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**Profiling Decision Makers:  
Exploring the Dimensions of  
Decision Making**

**Working Paper Series 02-29— September 2002**

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# Profiling Decision Makers: Exploring the Dimensions of Decision Making

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*Edges are important because they define a limitation in order to deliver us from it. When we come to an edge we come to a frontier that tells us that we are now about to become more than we have before. As long as one operates in the middle of things, one can never really know the nature of the medium in which one moves. – William Irwin Thomspson<sup>1</sup>*

Although there are a number of methods for exploring the dimensions of decision-making, the most prevalent in field research is the use of interviews. This is the methodology commonly used in the study of naturalistic decision-making<sup>2</sup>, where some significant progress has been made in identifying the key factors that affect the way “real-world” decisions are made. By analyzing the information gathered from a number of interview-based research studies, Orasanu and Connolly (1993) identified the following eight factors as determinates of the decision process:

1. Ill-structured problems
2. Uncertain, dynamic environments
3. Shifting, ill-defined, or competing goals
4. Action/feedback loops
5. Time stress
6. High stakes
7. Multiple players
8. Organizational goals and norms

Quantitatively, there is no indication as to the importance of each of these factors and how they interact. Instead the results provide only direction and intuitive insight. Further extensions of this research may provide additional insight and may even lead to a hypothetical model. At this point the confusion starts to occur between pure exploratory research, as described by the proponents of naturalistic decision making<sup>3</sup>, and what is traditionally called hypothesis testing. A complex model developed from multiple exploratory studies utilizing multiple methodologies is unlikely to subject itself favorably to a rigorous hypothesis test.<sup>4</sup> Thus, researchers are forced to validate these models using follow-up interviews assessing subjective fit, or by simply evaluating the model’s face validity.<sup>5</sup> The latter is a case of describing either verbally or diagrammatically the model and asking an expert to evaluate whether or not it “feels right.”

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<sup>1</sup> Quote taken from William Irwin Thomspson, “The Time Falling Bodies Take to Light,” presented in Sherman and Schultz (1998, p. 62).

<sup>2</sup> “The study of Naturalistic Decision Making asks how experienced people, working as individuals or groups in dynamic, uncertain, and often fast-paced environments, identify and assess their situation, make decisions and take actions whose consequences are meaningful to them and to the larger organization in which they operate.” (Zsombok 1997, p. 5)

<sup>3</sup> (Lindblom 1959; Wertheimer 1959; Klein 1993; Zsombok 1997; Zsombok and Klein 1997; Klein 1998)

<sup>4</sup> Under some very restrictive assumptions, a complex model can be subjected to a statistical hypothesis test or methodology called structural equation modeling.

<sup>5</sup> Anastasi (1988) describes face validity as follows: “face validity ... is not validity in the technical sense; it refers, not to what the test actually measures, but to what it appears superficially to measure. Face validity pertains to whether the test ‘looks valid’ to the examinees who take it, the administrative personnel who decide on its use, and

Data collected from this type of exploratory research is typically presented in literary essay form. Many are the merits of literary essays for describing and enlightening others about a particular phenomenon. However, from a scientific standpoint, this method presents several problems. The principal difficulty is that it is very hard to demonstrate rigorously that the conclusions are flawed. Moreover, the conclusions of these exploratory studies can only be judged based on face validity, a scientifically weak level of support.

## OBJECTIVE

This study extends prior exploratory research in an attempt to build a foundation on which rigorous hypothesis testing research can be conducted. The empirical measurement instrument developed explores the dimensions of decision-making and captures a testable profile of decision makers. The principal objective of a study is to provide a measurement instrument that can be easily adapted and modified for a variety of implementations. The methodology, developed and in the next several sections and implemented in this field research study, is focused on achieving this objective. The instrument is not designed as a custom measurement for the specific application described, but is instead designed to provide value by profiling the decision problems so that a quantitative measure of the “order<sup>6</sup>” of a decision problem can be assessed.

### Measuring Decision Orders

The decision order model is based on a triad in which all decisions can be categorized (Scherpereel 2002). As Scherpereel (2002) explains, a decision can be identified as first, second, or third-order based on certain factors. Each of these factors can be described as a dimension. The question regarding what exactly are those factors, or dimensions, is quantitatively vague.

