86.1	55	91.1	52.2	54.1		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	100	90	80	70	80	50	1	140
Work. Cond.	100	90	80	60	40	50	2	120
Salary	0	40	90	80	100	70	3	80
Benefits	70	95	100	0	60	65	5	30
Career Oppt.	80	60	100	85	70	70	4	40
Security	100	90	40	80	0	60	6	10
Overall Value	76.9	78	84.3	65.7	68.1	57		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	77	75	60	40	70	50	3	60
Work. Cond.	80	70	65	90	40	60	1	110
Salary	50	70	85	75	90	80	2	80
Benefits	80	90	100	0	40	82	5	20
Career Oppt.	75	80	60	50	40	45	4	40
Security	95	90	70	85	10	80	6	10
Overall Value	71.8	74.1	70.8	66.1	57.2	63.3		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	100	90	80	40	80	50	1	900
Stress	100	95	80	80	0	40	5	220
Phys. Demand	60	100	40	60	100	60	12	10
Work. Hrs.	100	40	0	90	30	45	2	610
Travel	100	90	50	80	0	40	6	210
Loc. of Empl.	80	100	0	90	0	40	8	180
Salary	0	40	90	80	100	70	3	600
Benefits	70	95	100	0	60	65	4	400
Promo. Level	80	60	100	85	70	70	7	200
Job Growth	100	80	30	75	65	0	11	40
Firm Security	100	95	90	60	0	80	10	80
Per. Job Sec.	100	90	25	40	0	50	9	160
Overall Value	77.8	73	62.9	61.3	53.2	53.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	70	85	30	50	60	1	230
Stress	65	72	80	80	70	73	2	170
Phys. Demand	60	90	70	60	90	60	12	10
Work. Hrs.	75	72	40	80	70	74	6	110
Travel	88	80	60	90	40	65	8	50
Loc. of Empl.	80	95	10	90	40	60	5	120
Salary	50	65	88	70	90	85	4	150
Benefits	65	85	100	0	83	70	3	160
Promo. Level	80	70	95	20	40	90	7	100
Job Growth	85	90	20	50	30	0	9	45
Firm Security	100	95	93	30	0	93	11	30
Per. Job Sec.	100	90	30	87	0	50	10	40
Overall Value	73.3	76.9	70.8	52.9	58.4	68.4		

Subject 2

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	80	45	20	90	55	35

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	80	90	20	90	70	50

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	25	10	75	80	20	1	50
Compensation	55	80	95	50	70	65	2	20
Outlook	95	85	45	60	20	50	3	10
Overall Value	69.4	46.3	35.6	66.9	70	35		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	75	65	20	75	50	35	1	50
Compensation	80	90	95	45	60	55	2	30
Outlook	90	85	55	75	30	65	3	10
Overall Value	78.3	75.6	48.9	65	51.1	45		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	85	70	60	55	30	10	2	100
Work. Cond.	85	55	30	95	65	70	1	110
Salary	55	60	74	65	75	70	3	60
Benefits	50	90	95	0	45	50	4	30
Career Oppt.	50	35	75	30	70	65	5	15
Security	100	95	70	80	30	80	6	10
Overall Value	75.1	64.1	56.7	64.9	53.4	49.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	65	90	60	90	50	30	1	150
Work. Cond.	95	80	30	90	45	60	2	100
Salary	74	62	78	68	80	54	3	60
Benefits	75	90	100	0	35	35	4	50
Career Oppt.	55	55	80	90	75	65	5	25
Security	100	95	50	80	20	65	6	10
Overall Value	75.5	81.1	61.2	75	52.2	45		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	75	55	50	10	30	25	2	200
Stress	85	75	60	60	25	5	4	110
Phys. Demand	70	100	45	70	100	70	7	40
Work. Hrs.	90	70	40	100	55	85	3	150
Travel	80	70	50	75	40	20	8	30
Loc. of Empl.	80	40	20	95	90	75	1	300
Salary	55	60	74	65	75	70	5	100
Benefits	50	90	95	0	45	50	6	50
Promo. Level	30	15	80	40	60	75	9	15
Job Growth	60	80	20	55	30	0	12	10
Firm Security	100	95	92	85	60	92	11	10
Per. Job Sec.	100	98	96	88	80	70	10	10
Overall Value	76.2	59.8	46.2	64.9	60	55.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	80	60	80	50	30	1	300
Stress	50	80	100	100	90	20	6	40
Phys. Demand	60	100	40	60	100	60	8	25
Work. Hrs.	100	90	45	85	70	48	3	150
Travel	90	80	50	90	35	65	7	30
Loc. of Empl.	90	60	35	95	90	75	2	200
Salary	74	62	78	68	80	54	4	100
Benefits	75	90	100	0	35	35	5	70
Promo. Level	70	60	90	90	75	85	9	20
Job Growth	70	80	20	60	40	0	11	10
Firm Security	100	95	90	65	30	90	12	10
Per. Job Sec.	100	95	50	90	35	75	10	15
Overall Value	82.9	76.8	58.5	77.5	65.8	48.5		

Subject 3

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	75	85	60	15	35	45

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	65	80	25	55	20	35

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	75	80	60	85	50	70	1	65
Compensation	60	65	85	55	80	75	3	10
Outlook	95	90	40	70	0	30	2	50
Overall Value	81.8	82.8	54	76.6	32.4	54.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	95	100	45	90	40	85	1	50
Compensation	65	70	80	75	85	80	3	10
Outlook	90	95	50	80	10	45	2	35
Overall Value	90	95	50.5	84.7	33.7	69.7		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	65	90	60	95	55	35	1	150
Work. Cond.	80	90	40	95	30	65	6	10
Salary	70	75	80	75	85	80	4	75
Benefits	70	60	90	10	65	75	5	60
Career Oppt.	75	95	55	70	35	40	3	80
Security	100	95	20	75	0	35	2	120
Overall Value	76.8	86.1	55.8	72.8	43.7	48.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	80	90	55	60	20	50	1	100
Work. Cond.	70	60	45	80	0	35	6	10
Salary	60	70	80	75	85	80	4	80
Benefits	75	80	85	0	65	70	5	50
Career Oppt.	85	100	55	65	50	60	2	90
Security	100	75	45	40	0	50	3	85
Overall Value	80.5	83.3	61.1	53.1	39.9	60		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	75	90	85	75	70	80	1	180
Stress	85	90	80	80	75	30	4	130
Phys. Demand	85	90	40	85	75	85	5	125
Work. Hrs.	100	95	30	90	65	85	6	125
Travel	100	100	65	95	20	35	11	20
Loc. of Empl.	80	85	80	85	85	75	12	10
Salary	60	70	80	75	80	80	8	100
Benefits	70	60	95	20	65	80	9	75
Promo. Level	80	100	100	75	90	75	10	65
Job Growth	85	100	25	60	45	0	3	140
Firm Security	100	95	80	60	30	70	7	100
Per. Job Sec.	100	95	40	85	20	95	2	150
Overall Value	85.1	89.9	62	73.4	59.1	61.6		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	90	95	85	70	85	1	250
Stress	100	95	90	85	70	60	2	215
Phys. Demand	80	85	60	80	70	80	8	100
Work. Hrs.	100	90	50	85	50	100	9	90
Travel	100	100	75	95	30	70	11	25
Loc. of Empl.	80	80	85	70	90	85	12	10
Salary	70	75	85	80	70	80	5	175
Benefits	80	85	100	25	85	70	10	75
Promo. Level	90	95	100	90	70	90	6	150
Job Growth	95	100	60	85	50	10	4	200
Firm Security	100	90	70	80	15	75	7	130
Per. Job Sec.	100	95	50	90	10	60	3	210
Overall Value	89.9	90.9	76.9	82.2	54.5	68		

Subject 4

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	80	60	85	65	75

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	75	90	50	80	60	85

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	90	65	95	50	60	1	60
Compensation	75	80	90	40	70	80	2	40
Outlook	90	95	70	80	40	80	3	10
Overall Value	81.8	86.8	74.5	73.6	56.4	69.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	95	75	80	60	65	1	50
Compensation	75	85	95	60	85	83	2	30
Outlook	83	85	77	90	60	70	3	10
Overall Value	84.2	90.6	81.9	74.4	68.3	71.6		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	80	95	70	80	75	70	1	120
Work. Cond.	70	70	60	95	50	55	4	30
Salary	60	65	90	70	90	85	5	15
Benefits	80	90	95	0	30	85	3	50
Career Oppt.	80	90	90	95	85	80	6	10
Security	100	95	70	80	30	75	2	80
Overall Value	83.3	90.1	74.8	68.4	54.4	73.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	85	90	70	75	60	65	1	90
Work. Cond.	85	87	48	90	50	70	2	60
Salary	55	60	85	70	90	80	4	35
Benefits	80	90	95	0	65	75	5	30
Career Oppt.	80	85	87	95	90	70	6	10
Security	100	95	70	85	60	83	3	50
Overall Value	83.2	86.3	70.5	72	63.3	72.5		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	95	90	85	80	70	1	220
Stress	100	95	80	80	50	20	5	120
Phys. Demand	100	100	90	100	95	100	3	180
Work. Hrs.	85	80	50	100	50	60	8	40
Travel	90	90	70	90	30	50	9	25
Loc. of Empl.	60	70	70	85	65	80	12	10
Salary	70	75	90	80	90	85	7	60
Benefits	90	90	95	0	70	85	6	90
Promo. Level	70	80	100	95	95	90	11	15
Job Growth	80	90	60	75	70	40	10	20
Firm Security	100	95	95	80	40	95	4	150
Per. Job Sec.	100	95	60	95	50	70	2	200
Overall Value	93.8	93.2	82.3	81.5	66	73.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	87	90	75	65	60	70	1	190
Stress	100	90	75	80	70	50	2	160
Phys. Demand	100	90	60	100	90	100	4	120
Work. Hrs.	80	67	50	95	65	80	3	140
Travel	95	100	80	93	50	70	9	45
Loc. of Empl.	75	77	70	90	80	83	12	10
Salary	70	77	90	80	90	85	6	100
Benefits	85	95	100	0	80	83	5	110
Promo. Level	80	90	100	95	95	85	11	20
Job Growth	95	100	65	90	80	30	10	40
Firm Security	100	95	90	70	50	90	8	60
Per. Job Sec.	100	97	55	95	50	85	7	80
Overall Value	89.8	87.8	73.6	75.2	70.2	75.5		

Subject 5

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	50	75	80	30	35	60

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	75	65	80	60	55	72

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	75	65	90	80	68	60	2	40
Compensation	60	80	90	50	70	75	1	50
Outlook	80	75	40	60	30	45	3	10
Overall Value	68	73.5	85	63	65.2	66		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	78	75	82	85	60	80	2	40
Compensation	65	80	90	55	70	60	1	65
Outlook	90	80	50	70	30	60	3	10
Overall Value	71.7	78.3	83.7	66.7	63	67		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	68	60	75	67	80	70	3	88
Work. Cond.	85	76	72	75	50	68	4	70
Salary	50	82	85	80	60	90	2	90
Benefits	70	90	95	30	60	80	1	95
Career Oppt.	90	64	68	80	70	62	6	50
Security	85	90	60	80	40	75	5	60
Overall Value	73.5	77.5	78	66.2	60.8	75.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	60	75	85	65	70	50	3	60
Work. Cond.	80	75	65	78	50	70	4	50
Salary	50	60	80	65	55	70	2	70
Benefits	70	80	90	10	40	60	1	80
Career Oppt.	70	45	72	55	75	65	6	10
Security	90	80	55	70	40	65	5	30
Overall Value	67	72.3	78.4	52.7	52.3	62.7		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	68	64	75	50	90	70	1	95
Stress	60	75	90	90	70	50	7	50
Phys. Demand	65	90	55	65	90	65	12	10
Work. Hrs.	82	80	60	70	85	78	4	69
Travel	85	80	88	75	58	72	6	65
Loc. of Empl.	88	75	80	95	90	60	5	67
Salary	68	85	80	75	50	90	3	80
Benefits	73	85	95	20	40	68	2	88
Promo. Level	78	60	85	83	90	88	10	30
Job Growth	80	87	65	72	60	50	11	18
Firm Security	90	85	80	78	35	82	9	40
Per. Job Sec.	95	92	85	90	30	80	8	45
Overall Value	77.2	78.6	80.5	68	64.9	72.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	75	55	80	50	72	65	2	90
Stress	65	70	85	85	65	45	9	42
Phys. Demand	70	80	65	70	80	70	12	10
Work. Hrs.	80	72	60	75	65	82	4	78
Travel	75	85	60	80	40	52	7	55
Loc. of Empl.	78	60	70	90	80	50	5	72
Salary	55	60	80	65	45	75	3	85
Benefits	75	80	90	10	40	65	1	95
Promo. Level	85	50	75	65	68	70	10	35
Job Growth	80	85	60	50	70	55	11	25
Firm Security	90	85	80	75	60	80	8	45
Per. Job Sec.	90	85	70	80	60	75	6	65
Overall Value	76.4	70.6	74.7	63.2	59.4	66.2		

Subject 6

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	75	95	20	80	35	90

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	40	70	30	30	20	80

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	90	50	80	10	50	1	95
Compensation	80	65	99	1	20	95	3	10
Outlook	99	90	70	65	3	7	2	90
Overall Value	91.2	88.7	61.7	69	7.28	32.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	85	20	75	20	80	1	100
Compensation	80	85	100	0	65	90	2	80
Outlook	75	80	80	85	20	35	3	75
Overall Value	74.6	83.5	62.7	54.4	34.1	69.9		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	60	95	65	50	45	80	1	99
Work. Cond.	95	80	11	90	16	45	5	88
Salary	60	85	93	88	95	91	2	95
Benefits	90	90	99	1	20	85	6	10
Career Oppt.	90	70	85	65	75	25	3	93
Security	99	95	50	45	1	65	4	90
Overall Value	80.4	85.2	62.4	66	46.6	62.2		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	60	95	70	70	70	50	1	100
Work. Cond.	80	90	55	100	20	60	3	85
Salary	65	75	95	75	100	95	2	90
Benefits	80	85	100	0	45	85	4	80
Career Oppt.	85	65	80	75	65	40	5	70
Security	100	90	20	65	0	50	5	70
Overall Value	76.8	83.9	71.2	64.7	52.2	64.1		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	90	75	50	35	70	1	99
Stress	1	3	90	90	80	75	5	80
Phys. Demand	70	95	55	70	95	70	6	78
Work. Hrs.	100	80	100	82	45	98	2	93
Travel	65	45	90	65	5	35	9	60
Loc. of Empl.	60	95	20	90	95	88	8	62
Salary	60	85	93	88	95	91	7	75
Benefits	90	90	99	1	20	85	12	10
Promo. Level	75	60	95	55	80	75	10	50
Job Growth	85	95	2	80	3	1	11	35
Firm Security	99	90	85	65	2	85	3	90
Per. Job Sec.	97	89	15	80	2	40	4	85
Overall Value	73	75.7	58	72.9	48.3	70.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	90	70	10	30	85	1	100
Stress	20	60	80	80	75	30	3	75
Phys. Demand	30	80	60	30	80	30	3	75
Work. Hrs.	80	80	50	95	70	80	2	90
Travel	80	60	75	90	20	45	10	20
Loc. of Empl.	65	95	30	90	85	75	9	25
Salary	70	70	85	75	85	80	2	90
Benefits	80	85	100	0	45	85	4	70
Promo. Level	50	60	100	80	75	75	5	65
Job Growth	90	100	5	75	20	0	80	50
Firm Security	100	90	85	75	0	85	7	55
Per. Job Sec.	95	95	25	90	0	75	6	60
Overall Value	68.4	80.1	66.9	60.7	51.8	64.7		