To this point, the factors that define a decision problem’s order have been exposed only descriptively. The strategy employed in the prior art is to take a generic problem or descriptor that neatly fits a category and use it as a comparison for the decision of interest. For example, if the decision is to use a hammer or a screwdriver to fix a broken cabinet, the decision might be seen as “deterministic,” a first-order descriptor, and the decision maker will classify the problem as first-order. Seeking a first-order solution, the decision maker will look at the cabinet to determine whether it was constructed with screws or nails and choose the appropriate tool based on this observation. Unfortunately not all decisions neatly fit this methodology. For example, if the decision-maker discovers the cabinet is built with Philips head screws and he/she looks at the screwdriver only to find it is straight headed the decision changes. The decision-maker must decide whether to use the hammer to pound the Philips head screw back into the wood possibly cracking the wood, or to attempt to use the straight headed screwdriver on the Phillips head screw and risk stripping out the head making it useless. Now the decision might be better classified as second-order, because it is considered a decision under risk, thus, fitting this second-order descriptor. Clearly, the decision order depends on the constraints and the perspective of the decision-maker. A decision may initially appear first-order, like the broken cabinet example, and later be reclassified as second-order based on additional information. There are many scientific examples where the decision initially fit the third-order descriptors but deeper investigation reclassified it as first or second-order.<sup>7</sup>

These are examples of reclassifications based on information and perspective changes. There are many more examples that, at the time the decision needs to be made, cannot be easily classified as entirely a single order. For example, the decision to purchase a particular stock may fit the first-order descriptor “simple,” the second-order descriptor “risky,” and the third-order descriptor “strategic.” What is the classification of such a decision? In aggregate, it might be argued that the decision is third-order since it has some third-order descriptors, and it may be similar to some other decisions which were previously classified as third-order. Unfortunately, once classified there is no methodology to distinguish this third-order decision from the decision to bet on the pull of a slot machine arm.<sup>8</sup>

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other technically untrained observers” (p. 144). In other words, face validity is a judgment concerning how relevant the test items appear to be. If a test appears to measure what it purports to measure “on the face of it,” it could be said to be high in face validity.

<sup>6</sup> Decision “orders” are described by Scherpereel (2002).

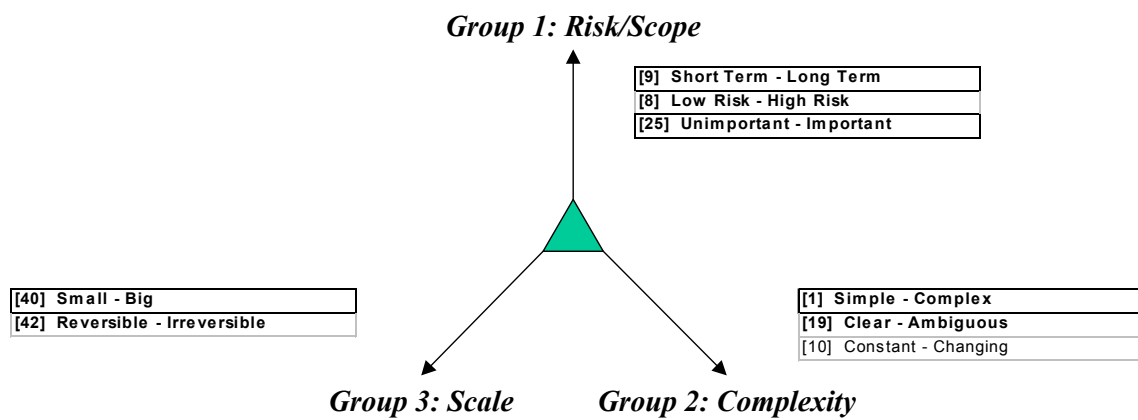
<sup>7</sup> For example, see the development of Einstein’s “theory of relativity” in Wertheimer (Wertheimer 1959).

<sup>8</sup> The example of a slot machine gamble is used because most people would clearly identify it as a third-order decision with an indeterminate outcome. Some may argue that it the outcome is probabilistic and therefore second-order, however, most gamblers would not be capable of performing the calculation and the calculation would only

The objective of profiling decision problems is to provide this distinction: to provide a measurement instrument that captures the “orderliness” of the decision. By taking the descriptors identified in decision order framework (Scherpereel 2002), in this study a series of dimensions are developed theoretically and verified using structural equation modeling. An attempt is made in this empirical investigation to measure these dimensions. The measurements along these dimensions are then used to explore, refine, and verify the theory.

**Preliminary Research (hypotheses)**

The work started in Scherpereel’s (2001) decision dimension study is extended by this research. The multidimensional models hypothesized for the “decision characteristic” concept and the “decision approach” concept are subjected to more rigorous testing. Thus, this experimental field study is designed to test the hypotheses that the “decision characteristic” concept has a three-dimensional structure in Figure 1 and that the following proxy semantic differential scales can be used to measure that structure: simple-complex S/C<sup>9</sup>, clear-ambiguous C/L, constant-changing C/C, short term-long term S/L, low risk-high risk L/H, unimportant-important U/I, small-big S/B, and reversible-irreversible R/I.



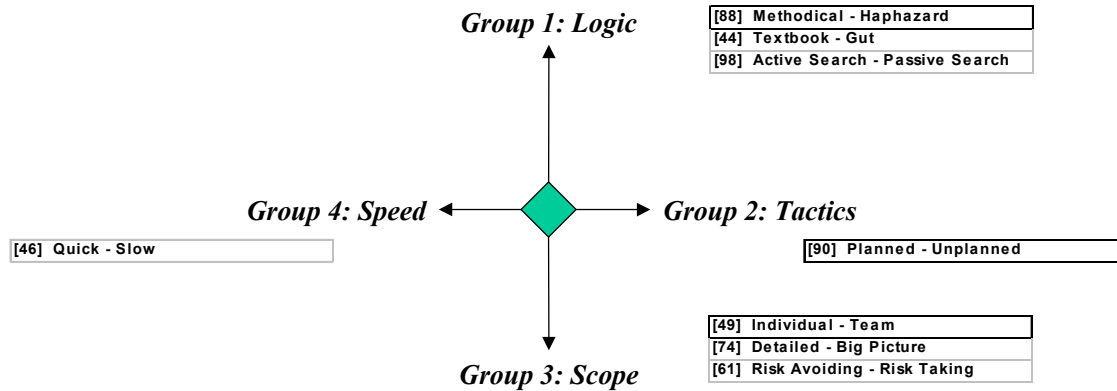
**Figure 1: Modified Three-Dimensional “Decision Characteristic” Semantic Space**

Additionally, the study seeks to confirm the hypothesis that the “decision approach” concept has a four-dimensional semantic structure illustrated in Figure 2. It is assumed that the following eight semantic differential scales can measure this structure: quick-slow Q/S, planned-unplanned P/U, individual-team I/T, detailed-big picture D/B, risk avoiding-risk-taking R/R, methodical-haphazard M/H, textbook-gut T/G, and active search-passive search A/P. Success in confirming the decision characteristic and decision approach structures will result in a visualization tool that can be used to quickly identify and target change in an individual’s perspective on, and approach to, specific decisions.

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be valid if the gamble were undertaken multiple times. Therefore, it is assumed that the slot machine gamble is only performed once and that no probability can be justifiably assigned.

<sup>9</sup> The shorthand notation S/C, C/A, etc. is used in several graphics in this document. The shorthand simply identifies the first letter of the polar measurement scales.



**Figure 2: Modified Four-Dimensional “Decision Approach” Semantic Space**

### Methodology

Measuring abstract business concepts, like decision orders, which often have multiple interrelated dimensions, do not evoke many standard measurement instruments. This section discusses a standard measurement instrument that is utilized in this research. Although repeated research has given indication of its validity, the application employed here is unique. The intent is to hold relatively true to the methodology as originally developed, but to make modifications to the implementation as dictated by the specific research problem.

#### *Semantic Differential*

The semantic differential is a scaling and research methodology developed by Osgood et al. (1957) to measure the psychological meaning of an object to an individual. The technique is developed to deal with the multiple dimensions of meaning and to explore the latent, or hidden, dimensions that cannot be directly measured. It is based on the proposition that any object, or concept, can be located in a multidimensional property space by the words, or semantics, used to describe it. For example, the semantic differential may be used to identify how the meaning of the word “cow” differs from the meaning of the word “pig.” The multidimensional representation evolved is called the semantic space.

The semantic differential technique can be compared to the psychological technique of using associations to elucidate some repressed disorder. It is a method of indirect investigation that reveals information, which would be difficult or impossible to garner through direct questioning. The technique has been widely used in marketing, political, organizational, and informational research.<sup>10</sup> For example, in a study on information quality and information alignment, the semantic differential technique was used to identify the latent dimensions of what constitutes quality information (Lefebvre 1992). In a marketing study on brand image, the technique was used to compare different brands of beer (Mindak 1969). In both these studies, its primary purpose was to identify the dimensions on which to focus change.