Subject 7

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	55	65	63	60	50	53

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	50	60	64	70	55	55

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	40	70	20	60	50	30	1	12
Compensation	40	50	70	40	63	55	2	11
Outlook	60	70	50	45	35	48	3	10
Overall Value	46.1	63.3	45.8	48.8	49.8	43.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	56	65	50	70	60	55	2	12
Compensation	50	55	70	55	70	65	3	10
Outlook	65	65	56	60	50	50	1	13
Overall Value	57.6	62.1	57.9	62	59.1	56		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	55	71	65	60	60	56	2	19
Work. Cond.	60	65	40	69	65	60	3	18
Salary	55	60	70	60	73	65	1	20
Benefits	60	65	70	40	65	66	4	16
Career Oppt.	54	60	65	70	54	55	5	13
Security	70	65	53	61	40	55	6	10
Overall Value	58.2	64.5	60.9	59.8	61.6	60.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	55	65	50	60	58	50	4	22
Work. Cond.	58	60	45	65	55	55	3	23
Salary	40	53	68	60	72	63	1	26
Benefits	58	68	75	0	50	55	6	15
Career Oppt.	39	56	55	70	65	0	2	24
Security	80	70	45	50	30	60	5	20
Overall Value	53.8	61.2	55.8	54.3	56.3	46.4		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	53	70	60	50	50	46	1	50
Stress	55	53	65	65	55	50	10	28
Phys. Demand	65	70	60	70	70	65	11	27
Work. Hrs.	65	60	50	70	55	60	3	45
Travel	70	56	60	68	50	54	9	29
Loc. of Empl.	55	65	50	45	70	53	12	20
Salary	55	60	70	60	73	65	2	48
Benefits	55	56	65	30	54	62	8	30
Promo. Level	46	50	65	60	50	60	4	35
Job Growth	65	70	45	60	50	35	7	31
Firm Security	69	65	55	59	35	55	6	32
Per. Job Sec.	70	65	45	60	35	55	5	34
Overall Value	59.9	61.8	57.9	58.4	53.8	55.2		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	53	65	48	60	55	50	2	30
Stress	58	60	70	70	56	45	6	23
Phys. Demand	80	75	58	80	75	80	5	24
Work. Hrs.	70	65	50	80	60	63	4	27
Travel	60	58	50	70	55	45	7	21
Loc. of Empl.	60	58	50	60	70	55	11	10
Salary	45	50	67	60	70	64	1	31
Benefits	60	50	70	0	58	63	12	10
Promo. Level	50	55	65	68	70	67	3	28
Job Growth	68	80	20	55	30	0	9	19
Firm Security	90	75	65	55	25	65	8	20
Per. Job Sec.	95	80	58	75	40	64	10	18
Overall Value	64.3	64.1	56.2	64.4	56.4	55.9		

Subject 8

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	50	70	60	55	62	75

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	55	65	65	70	75	60

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	55	60	70	75	70	75	1	30
Compensation	57	65	68	50	60	70	2	20
Outlook	60	63	75	65	60	70	3	10
Overall Value	56.5	62.2	70.2	65	65	72.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	65	65	65	75	60	70	1	90
Compensation	60	65	85	50	75	65	3	50
Outlook	50	75	60	65	55	50	2	70
Overall Value	58.8	68.3	68.1	65.7	61.9	62.1		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	55	60	60	70	80	75	1	100
Work. Cond.	70	60	50	80	40	70	6	10
Salary	55	60	80	62	80	73	3	75
Benefits	50	65	70	5	60	75	4	35
Career Oppt.	60	65	60	55	70	68	2	80
Security	40	60	57	55	45	65	5	20
Overall Value	55.2	61.8	85.3	56.6	72.9	72		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	50	70	70	60	80	70	1	90
Work. Cond.	60	75	60	85	60	70	6	20
Salary	40	60	80	70	85	75	2	75
Benefits	65	65	80	20	40	70	2	75
Career Oppt.	60	65	65	70	60	40	4	50
Security	40	60	60	60	40	70	5	35
Overall Value	52.1	65.3	72	56.4	64.3	66.7		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	70	50	40	40	60	1	100
Stress	25	35	45	45	60	75	10	20
Phys. Demand	30	45	50	30	80	30	12	10
Work. Hrs.	80	60	50	70	65	78	6	40
Travel	60	40	50	60	20	40	11	30
Loc. of Empl.	25	60	50	80	65	70	5	35
Salary	45	50	75	60	75	70	3	80
Benefits	60	70	80	20	60	75	4	40
Promo. Level	40	60	80	65	70	65	9	40
Job Growth	70	80	20	60	30	0	2	75
Firm Security	70	75	73	65	40	73	8	35
Per. Job Sec.	50	60	58	65	50	70	7	40
Overall Value	59.4	62.5	55.8	55.4	52	57.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	85	75	75	65	65	70	1	90
Stress	50	60	65	65	85	75	6	60
Phys. Demand	60	65	55	60	90	60	12	20
Work. Hrs.	85	80	40	90	75	85	7	55
Travel	85	70	70	80	55	65	8	50
Loc. of Empl.	50	80	70	90	60	85	9	43
Salary	50	75	75	70	90	73	3	75
Benefits	70	75	90	20	40	75	2	80
Promo. Level	60	75	90	80	80	70	5	65
Job Growth	90	80	40	70	60	20	4	70
Firm Security	80	70	70	60	40	70	11	25
Per. Job Sec.	40	60	40	65	35	75	10	40
Overall Value	68.5	73.2	67.3	66.6	65.3	68		

Subject 9

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	90	100	55	80	0	30

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	50	70	100	60	10	40

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	100	65	10	45	20	2	40
Compensation	70	90	100	0	20	50	3	10
Outlook	90	100	40	70	0	25	1	50
Overall Value	88	99	56	39	20	25.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	30	50	75	40	80	1	50
Compensation	80	90	100	0	20	60	2	50
Outlook	80	90	50	35	0	20	3	10
Overall Value	84.5	62.73	72.73	37.3	27.3	65.5		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	90	100	70	50	25	0	2	50
Work. Cond.	60	100	70	40	0	90	6	10
Salary	50	60	90	80	100	70	4	25
Benefits	65	90	100	0	5	20	5	15
Career Oppt.	80	100	55	75	25	0	3	40
Security	100	90	25	70	0	50	1	60
Overall Value	82.6	91.25	58.25	60.5	24.1	29.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	90	100	50	70	80	25	1	60
Work. Cond.	55	25	60	70	10	90	6	10
Salary	30	50	90	70	100	80	2	70
Benefits	80	90	100	0	20	60	3	70
Career Oppt.	25	100	40	60	45	10	4	70
Security	100	90	10	20	0	60	5	60
Overall Value	62.9	83.68	59.71	44.7	48.4	48.5		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	100	70	50	25	10	1	100
Stress	100	90	60	60	35	20	8	20
Phys. Demand	90	75	50	90	75	90	12	10
Work. Hrs.	70	60	0	100	10	60	9	20
Travel	40	20	55	40	0	70	11	20
Loc. of Empl.	25	100	90	40	0	70	10	15
Salary	40	60	90	70	90	75	4	100
Benefits	60	90	100	0	10	30	5	100
Promo. Level	20	35	90	75	100	55	3	90
Job Growth	90	100	10	70	25	0	6	40
Firm Security	100	90	80	40	0	80	7	40
Per. Job Sec.	100	90	0	65	0	20	2	40
Overall Value	63.7	75.63	70.34	52.5	40.6	42.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	100	90	60	20	40	1	50
Stress	100	10	90	90	30	0	8	25
Phys. Demand	90	60	20	90	60	90	9	25
Work. Hrs.	70	40	10	100	20	70	11	20
Travel	40	10	75	40	0	100	10	35
Loc. of Empl.	50	100	80	50	0	90	12	10
Salary	30	50	90	70	100	80	2	55
Benefits	60	90	100	0	10	40	3	60
Promo. Level	20	60	100	90	80	20	4	60
Job Growth	90	100	20	70	40	0	7	50
Firm Security	100	70	50	20	0	50	6	40
Per. Job Sec.	100	7	10	50	0	20	5	40
Overall Value	66	61.13	66.44	57.3	35.2	44.4		