The semantic differential technique as originally developed consists of a set of bipolar rating scales, usually seven points,<sup>11</sup> on which respondents are requested to rate one or more concepts. The general format as described by Osgood et al. (Osgood, Suci et al. 1957) can be found in Figure 3, along with an example in which the concept of “polite” is semantically differentiated. The claim is made by Osgood et al. that “the terms ‘extremely,’ ‘quite,’ and ‘slightly’ as linguistic quantifiers have been associated with more or less equal degrees of intensity” (Snider and Osgood 1969, p. 67). Data and support for this claim are offered in their book, “The Measurement of Meaning” (Osgood, Suci et al. 1957). This assumption allows the proponents of the semantic differential technique to justify

<sup>10</sup> A sampling of applications can be found in (Kernan and Sommers 1967; Mindak 1969; Szalay and Deese 1978; Hirschman 1980; Levy 1981; Friedman 1986; Lefebvre 1992; Scharlemann, Eckel et al. 1999).

<sup>11</sup> A 1980 review of rating scale research by E. P. Cox (1980), concluded that there should be between five and nine levels in a scale. This conclusion is consistent with Miller’s (1954) thesis, titled “The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information.” It is clear from this research that too many divisions of a scale’s continuum leads to dimensioning returns and confusion, while too few divisions results in an inability to discriminate what may be significant differences.

their data analysis techniques by declaring that the ordinal data collection method results in approximately interval data.

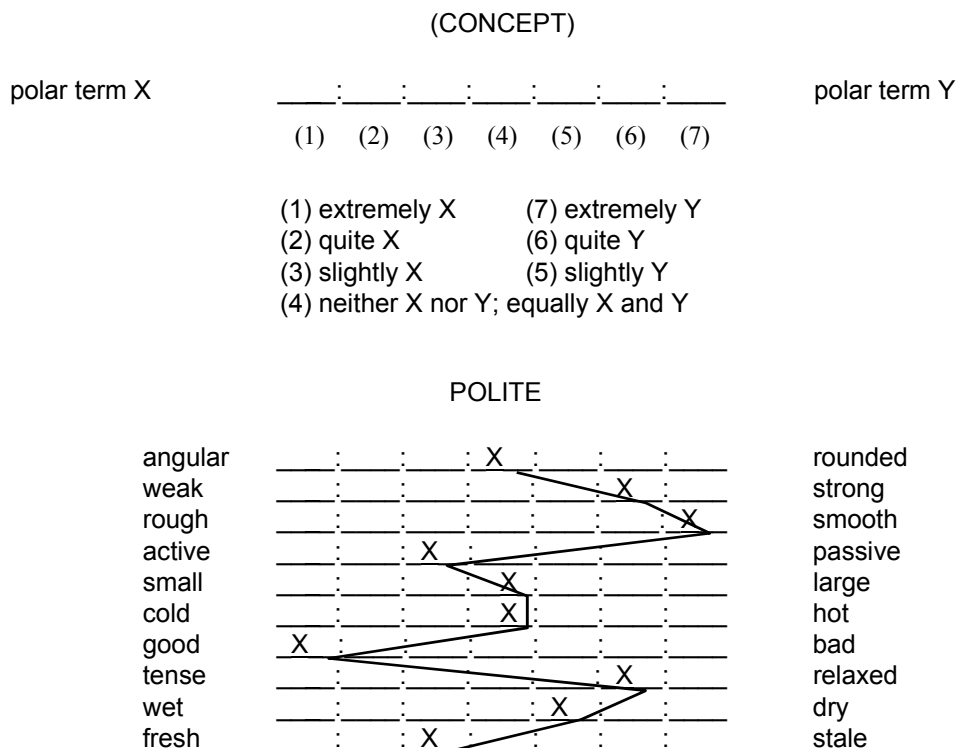


Figure 3: General Format for Semantic Differential (Osgood, Suci et al. 1957)

*Benefits of the Semantic Differential for Decision Order Evaluation*

The decision order model is developed as an objective classification taxonomy (Scherpereel 2002). However, since humans are intimately involved in the application of the taxonomy, it is their subjective perceptions of these objective factors that must be captured. The semantic differential is developed specifically to measure perceptions. While other techniques have been developed to measure perceptions, the semantic differential offers three key advantages. The first advantage is that the ordinal data collected, when properly described,<sup>12</sup> can be analyzed using interval techniques. This assumption may justify the use of some of the powerful parametric statistical techniques used in the analysis that follows.

Unlike other scaling techniques, the semantic differential can measure perceptions in both direction and intensity. The scales are designed to capture a directional measure of the concept relative to some neutral or central position and simultaneously provide data on how intensely the individual rates the concept. A response near the poles of a semantic differential scale indicates stronger concept agreement with the word on that pole than a response near the scales center or neutral point. The complete set of responses for a single concept provides a comprehensive picture of the concept's meaning and yields data on an individual's perception of the concept's meaning.

Finally, the technique allows for the extraction of a large amount of information in a relatively short period of time. To get both intensity and directional information using other scaling techniques requires much longer and more complex questionnaires. An alternative might be using open-ended questionnaires or interviews. These methods however, are not efficient at capturing a standardized image of the concept. Although they might be useful for exploring the appropriate terminology to incorporate in the semantic differential questionnaire, these alternatives

<sup>12</sup> See Osgood et al. (1957)

produce results that are difficult to aggregate. The ability to capture information about a specific concept quickly and aggregate it easily is probably the greatest advantage of the semantic differential technique.

**General Background** – The Setting This initial experimental study is conducted using a relatively homogeneous group of twenty-one senior vice presidents from a medium-sized service business. These participants all have a high level of understanding of their particular industry’s dynamics and are familiar with the decisions that drive business profitability. All participants perform the same job function for the company and have similar responsibilities. These participants are divided into four groups by the executive management.<sup>13</sup>

The intervention is a custom business war game that provides a rehearsal simulation environment for the teams of participants to run the branch office of a service company. The language and dynamic of the war game are designed to simulate the actual environment with which these participants are familiar. The teams of participants are given the mission to develop and execute strategies for the simulated branch office for a period of five years. At the end of this period, the team that performs “the best,” as judged by the executive management team, will be crowned the winner.

The environment is competitive. Each team is given a similar branch office to start the war game. They are also given some public information on the environment and competitive landscape. Each year of the war game is interspersed with mini-lectures highlighting the common techniques for analyzing both the internal and external conditions that the branch office is experiencing. Specifically, there are mini-lectures on team dynamics, finance, marketing, and strategy. At the start of each simulated year, teams are debriefed on their relative position and performance. They are then given the new starting positions and directed to breakout rooms where they can formulate decisions for the next simulated year. Participants are completely immersed in the war game for three full days; a minimum of eight hours of formal activity is scheduled for each day.

The custom war game is specifically designed to imitate a branch office operation in a competitive environment. The decisions made by participant teams are those that are typically made in the management of a branch office and include the key drivers of business success. Performance in any particular year is based on a model of typical industry dynamics and the competitive landscape created by other participant teams. Facilitators (non-participants) are responsible for assuring that the teams are engaging in the conversations that are appropriate for making the simulated branch’s decisions. These facilitators provide guidance and focus to the team conversations.

The intervention, briefly described above, is the typical package called a business war game or business simulation exercise. In this application it is being used as a development exercise, to improve or enhance participants’ performance in their existing positions. It is also commonly used as a training exercise to expedite the development of skills in a new position or industry. These are very different purposes and the reader is warned not to generalize specific results beyond the constraints of this study. More details on the study constraints will be given in a later section when specific parameters are addressed.

## **Research Constraints**

In addition to clarifying the appropriate methodology, the preliminary research isolates several major constraints on the research. The first constraint is the small sample size within any particular intervention group and limited ability to retest the same or similar group. The second is the time restrictions on the participants, and lastly, the tradeoff between the homogeneity of the participant group and the ability to generalize the results.

### *Small Sample Sizes*

Business war games, or business simulation exercises, are typically used on groups of between 12 and 36 individuals. Since it is a team-based activity, groups outside this range are administratively ineffective. Thus, the measurement of effect from a particular intervention is initially limited to relatively small sample sizes. Attempting to aggregate data from multiple small studies is difficult since the objectives established for the particular exercise are often group specific. It is these objectives that drive the selection of decision problems being queried, and these

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<sup>13</sup> Random team membership is not utilized because the small sample size created concern that several of the individuals, who were deemed “strong” by the executive management, could be placed on the same team. The executive management is in the best position to assure that the final team makeup is homogeneous in terms of individual strengths and weaknesses.

queries that drive correlations among the study variables. Thus, much of the analysis is restricted to the group that participated in one particular business simulation exercise.