Subject 10

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	80	83	65	40	33	55

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	90	75	40	55	68	45

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	72	60	68	71	71	2	20
Compensation	60	65	70	10	67	75	3	10
Outlook	90	88	40	60	40	20	1	50
Overall Value	81.3	81.1	48.8	55.8	51.1	39.6		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	70	88	75	65	70	2	20
Compensation	10	60	65	69	75	90	3	10
Outlook	70	20	90	100	15	30	1	40
Overall Value	88.4	85.9	50	64.3	40	37.9		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	90	85	70	75	68	63	2	90
Work. Cond.	80	82	75	85	70	79	4	50
Salary	50	53	60	55	62	61	5	30
Benefits	80	92	100	0	30	70	3	80
Career Oppt.	85	90	40	38	20	5	6	10
Security	100	88	30	42	10	50	1	120
Overall Value	86.4	84.6	62.8	47.6	40.2	60.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	88	80	45	70	75	40	6	10
Work. Cond.	65	90	50	85	40	70	5	20
Salary	66	65	70	70	80	75	3	40
Benefits	80	75	99	0	70	83	4	50
Career Oppt.	85	85	15	70	60	5	2	60
Security	100	95	50	60	5	70	1	80
Overall Value	84.3	83.3	55.6	54.6	47.1	57.1		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	80	80	60	90	60	12	10
Stress	100	90	85	85	70	40	1	300
Phys. Demand	90	80	20	90	80	90	11	40
Work. Hrs.	80	76	70	85	74	78	5	98
Travel	80	78	82	84	40	36	6	85
Loc. of Empl.	30	80	40	90	20	85	7	80
Salary	60	65	70	67	74	68	4	120
Benefits	88	99	100	0	30	40	8	75
Promo. Level	80	80	81	83	82	80	9	68
Job Growth	90	99	5	30	10	0	10	55
Firm Security	100	90	85	80	8	80	3	160
Per. Job Sec.	100	90	20	88	18	40	2	250
Overall Value	87	85.4	62.9	76.4	45	54.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	80	80	70	90	90	12	10
Stress	100	80	60	70	40	20	5	100
Phys. Demand	80	70	20	80	70	80	4	120
Work. Hrs.	81	83	60	90	80	82	9	50
Travel	75	80	60	90	50	45	8	60
Loc. of Empl.	30	90	40	85	25	95	6	90
Salary	65	80	88	70	90	83	7	70
Benefits	86	85	99	0	75	82	3	150
Promo. Level	75	75	85	70	70	85	11	20
Job Growth	90	95	10	50	20	0	10	40
Firm Security	100	88	85	50	10	85	2	170
Per. Job Sec.	100	95	15	80	90	60	1	200
Overall Value	84.5	85.1	55.5	64.3	42.6	68.6		

Subject 11

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	65	90	40	35	10	30

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	60	90	35	60	30	35

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	30	60	20	20	10	50	2	15
Compensation	40	70	70	30	40	50	1	16
Outlook	30	70	10	20	50	10	3	10
Overall Value	33.9	66.3	37.1	23.9	31.5	40.2		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	20	65	40	35	10	40	2	25
Compensation	60	90	50	40	80	70	1	30
Outlook	80	90	30	60	10	60	3	10
Overall Value	47.7	80.4	43.1	41.2	42.3	56.9		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	30	70	50	60	40	30	3	20
Work. Cond.	60	70	70	60	10	20	6	10
Salary	50	60	80	70	80	80	1	40
Benefits	60	90	100	0	30	30	5	10
Career Oppt.	40	60	40	50	50	40	4	15
Security	100	80	40	50	10	30	2	30
Overall Value	59.2	69.6	61.6	54.8	43.6	46.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	50	80	50	60	10	50	2	40
Work. Cond.	70	80	30	70	10	20	4	30
Salary	60	70	80	70	90	75	1	41
Benefits	70	70	90	10	30	60	6	10
Career Oppt.	50	70	80	60	60	60	5	15
Security	100	80	40	70	10	70	3	35
Overall Value	67.3	76.1	56.6	63.3	34.7	56.3		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	20	70	40	60	10	30	3	50
Stress	20	30	60	60	60	50	8	20
Phys. Demand	30	60	20	30	70	30	12	10
Work. Hrs.	80	70	20	60	70	80	5	30
Travel	60	40	20	60	5	20	10	15
Loc. of Empl.	60	90	90	70	80	80	9	20
Salary	60	70	80	80	80	80	1	60
Benefits	50	80	90	0	30	40	7	25
Promo. Level	50	70	80	70	40	50	4	40
Job Growth	70	90	10	50	20	0	11	11
Firm Security	80	50	50	30	5	40	6	25
Per. Job Sec.	80	80	40	70	5	30	2	50
Overall Value	55.7	68.7	55.4	59	39.1	48.9		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	40	90	35	60	10	40	2	50
Stress	40	50	70	70	70	50	11	10
Phys. Demand	40	75	50	45	75	40	10	15
Work. Hrs.	65	60	55	70	60	65	9	15
Travel	70	90	40	60	10	20	7	25
Loc. of Empl.	70	90	90	80	90	90	12	10
Salary	70	80	85	80	90	75	1	51
Benefits	70	90	100	10	30	60	6	25
Promo. Level	40	70	80	65	65	60	5	30
Job Growth	70	90	40	70	60	20	8	20
Firm Security	100	70	40	40	5	40	4	40
Per. Job Sec.	100	80	20	60	10	30	3	40
Overall Value	67.5	79.8	55.5	58.6	40.7	47.7		

Subject 12

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	20	20	60	70	50	80

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	20	10	60	70	80	90

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	50	0	50	70	70	100	1	80
Compensation	70	50	100	10	40	60	2	50
Outlook	80	70	20	20	0	10	3	10
Overall Value	59.3	22.9	65.7	45	54.3	79.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	40	20	50	70	60	80	1	80
Compensation	30	40	90	10	80	70	2	60
Outlook	60	70	20	50	10	40	3	10
Overall Value	37.3	31.3	64	44.7	64.7	73.3		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	40	20	30	60	80	75	1	150
Work. Cond.	20	10	20	70	60	70	6	10
Salary	10	20	70	50	80	60	2	120
Benefits	50	60	100	0	20	30	4	60
Career Oppt.	60	80	20	40	40	0	5	30
Security	100	90	50	60	10	30	3	80
Overall Value	44.9	41.6	52.7	48.2	56.4	51.9		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	20	10	40	50	90	80	1	180
Work. Cond.	40	30	10	80	50	90	4	60
Salary	20	40	80	50	90	70	2	130
Benefits	30	80	90	0	50	40	3	90
Career Oppt.	30	20	70	40	60	50	6	10
Security	80	10	40	50	30	60	5	30
Overall Value	28	33	56.4	44.4	73.8	69.6		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	20	20	40	70	80	100	1	150
Stress	0	20	50	50	70	50	10	25
Phys. Demand	0	80	20	10	80	0	11	25
Work. Hrs.	50	40	70	80	30	40	8	60
Travel	40	0	70	40	20	60	12	10
Loc. of Empl.	20	60	10	100	50	80	9	40
Salary	10	20	80	60	90	70	2	120
Benefits	60	70	100	0	20	50	3	85
Promo. Level	60	60	70	70	80	80	5	70
Job Growth	60	70	20	50	30	0	7	65
Firm Security	100	80	70	50	10	60	6	70
Per. Job Sec.	100	90	10	80	0	50	4	70
Overall Value	45.1	49.7	54.4	57.8	51.3	61.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	10	70	50	70	60	80	1	250
Stress	10	30	60	70	90	80	6	120
Phys. Demand	10	70	0	40	80	50	9	60
Work. Hrs.	40	50	20	80	70	90	4	150
Travel	40	0	30	60	20	70	10	50
Loc. of Empl.	60	70	20	100	50	80	5	140
Salary	20	50	90	60	100	80	2	210
Benefits	50	90	100	0	70	60	3	180
Promo. Level	50	10	70	60	70	80	12	10
Job Growth	40	20	10	50	30	0	11	20
Firm Security	80	30	50	40	10	40	8	80
Per. Job Sec.	10	30	20	50	20	60	7	100
Overall Value	31.1	54.9	51.7	58.2	63.4	71.8		

Subject 13

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	80	70	50	70	40	60

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	60	40	80	50	90

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	70	40	80	60	50	2	25
Compensation	60	70	90	30	50	80	3	10
Outlook	90	80	50	70	40	60	1	40
Overall Value	86	75.3	52	68	48	59.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	80	40	90	50	60	2	20
Compensation	50	60	90	40	70	80	3	10
Outlook	90	80	50	70	40	60	1	30
Overall Value	76.7	76.7	53.3	71.7	48.3	63.3		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	70	90	60	80	70	80	4	40
Work. Cond.	60	70	50	80	90	80	2	80
Salary	30	50	80	40	90	70	3	60
Benefits	80	90	100	10	50	70	6	10
Career Oppt.	80	90	20	50	40	30	5	30
Security	100	90	30	80	40	70	1	90
Overall Value	69.7	77.1	50	67.1	66.8	70		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	90	70	80	60	40	50	4	20
Work. Cond.	70	50	40	90	60	80	2	30
Salary	40	50	80	60	90	70	3	25
Benefits	60	70	90	20	50	80	6	10
Career Oppt.	70	80	40	60	50	20	5	15
Security	90	80	50	70	40	60	1	35
Overall Value	71.9	65.6	59.6	66.3	55.6	61.9		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	80	70	40	50	60	7	60
Stress	90	80	60	60	50	40	6	70
Phys. Demand	80	60	50	70	60	80	10	30
Work. Hrs.	70	50	30	80	40	60	11	20
Travel	70	70	50	60	30	40	12	10
Loc. of Empl.	50	70	40	60	70	80	5	80
Salary	40	50	80	60	90	70	4	90
Benefits	60	70	90	10	50	80	8	50
Promo. Level	50	60	90	60	80	70	3	100
Job Growth	70	80	30	60	40	10	9	40
Firm Security	90	80	70	60	40	70	2	110
Per. Job Sec.	90	80	50	70	40	60	1	120
Overall Value	70.9	70.6	63.8	57.7	56.9	63.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	80	70	60	40	50	3	100
Stress	90	80	80	80	70	60	5	80
Phys. Demand	90	80	70	90	80	90	8	50
Work. Hrs.	70	50	30	80	40	60	11	20
Travel	80	70	60	90	40	50	12	10
Loc. of Empl.	50	60	40	80	90	70	2	110
Salary	40	50	80	60	90	70	4	90
Benefits	60	70	90	20	50	80	7	60
Promo. Level	60	50	90	70	80	70	9	40
Job Growth	90	80	30	70	60	20	6	70
Firm Security	90	80	70	50	40	60	10	30
Per. Job Sec.	90	80	50	70	40	60	1	120
Overall Value	74.1	70.5	62.7	67.2	63.1	61.5		

Subject 14

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	65	75	60	75	70	70

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	85	80	75	80	60

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	85	70	90	80	70	1	40
Compensation	80	85	90	50	60	70	3	10
Outlook	85	85	70	75	60	60	2	20
Overall Value	84.3	85	72.9	80	71.4	67.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	75	80	80	70	70	1	40
Compensation	60	70	95	40	70	70	3	10
Outlook	70	80	70	60	40	50	2	20
Overall Value	68.6	75.7	79.3	68.6	61.4	64.3		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	85	85	90	85	85	70	1	50
Work. Cond.	70	40	30	90	80	80	4	30
Salary	20	60	60	40	70	90	2	35
Benefits	50	90	100	0	40	45	5	15
Career Oppt.	70	80	20	60	50	0	3	35
Security	100	95	50	70	55	70	6	10
Overall Value	64.3	72.3	58.3	63.7	68.6	60.2		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	60	80	90	90	80	65	1	50
Work. Cond.	85	85	70	90	70	85	3	40
Salary	60	90	85	70	80	90	4	25
Benefits	80	90	90	0	40	60	5	20
Career Oppt.	75	80	40	70	50	30	2	50
Security	100	80	60	60	30	70	6	10
Overall Value	73.1	83.3	70.9	71.5	63.6	63.1		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	70	60	40	80	60	1	40
Stress	40	60	90	90	70	40	2	30
Phys. Demand	50	90	75	50	75	50	11	10
Work. Hrs.	90	70	50	90	80	90	3	25
Travel	80	80	40	70	0	20	12	10
Loc. of Empl.	80	70	60	80	80	80	10	15
Salary	50	70	80	75	80	75	4	25
Benefits	70	80	90	0	50	55	5	25
Promo. Level	75	75	80	80	80	70	7	20
Job Growth	80	90	10	75	20	0	6	20
Firm Security	100	95	90	85	60	90	8	18
Per. Job Sec.	100	95	75	95	70	90	9	15
Overall Value	73.3	76.2	68	66.7	65.7	60.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	80	80	70	70	80	1	50
Stress	70	80	90	90	85	70	2	50
Phys. Demand	80	90	75	80	90	80	12	10
Work. Hrs.	80	80	60	85	70	80	9	20
Travel	90	80	60	90	40	60	11	12
Loc. of Empl.	80	75	70	80	80	80	10	15
Salary	75	60	80	70	80	75	6	30
Benefits	75	80	90	0	60	70	7	30
Promo. Level	60	80	90	75	80	75	3	40
Job Growth	90	90	50	80	60	0	5	35
Firm Security	100	95	90	85	60	80	8	25
Per. Job Sec.	100	95	60	95	50	80	4	40
Overall Value	81.9	82.1	76.5	74.5	69.3	68.3		

Subject 15

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	90	90	80	70	50	80

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	85	85	80	70	60	75

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	90	40	70	45	60	1	70
Compensation	90	95	100	20	60	80	2	30
Outlook	100	90	70	80	30	30	3	10
Overall Value	90.9	91.4	59.1	57.3	47.7	62.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	95	80	70	80	70	1	50
Compensation	75	70	100	60	70	85	2	15
Outlook	100	90	70	70	10	60	3	10
Overall Value	81.7	89.3	82.7	68	68.7	71.7		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	80	100	80	80	40	50	1	100
Work. Cond.	40	70	40	90	80	90	2	50
Salary	40	45	70	55	85	50	3	40
Benefits	70	90	100	10	30	45	6	10
Career Oppt.	70	100	60	60	50	60	5	15
Security	100	80	70	70	10	50	4	20
Overall Value	65.3	82.1	68.5	72.8	53.8	58.9		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	70	90	80	60	60	60	1	100
Work. Cond.	70	70	70	80	30	60	3	50
Salary	65	70	75	70	80	75	2	60
Benefits	80	70	85	10	30	70	5	15
Career Oppt.	80	90	70	70	60	70	4	25
Security	85	90	60	70	15	65	6	10
Overall Value	71	80.4	75.5	64.6	55.4	65.2		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	70	80	70	40	40	60	1	100
Stress	90	100	90	90	60	40	5	60
Phys. Demand	40	100	90	40	100	40	6	55
Work. Hrs.	100	95	80	85	90	95	7	55
Travel	80	100	60	80	0	10	12	10
Loc. of Empl.	10	70	20	70	70	80	4	60
Salary	70	75	80	75	85	80	2	75
Benefits	90	90	95	10	30	50	3	70
Promo. Level	70	80	90	80	60	80	8	50
Job Growth	90	95	30	50	45	25	11	10
Firm Security	100	90	85	85	45	70	10	25
Per. Job Sec.	100	90	40	90	60	70	9	30
Overall Value	71.6	86.3	73.9	61.5	61.6	63.9		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	95	90	90	70	50	80	1	110
Stress	50	90	100	85	70	20	10	15
Phys. Demand	60	100	70	60	100	60	8	30
Work. Hrs.	100	85	80	90	85	96	5	45
Travel	90	95	65	90	20	60	12	10
Loc. of Empl.	30	85	35	85	60	90	4	70
Salary	83	80	85	80	85	85	3	75
Benefits	75	70	87	20	70	75	2	85
Promo. Level	85	85	90	75	70	86	7	40
Job Growth	80	85	35	80	60	25	6	40
Firm Security	100	75	70	60	20	70	9	20
Per. Job Sec.	90	100	50	90	30	75	11	15
Overall Value	77.6	84.2	74.1	68.7	65.1	75.4		

Subject 16

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	85	95	75	80	70	80

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	85	95	70	90	75	85

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	80	75	95	95	85	1	50
Compensation	80	90	95	80	90	90	3	10
Outlook	85	90	80	75	60	65	2	25
Overall Value	81.5	87.1	78.8	87.4	84.1	79.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	85	70	90	75	75	1	40
Compensation	85	90	95	75	80	80	3	10
Outlook	85	85	75	80	70	80	2	25
Overall Value	82.3	84	75	84.7	74	77.3		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	90	80	75	95	100	85	2	40
Work. Cond.	80	80	70	95	90	90	3	30
Salary	80	80	85	90	95	85	5	15
Benefits	85	90	95	80	85	90	6	10
Career Oppt.	90	90	50	70	65	30	4	20
Security	85	95	75	60	50	80	1	45
Overall Value	85.5	86.1	73.1	80.6	78.3	78		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	75	80	60	90	95	70	1	55
Work. Cond.	75	95	70	90	75	80	2	50
Salary	75	90	75	90	85	80	6	10
Benefits	70	90	100	50	60	70	5	20
Career Oppt.	85	90	75	85	85	40	4	30
Security	85	80	70	75	50	75	3	30
Overall Value	77.6	86.9	71.3	82.8	77.3	69.2		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	80	80	90	95	95	3	50
Stress	85	85	90	90	90	85	4	45
Phys. Demand	90	85	75	85	85	85	5	35
Work. Hrs.	90	85	70	90	80	85	8	20
Travel	85	80	85	90	70	75	10	20
Loc. of Empl.	70	95	90	95	80	90	9	20
Salary	75	80	85	95	95	90	12	10
Benefits	85	95	95	80	85	90	11	15
Promo. Level	75	80	85	75	90	80	7	30
Job Growth	90	95	40	70	5	10	6	30
Firm Security	100	95	70	50	20	70	1	70
Per. Job Sec.	80	90	80	60	60	90	2	60
Overall Value	85.6	87.2	77.3	75.6	65.6	78.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	85	70	85	70	90	95	1	70
Stress	70	75	95	95	85	80	2	65
Phys. Demand	90	95	85	90	95	90	8	20
Work. Hrs.	95	90	70	95	90	95	6	30
Travel	85	90	70	85	70	70	7	30
Loc. of Empl.	75	100	85	100	75	90	5	50
Salary	75	90	75	85	85	85	11	15
Benefits	75	95	100	50	60	80	12	10
Promo. Level	80	85	90	85	90	75	10	15
Job Growth	75	85	75	85	80	60	9	20
Firm Security	95	90	90	75	60	90	3	60
Per. Job Sec.	80	85	80	90	80	90	4	60
Overall Value	82.1	85.1	84.2	85.2	79.8	86.1		