The group participating in the primary portion of this study consisted of twenty-one individuals, approximately in the middle of the typical range. The objectives were targeted specifically at the common decisions made by these individuals. Constrained by the small sample size, high response rates became a major issue. To achieve the required level of response, a letter written by an influential insider was attached to the front of each questionnaire to encourage full participation. The executive management followed up by introducing the study with a verbal directive on its importance.

#### *Time Limitations*

The typical participants of a business war game exercise are university students and/or business executives. This study uses an exercise custom designed for business executives. Thus, it is imperative that participant's limited time is respected. Lengthy open-ended questions, questionnaires, and pre-post interviews could not be considered due to time constraints. There are five to ten minutes allocated for collecting data prior to the exercise, and approximately the same length of time available post exercise.

The participants represent all geographic regions of the United States, and are collocated to a single location in Vernon Hills, Illinois, for the three-day custom business war game exercise. All data must be collected by a set "end of exercise" time on the third day, so the participants can board buses to the airport and return home, and to eliminate parameters that could confound responses after the participants have returned to their home office responsibilities.

#### *Group Homogeneity*

The study is constrained to a relatively homogeneous group of participants. When business war game exercises are conducted in a corporate environment, the participants are typically of a similar educational, social, and personality type. Thus, the ability to generalize beyond the specific group, or groups with similar characteristics, becomes suspect. The issue is; how can the conclusions drawn from a homogeneous group be extended to a heterogeneous group? This question is addressed in a number of research studies<sup>14</sup> and will be discussed in the study's conclusions.

Because of the difficulty generalizing from a study conducted on a homogeneous group, it might seem prudent to select a group that is heterogeneous. Even if possible, this strategy can be dangerous, especially when the sample size is small. A heterogeneous group requires the researcher to control for a large number of additional parameters, such as; common language and understanding of the questions— none may exist, representative of the population – sample too small to reflect population, and different levels of motivation - high versus low involvement. Thus, utilizing a homogeneous sample group may in reality be the optimal choice. Gaining insights from a homogeneous sample and later testing those insights on other groups may be the only methodology for formulating valid conclusions.

Although admittedly limited in generality, this study collects and analyzes the data from one homogeneous group. The methodology, however, is applicable to any number of different groups, which might be used over time to provide stronger validation to the conclusions. The homogeneous group selected for this study is unique. The participants are senior sales vice presidents from a medium-sized mortgage-banking company. All participants have similar job responsibilities and educational backgrounds.

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<sup>14</sup> This issue is especially prevalent in weaker empirical research designs, such as the "case study." The criteria for generalizability is whether or not conclusions seem reasonable to a broad cross section of readers and they facilitate greater understanding of the phenomenon in question (Snow and Anderson 1991). Under this view, it is considered legitimate to make generalizations based on the degree to which a case is representative of some larger population. It is not merely a question of how many units but rather what kind of unit is under study. The nature of the phenomenon is the true gauge of the population to which one seeks to generalize (Feagin, Orum et al. 1991). (Kratochwill 1978; Kennedy 1979; Robson 1993; Guba and Lincoln 1994; Wolcott 1994; Maxwell 1998) debate these views.



## METHODOLOGY

This section describes the methodology used in this experimental field study. It incorporates both the explicit and implicit learning from the prior pilot and data dimension studies (Scherpereel 2001). This brief description of the research design is followed by the results and analysis.

Confirming the dimensions for both the “decision characteristic” and “decision approach” concepts requires large data sets,<sup>15</sup> which are unavailable with this particular intervention. Therefore, the decision is made to include multiple decision targets for each decision concept. This innovation allows six times as much data to be collected for confirming the multidimensional space models from the same sample. Although aggregation of these data is not theoretically justified, the use of replicate data does provide some credibility to the hypothetical claims. To claim that the model is supported by the small sample using a single decision target is weaker than the claim that the model is supported in six different applications. By designing the experiment to capture six data sets from the same participant, the model can be tested six times, thus, supporting the stronger claim.