Subject 17

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	80	70	60	90	40	50

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	60	80	70	70	40	50

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	90	70	80	60	50	1	60
Compensation	50	80	90	40	60	70	2	30
Outlook	80	90	60	70	60	40	3	10
Overall Value	65	87	75	67	60	55		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	60	80	50	90	50	60	1	70
Compensation	60	70	90	40	80	80	2	40
Outlook	80	90	60	70	50	60	3	10
Overall Value	61.7	77.5	64.2	71.7	60	66.7		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	70	80	60	70	60	70	2	80
Work. Cond.	80	70	90	100	80	100	1	100
Salary	50	60	90	70	100	80	3	60
Benefits	80	90	100	0	60	70	4	50
Career Oppt.	90	100	50	80	60	0	6	10
Security	100	90	60	70	50	80	5	30
Overall Value	74.2	76.4	80.3	68.8	72.4	79.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	70	90	50	80	60	60	2	80
Work. Cond.	70	70	85	60	90	70	3	60
Salary	40	50	80	60	90	70	3	60
Benefits	70	80	90	0	50	70	4	40
Career Oppt.	80	90	50	70	60	40	6	10
Security	90	80	50	70	40	70	5	20
Overall Value	65.8	73.9	72.3	68.1	63.2	69.7		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	70	100	80	80	90	80	3	80
Stress	80	90	80	80	70	60	2	90
Phys. Demand	80	90	70	80	90	80	6	50
Work. Hrs.	90	70	40	50	60	80	1	100
Travel	80	60	90	70	40	50	7	45
Loc. of Empl.	40	60	50	80	90	70	12	10
Salary	40	50	80	60	90	70	4	70
Benefits	70	80	100	0	50	60	5	60
Promo. Level	60	70	90	70	80	60	10	25
Job Growth	80	90	30	70	50	0	11	15
Firm Security	100	80	70	60	40	70	9	35
Per. Job Sec.	100	90	60	80	50	70	8	40
Overall Value	75.8	78.5	72.3	62.7	68	67.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	60	90	70	70	80	60	3	120
Stress	90	80	70	70	60	40	1	140
Phys. Demand	80	70	80	80	70	80	4	110
Work. Hrs.	80	70	50	60	60	80	2	130
Travel	90	70	80	90	60	70	9	40
Loc. of Empl.	50	70	50	90	60	80	10	30
Salary	40	50	80	60	90	70	6	70
Benefits	80	80	90	0	40	50	5	90
Promo. Level	70	60	90	70	80	50	12	10
Job Growth	80	90	0	70	60	50	11	20
Firm Security	90	80	70	60	50	70	8	50
Per. Job Sec.	90	80	50	70	40	60	7	60
Overall Value	76.2	75.4	68.2	62.8	62.6	63.4		

Subject 18

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	85	45	60	75	30	55

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	94	60	90	70	55	85

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	30	70	75	20	15	1	45
Compensation	85	95	100	50	80	100	2	40
Outlook	97	80	70	75	50	40	3	10
Overall Value	86.3	62.6	82.6	64.5	48.4	53.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	72	30	60	70	25	75	1	50
Compensation	88	93	100	50	90	99	2	30
Outlook	2	84	70	80	55	75	3	10
Overall Value	79.6	57	74.4	64.4	50	83		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	100	15	75	60	40	65	1	60
Work. Cond.	60	88	10	90	0	5	2	45
Salary	80	85	90	88	92	90	3	40
Benefits	90	100	100	0	90	100	4	30
Career Oppt.	90	90	70	70	70	10	6	10
Security	100	88	25	45	0	30	5	30
Overall Value	86	68.8	60.5	61.5	44.1	54.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	95	45	85	80	70	90	4	35
Work. Cond.	60	70	40	65	25	55	1	60
Salary	75	80	100	80	100	95	5	30
Benefits	90	98	100	10	55	95	3	35
Career Oppt.	70	50	65	60	60	55	6	10
Security	100	90	50	75	40	70	2	50
Overall Value	81.9	75.5	68.3	62.7	52.2	75.8		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	100	0	80	75	15	55	1	80
Stress	90	80	50	50	10	0	11	15
Phys. Demand	100	80	20	100	80	100	12	10
Work. Hrs.	100	100	75	80	90	100	12	10
Travel	98	100	35	50	0	8	6	40
Loc. of Empl.	40	50	10	35	60	70	7	40
Salary	70	75	100	95	100	98	3	70
Benefits	90	98	100	0	70	100	4	50
Promo. Level	85	20	98	80	40	90	9	25
Job Growth	70	95	60	60	40	15	10	25
Firm Security	100	80	75	60	30	20	8	30
Per. Job Sec.	100	90	40	80	30	50	2	75
Overall Value	87.3	68.4	66.7	64.6	47.6	62.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	95	25	90	50	55	85	1	60
Stress	80	90	85	85	69	40	11	15
Phys. Demand	75	85	25	75	85	75	12	10
Work. Hrs.	88	80	70	75	70	90	7	35
Travel	95	98	48	60	5	45	8	30
Loc. of Empl.	45	55	20	60	65	60	2	55
Salary	68	70	78	70	100	95	4	50
Benefits	90	98	100	20	75	99	3	50
Promo. Level	70	60	75	65	70	62	9	20
Job Growth	75	65	35	70	50	10	10	20
Firm Security	100	85	85	65	50	85	5	35
Per. Job Sec.	100	95	55	88	60	80	6	35
Overall Value	81.6	71.5	67.3	61	63.2	75.1		

Subject 19

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	100	90	75	80	85

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	100	90	60	95	80

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	100	70	90	60	50	1	22
Compensation	70	80	100	50	85	90	2	20
Outlook	90	100	80	70	50	55	3	10
Overall Value	80.2	92.31	83.5	70.8	67.7	66.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	100	70	80	60	90	1	55
Compensation	70	80	100	50	90	90	2	50
Outlook	90	100	60	80	70	50	3	10
Overall Value	78.9	91.3	82.2	67	73.9	88.7		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	100	95	80	90	70	50	1	90
Work. Cond.	80	100	50	90	60	75	3	30
Salary	50	60	90	70	100	80	2	80
Benefits	60	90	100	50	70	80	2	80
Career Oppt.	90	100	60	80	70	50	3	30
Security	100	90	60	80	50	70	4	10
Overall Value	74.7	85.8	82.2	73.8	75.9	68		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	90	100	60	80	50	70	1	65
Work. Cond.	80	100	60	90	50	70	3	40
Salary	50	60	90	70	100	80	2	60
Benefits	60	90	100	50	80	70	2	60
Career Oppt.	80	100	70	90	75	60	3	40
Security	100	90	60	80	50	70	4	10
Overall Value	72.2	88.7	76.7	74.2	71.1	70.7		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	100	85	80	50	70	1	100
Stress	100	90	80	80	70	60	6	30
Phys. Demand	100	90	80	100	90	100	8	15
Work. Hrs.	90	80	60	100	70	85	7	25
Travel	90	100	80	100	60	70	8	15
Loc. of Empl.	90	100	85	60	80	60	5	70
Salary	50	60	90	70	100	80	2	95
Benefits	70	95	100	50	80	90	3	90
Promo. Level	50	70	80	100	90	85	4	85
Job Growth	90	100	95	80	40	0	4	85
Firm Security	100	90	80	70	60	80	9	10
Per. Job Sec.	100	90	65	80	50	60	5	70
Overall Value	78.8	87.6	84.8	76.6	70.4	66.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	80	100	90	50	70	60	1	100
Stress	100	90	80	80	70	60	4	40
Phys. Demand	100	90	80	100	90	100	5	30
Work. Hrs.	90	80	60	100	70	85	7	25
Travel	95	100	80	90	60	70	8	20
Loc. of Empl.	60	90	80	70	100	75	3	50
Salary	50	60	90	70	100	80	2	90
Benefits	60	80	100	50	70	90	2	90
Promo. Level	60	70	80	100	75	90	3	30
Job Growth	90	100	60	80	70	50	3	50
Firm Security	100	90	80	70	60	80	9	10
Per. Job Sec.	100	90	60	80	50	70	6	15
Overall Value	74.3	85	83.5	70.4	77.9	74.6		