### *Target Decision Selection*

The target decisions are selected considering both the common decision set for the participants and the ability to rate these decisions along a variety of semantic scales. As an individual obtains more and more experience with a particular decision, a concept emerges. This process is exemplified by the learning of Hull’s Chinese characters (Hull 1920). By selecting common decisions, or decisions with which the participants are familiar, participants are able to recall an unambiguous mental concept that they can then use for rating the semantic differential scales. This reduces the major concern that participants will be rating the semantic scales based on different concepts, and increases the likelihood that the data can reliably be aggregated to generate the true meaning of the concept.

Another consideration is that the decisions selected are those also made during the business war game exercise. Since the intervention being tested, a custom business war game exercise, is designed with a limited number of decisions that focus upon participant learning, the set of possible decision concepts is constrained. The decisions included in a custom exercise are typically those that are identified by the designer consultants as “critical” to the running of the business. These critical decisions are the ones targeted for change by the business war game designers and therefore are the ones selected for measurement.

Interviews with the business war game exercise designers and sponsors resulted in six concepts to be tested. These six concepts cover a large range of business decisions, from personnel management to business strategy, and span the common decision set of the participants.

The six targets are abbreviated as follows: Strategy (establishing strategy), Hiring (hiring a loan officer), Time Block or Time Blocking (allocating loan officer time), Training (training loan officers), Targeting (targeting customers) and Sourcing (sourcing leads). These abbreviations are used in the remainder of this chapter.

### *Questionnaire Design*

Two sets of eight bipolar semantic differential scales are developed as the measurement instruments for the “decision characteristic” and “decision approach” concepts. These scales are applied across six specific decision targets for a total of ninety-six measurements per respondent. The scale is constructed in the standard seven-point rating format as described by Osgood et al. (1957). The result is a questionnaire instrument that collects data on the perceived magnitude and direction of the “decision characteristic” and “decision approach” concepts’ meaning.

**Layout** – The decision dimension questionnaire begins with a page of detailed instructions, describing the correct marking of the instrument. The instructions are presented in three sections; the general information, specific example and important notes;<sup>16</sup> and the landscape layout is used to conform to the space requirements of the dual column question format. As suggested by the pilot study, the questions are grouped first by decision concept, with the “decision characteristic” concept in the left column and the “decision approach” concept in the right column.

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<sup>15</sup> The statistical techniques used to confirm these complex models typically require large data sets (Hair, Anderson et al. 1998).

<sup>16</sup> For details on the instruction design, see the pilot test design details.

Across columns, the target decisions are presented so that the same decision-target that appears in the “decision characteristic” column is mirrored in the “decision approach” column. Finally, space limitations allow only two decision targets to be included on each page. This layout is illustrated in Figure 4.

BUYING a new car		BUYING a new car	
Buying a new car is considered a(n) _____ decision?		Buying a new car requires you to take a(n) _____ approach?	
Big	: <input checked="" type="checkbox"/> : _____ : _____	Organized	: <input checked="" type="checkbox"/> : _____ : _____
Small	: _____ : _____	Disorganized	: _____ : _____
Risky	: _____ : <input checked="" type="checkbox"/> : _____	Textbook	: _____ : _____ : <input checked="" type="checkbox"/> : _____
Safe	: _____ : _____	Gut	: _____ : _____

**Figure 4: Experimental Field Study – Question Layout**

**Target Decision Order** – Six target decisions are included in the decision dimension questionnaire. The placement of each target is consistent with the suggestion to place easier decisions earlier in the questionnaire (Emory 1985, p. 222). Therefore, the first target is selected because it is the most familiar among the participants. The decision familiarity decreases as the respondent moves from decision target number one through decision target number four. The final decisions, five and six, return to a moderate level of familiarity.

It is worth noting that the first three decision targets can be categorized as tactical decisions, having a more immediate impact on the business, while the last three decision-targets are primarily strategic. This order allows the respondent to answer the easier tactical decisions before having to switch to the more difficult strategic decisions. The fourth decision target, “establishing strategy,” is designed to help respondents switch from a tactical mindset to a strategic mindset as they complete the questionnaire.