Subject 20

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	80	60	90	80	75

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	95	80	65	85	70	60

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	60	80	60	70	70	50	1	100
Compensation	70	80	90	85	90	95	2	50
Outlook	85	95	90	95	40	40	3	10
Overall Value	64.7	84.1	71.3	74.4	63.4			

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	85	80	70	80	70	65	1	100
Compensation	80	85	95	70	80	85	2	50
Outlook	100	95	60	85	60	70	3	10
Overall Value	84.4	82.5	77.2	77.2	72.5	71.6		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	70	80	50	80	70	50	2	90
Work. Cond.	80	90	50	90	70	70	4	50
Salary	60	70	50	80	75	75	1	100
Benefits	70	80	50	0	60	70	3	70
Career Oppt.	70	80	50	95	60	0	6	10
Security	100	95	70	85	0	50	5	40
Overall Value	71.9	80.3	59	66.8	61.4	62.2		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	95	85	20	85	80	20	1	100
Work. Cond.	85	70	70	95	80	90	5	20
Salary	60	70	90	90	95	90	2	90
Benefits	90	90	95	0	60	95	3	60
Career Oppt.	95	95	20	70	80	20	6	10
Security	100	90	50	70	0	60	4	40
Overall Value	84.2	81.7	60.6	68.8	70.5	63.1		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	50	95	80	90	90	80	1	110
Stress	90	100	80	80	70	0	4	90
Phys. Demand	90	95	60	95	85	90	9	20
Work. Hrs.	90	85	0	95	50	90	5	70
Travel	95	80	90	95	80	80	10	20
Loc. of Empl.	50	95	60	95	80	100	12	10
Salary	70	70	80	95	90	90	2	100
Benefits	70	80	90	0	60	75	3	90
Promo. Level	80	80	85	85	80	80	6	60
Job Growth	85	85	50	90	70	0	8	40
Firm Security	100	90	85	85	40	50	11	30
Per. Job Sec.	100	95	40	95	30	70	7	60
Overall Value	77.9	86.4	68.4	78.7	70	65.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	85	85	90	90	85	95	1	190
Stress	100	90	70	80	60	0	3	130
Phys. Demand	95	90	0	95	90	95	8	60
Work. Hrs.	80	70	0	100	70	80	7	70
Travel	95	90	85	90	20	70	10	30
Loc. of Empl.	70	95	70	90	80	95	12	10
Salary	85	80	60	95	90	95	2	180
Benefits	90	95	95	0	60	95	5	110
Promo. Level	90	90	85	95	90	80	9	40
Job Growth	80	75	10	95	70	0	11	20
Firm Security	100	95	95	90	20	95	6	90
Per. Job Sec.	100	100	60	95	20	90	4	120
Overall Value	90	87.9	66.7	82	64.4	78.6		

Subject 21

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	60	70	90	50	80

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	60	70	50	80	30	50

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	50	70	80	30	60	1	30
Compensation	60	80	90	40	60	85	2	20
Outlook	80	70	80	90	50	80	3	10
Overall Value	68.3	63.3	78.3	68.3	43.3	71.7		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	70	30	90	40	40	1	40
Compensation	50	70	90	40	60	75	2	20
Outlook	50	70	40	80	40	30	3	10
Overall Value	67.1	70	48.6	74.3	45.7	48.6		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	80	50	70	90	40	60	2	70
Work. Cond.	80	80	20	90	0	30	5	20
Salary	40	60	80	70	90	80	3	60
Benefits	70	80	100	0	50	75	6	10
Career Oppt.	80	50	60	100	70	70	1	70
Security	100	90	70	70	40	50	4	50
Overall Value	74.6	62.5	67.1	81.4	55.7	63.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	60	60	40	80	70	40	2	50
Work. Cond.	80	90	40	80	30	40	4	20
Salary	30	50	85	60	90	70	3	30
Benefits	50	70	95	0	50	60	5	10
Career Oppt.	60	70	50	90	70	50	1	60
Security	100	80	40	30	10	50	3	30
Overall Value	63	68	52.5	68.5	59	50		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	90	50	80	40	20	70	1	100
Stress	50	60	100	100	70	20	6	80
Phys. Demand	60	90	40	50	80	50	8	50
Work. Hrs.	80	50	10	70	20	50	10	30
Travel	50	75	20	50	0	10	9	20
Loc. of Empl.	10	30	50	100	70	80	11	10
Salary	25	50	80	50	90	70	3	90
Benefits	70	90	100	0	40	50	5	80
Promo. Level	50	30	90	80	80	90	2	100
Job Growth	90	70	10	0	25	0	4	90
Firm Security	100	80	70	50	30	70	8	70
Per. Job Sec.	100	90	50	80	30	70	7	70
Overall Value	68.9	63.9	66.7	50.9	48.9	54.1		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	70	50	60	100	20	80	1	105
Stress	40	70	90	90	70	30	8	40
Phys. Demand	50	90	20	50	90	50	9	30
Work. Hrs.	80	70	10	100	60	75	7	50
Travel	70	80	40	70	0	20	8	40
Loc. of Empl.	30	70	50	90	70	70	10	10
Salary	20	40	80	50	90	70	3	90
Benefits	50	80	100	0	50	65	6	60
Promo. Level	50	50	90	90	80	95	2	100
Job Growth	75	100	10	50	30	0	7	50
Firm Security	100	80	80	60	30	80	4	80
Per. Job Sec.	100	85	30	70	20	50	5	70
Overall Value	63.6	67.4	61.1	69	49.2	63.4		

Subject 22

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	90	90	50	80	70	60

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	90	85	50	60	20	60

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	60	70	80	40	40	1	60
Compensation	45	50	100	30	80	70	2	30
Outlook	90	100	50	60	30	40	3	10
Overall Value	76.5	61	77	63	51	49		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	70	70	50	90	30	40	1	40
Compensation	50	60	100	20	60	80	2	20
Outlook	100	90	20	40	10	40	3	10
Overall Value	68.6	70	60	62.9	35.7	51.4		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	100	80	80	70	60	50	1	80
Work. Cond.	80	80	65	90	50	60	3	60
Salary	60	70	95	75	100	85	2	50
Benefits	70	90	100	0	70	80	6	10
Career Oppt.	90	100	70	70	80	60	5	20
Security	100	90	50	60	10	40	4	40
Overall Value	85.8	81.5	74.8	71.3	59.6	59.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	100	90	70	80	40	30	1	80
Work. Cond.	60	80	40	90	20	40	3	50
Salary	45	60	95	70	100	85	2	65
Benefits	60	70	100	0	40	80	5	20
Career Oppt.	85	90	20	60	30	10	6	10
Security	100	90	20	40	10	40	4	30
Overall Value	74.4	78.8	65	67.6	47.5	50.3		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	70	60	90	40	30	20	1	90
Stress	70	80	90	90	40	10	10	16
Phys. Demand	50	100	10	50	100	50	11	12
Work. Hrs.	100	80	10	80	70	90	6	44
Travel	90	100	50	75	25	0	12	10
Loc. of Empl.	40	50	10	50	30	70	2	76
Salary	50	60	90	70	100	80	3	72
Benefits	60	50	100	0	75	80	8	30
Promo. Level	60	70	80	30	40	30	7	36
Job Growth	90	100	10	60	25	0	5	58
Firm Security	100	80	70	50	0	70	9	24
Per. Job Sec.	100	90	30	80	10	60	4	60
Overall Value	71.1	71.3	52.6	55.5	43.7	49.9		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	85	70	90	40	50	30	1	130
Stress	70	100	80	80	40	20	5	70
Phys. Demand	80	70	20	80	70	80	12	10
Work. Hrs.	60	80	20	100	80	50	4	80
Travel	90	75	50	75	10	40	11	15
Loc. of Empl.	10	30	20	70	50	80	2	110
Salary	50	60	90	70	90	80	3	100
Benefits	70	80	90	0	60	70	8	50
Promo. Level	80	80	80	60	60	70	9	30
Job Growth	70	90	20	60	40	0	10	20
Firm Security	100	90	80	60	20	80	6	60
Per. Job Sec.	100	95	20	90	10	40	7	55
Overall Value	65	72	61	64	53	55		

Subject 23

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	95	85	65	95	70	85

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	85	85	79	90	80	85

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	90	80	70	90	80	83	2	50
Compensation	83	79	95	80	87	90	3	10
Outlook	95	95	80	90	60	80	1	80
Overall Value	92.4	88.5	77.5	89.3	69.1	81.8		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	87	90	70	95	80	85	2	30
Compensation	85	87	90	70	80	80	3	10
Outlook	85	90	90	95	80	80	1	50
Overall Value	85.7	89.7	83.3	92.2	80	81.7		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	80	95	90	90	95	80	3	70
Work. Cond.	85	70	70	95	80	90	1	80
Salary	60	80	70	90	75	92	5	40
Benefits	85	70	85	75	79	80	4	60
Career Oppt.	80	90	95	85	85	70	2	50
Security	70	90	80	98	60	80	6	10
Overall Value	79.4	80.8	81.8	87.8	82.7	82.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	70	95	90	90	95	90	2	80
Work. Cond.	85	85	70	95	70	80	1	80
Salary	70	87	85	85	80	85	4	60
Benefits	90	90	95	70	85	90	3	70
Career Oppt.	80	80	95	85	75	85	5	50
Security	80	80	85	90	90	87	6	10
Overall Value	79.1	87.8	86.1	85.6	81.7	86.1		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	88	85	90	85	75	92	6	60
Stress	95	80	90	95	90	93	9	35
Phys. Demand	90	80	60	90	70	90	8	40
Work. Hrs.	95	85	50	50	60	90	5	70
Travel	93	92	80	90	70	80	10	30
Loc. of Empl.	90	60	85	90	100	70	4	70
Salary	80	85	87	89	90	95	2	90
Benefits	80	80	95	60	80	80	7	55
Promo. Level	95	85	95	90	92	85	11	20
Job Growth	93	80	85	90	70	60	12	10
Firm Security	95	90	90	80	50	90	3	85
Per. Job Sec.	90	90	70	90	60	80	1	100
Overall Value	89.4	83	80.1	81.7	73.7	85.5		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	75	90	92	90	70	91	2	80
Stress	80	83	90	90	70	85	12	10
Phys. Demand	90	90	90	85	85	80	11	12
Work. Hrs.	80	78	85	90	60	70	5	70
Travel	87	90	90	95	65	87	7	60
Loc. of Empl.	90	80	85	90	95	90	8	55
Salary	60	80	70	90	80	80	9	50
Benefits	90	85	95	70	80	90	1	95
Promo. Level	80	85	100	90	85	85	6	85
Job Growth	80	85	80	95	95	70	10	30
Firm Security	95	90	90	90	70	90	3	90
Per. Job Sec.	80	85	75	87	90	85	4	90
Overall Value	82.7	85.2	87.5	87.6	78	85		

Subject 24

Scoring Sheet #1

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	90	50	70	60	60

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6
Overall Value	70	90	70	70	50	70

Scoring Sheet #2

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	100	50	80	70	75	2	15
Compensation	60	70	100	50	80	90	3	10
Outlook	100	90	70	60	10	10	1	30
Overall Value	87.3	89.1	70	63.6	39.1	42.3		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Work	80	100	80	80	50	80	2	20
Compensation	80	90	100	0	90	90	3	10
Outlook	100	100	70	75	60	60	1	40
Overall Value	91.4	98.6	77.1	65.7	61.4	70		

Scoring Sheet #3

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	20	100	70	70	70	80	3	60
Work. Cond.	80	80	50	90	40	45	6	10
Salary	40	60	90	70	100	80	4	40
Benefits	60	70	100	0	40	50	5	30
Career Oppt.	90	100	50	80	70	30	1	140
Security	100	90	40	60	0	20	2	70
Overall Value	71.4	90.3	60.3	66.6	56	44.4		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Cont. of Work	50	100	70	80	80	70	3	60
Work. Cond.	80	80	70	90	50	75	6	10
Salary	20	50	90	60	100	80	4	45
Benefits	70	90	100	0	70	90	5	30
Career Oppt.	90	100	60	80	70	50	1	160
Security	80	100	70	70	20	75	2	80
Overall Value	75.8	88.7	70.5	69.6	64.2	65.6		

Scoring Sheet #4

Session 1

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	50	100	40	40	60	50	5	160
Stress	10	40	90	90	70	70	10	30
Phys. Demand	100	70	20	100	70	100	11	15
Work. Hrs.	90	85	70	100	80	90	9	40
Travel	90	100	50	85	0	10	8	60
Loc. of Empl.	100	100	100	100	100	100	12	10
Salary	50	60	90	70	100	80	6	90
Benefits	70	90	100	10	40	70	7	80
Promo. Level	80	100	100	100	100	100	2	560
Job Growth	90	90	10	50	20	0	1	620
Firm Security	100	90	80	50	0	80	4	240
Per. Job Sec.	100	90	40	85	30	50	3	380
Overall Value	84.2	91.4	56.4	69.6	47.7	54.2		

Session 2

Attribute	Alt 1	Alt 2	Alt 3	Alt 4	Alt 5	Alt 6	Rank	Weight
Duties	65	100	50	60	70	60	5	380
Stress	60	80	100	100	90	80	10	30
Phys. Demand	100	80	50	100	80	100	11	15
Work. Hrs.	85	85	70	100	80	85	9	45
Travel	90	100	80	90	50	70	8	80
Loc. of Empl.	100	100	100	100	100	100	12	10
Salary	40	50	90	60	100	80	6	240
Benefits	80	90	100	0	80	90	7	160
Promo. Level	80	100	90	90	95	90	1	810
Job Growth	100	90	10	80	20	0	2	700
Firm Security	100	90	80	50	20	80	4	560
Per. Job Sec.	100	90	40	80	10	60	3	640
Overall Value	86.4	90.7	60.3	71.5	50.3	61.8		

Appendix E. Experimental Data Analysis With the Equal Weighting Scheme

Table E-1 The Means of MABS and Pearson **r** Values

MABS				Pearson **r**			
Decomposition Level				Decomposition Level			
0	1	2	3	0	1	2	4
12.076	7.826	6.560	5.155	0.851	0.762	0.722	0.641

Table E-2 Summary of MANOVA Results

Statistic	Value	F	Num df	Den df	p
Wilks' Lambda	0.4813	10.006	6	136	0.0001
Pillai's Trace	0.5527	8.784	6	138	0.0001
Hotelling-Lawley Trace	1.0071	11.246	6	134	0.0001
Roy's Greatest Root	0.9312	21.417	3	69	0.0001

Note. The analysis was performed using the log-transformed values for MABS and Fisher's **z** values for Pearson **r**.

Table E-3 Summary of ANOVA Results for MABS Measure

Source	df	MS	F	p
Subjects	23	0.0832		
Decomposition	3	0.5028	17.59	0.0001
Error	69	0.0286		
Total	95			

Note. The analysis was performed using the log-transformed values.

Table E-4 Summary of ANOVA Results for Pearson **r** Measure

Source	df	MS	F	p
Subjects	23	0.3238		
Decomposition	3	1.9847	10.82	0.0001
Error	69	0.1834		
Total	95			

Note. The analysis was performed using Fischer's **z** statistic.

Vita

Young Jin Cho was born on February 14, 1957, in Milyang, Korea. He graduated Seoul National University in Seoul, with a B.S. degree in Industrial Engineering, in February 1980. He then acquired an M.S. degree in Industrial Engineering at the same university, in February 1992. After receiving his Master degree, he worked at Korea Institute of Energy and Resources for one year, as a research associate. He also worked at Korea Institute for Defense Analyses as a researcher from January 1984, to August 1987.

Young Jin Cho began his Ph.D. study at Virginia Polytechnic Institute and State University in September 1987. During his doctoral track, he concentrated on Management Systems Engineering. Upon receiving a Ph.D. degree, he will return to Korea Institute for Defense Analyses. His primary career objective is to be a senior researcher and consultant in the fields of management systems design and evaluation of public and business organizations.

He has been married with Hosun Ahn since January 1986, and has two children, Mookeun and Yoonjung.

Young Jin Cho

Young Jin Cho