**Scale Order and Polarity** – The eight semantic differential scales, for each of the two decision concepts, are pseudo-randomly ordered. A heuristic is applied that attempts to separate scales that are intuitively similar, or were previously found to measure the same dimension. If the scales cannot be separated, then an attempt is made to reverse the polarity of one of the scales. Reversal of scale polarity is also done to select scales, when the interpretation of the scale would not be significantly impacted. For example, the polarity of the scale “small-big” is reversed to “big-small” without significantly impacting the scale’s difficulty, since the opposite pole is obvious given either term. In contrast, the scale simple-complex is intuitively more appealing than the reversed scale complex-simple. Therefore, the scale simple-complex is not considered for reversal. The goal of the heuristic is to keep a term that is most “familiar”<sup>17</sup> to the respondent on the left-hand pole of the scale. This ordering heuristic procedure encourages the respondent to read the polar terms carefully before marking the scale.

Scale order and polarity is maintained from decision target to decision target. Although increasing the repetitiveness of the questionnaire, this feature speeds the marking process. It also provides some assurance that each decision target is receiving similar consideration by the respondent.

**Additional Design Features** – Since this study is designed to gather data on individual change, a space for the respondent’s name is included on the first page of the questionnaire. The respondent’s name is then used to match their pretest with their posttest questionnaire, which is critical for analysis. The posttest questionnaire is identical to the pretest questionnaire except for an indication that the questionnaire is a follow-up. The posttest questionnaire presents the concepts and the associated semantic differential scales in exactly the same format as the pretest questionnaire. This avoids some of the instrumentation bias<sup>18</sup> concerns that might be introduced by altering the design.

A cover letter is included with each questionnaire to encourage response. On the initial questionnaire, the cover letter is from the company’s director of training, introducing the research and its importance to the business. The cover letter attached to the posttest questionnaire is a letter from the researcher, thanking the respondents.

<sup>17</sup> Scale reversal is restricted to scales that have a common polar opposite. This implies that the term is “familiar” to the respondent. In other words, the scale’s left-hand term is most likely to be in the respondent’s common language set and there is little confusion about its meaning.

<sup>18</sup> Instrumentation bias is a threat to the internal validity of the experimental design. This bias is the result of changes between the pretest and posttest measurements, which arise from changes in the instrument design.

**Administration** – The experimental field study is administered in two parts. The program facilitator distributes the pretest questionnaire at the beginning of the first day, of a three-day business war game exercise. Instructions are given to return the completed questionnaires at the first program break. Fifteen minutes is explicitly allocated for completing the questionnaire, with additional time available during the participant’s break. Both the program director and the firm’s executive management verbally highlight the importance of the study, which is reinforced in the cover letter. The questionnaires are collected and the inclusion of the respondent’s name is verified visually.

The posttest questionnaire is distributed during the final session of the third day. Again, fifteen minutes are allocated for completing the questionnaire, with additional time available at the session’s end. Instructions are given to return the questionnaires before departing, however, in the event that it cannot be completed, an alternative collection method is offered.<sup>19</sup>

## ANALYSIS

The analysis seeks support for the decision concept structural hypotheses and requires sophisticated multivariate techniques. These techniques include cluster and factor analysis, both of which are classified as exploratory in the literature. A more powerful, but restrictive, statistical theory based technique called structural equation modeling will follow from these exploratory analyses. Often used as an exploratory technique itself, structural equation modeling can be used in theoretically confirming complex a-priori hypothetical models. Together these three techniques form the basis for supporting the following two claims:

1. The “decision characteristic” concept has a three-dimensional structure (Figure 1) and the following proxy semantic differential scales can be used to measure that structure: simple-complex, clear-ambiguous, constant-changing, short term-long term, low risk-high risk, unimportant-important, small-big, and reversible-irreversible.
2. The “decision approach” concept has a four-dimensional semantic structure (Figure 2) and the following proxy semantic differential scales can be used to measure that structure: quick-slow, planned-unplanned, individual-team, detailed-big picture, risk avoiding-risk-taking, methodical-haphazard, textbook-gut, and active search-passive search.

## EXPLORATORY RESULTS

Cluster and factor analysis are used in the initial investigation of the data. These techniques are identified as exploratory because the techniques themselves do not impose any a-priori constraints on the solution set and the results of these techniques are not unique.<sup>20</sup> In this study, there exists a basis for an a-priori model of the decision concepts; however, it is not sufficiently developed to use more rigorous testing. The exploratory techniques are used to search the data structure to find confirming evidence for these a-priori hypotheses and to provide the additional development necessary for future validation. Although the techniques do explicitly test the hypotheses, support is offered based on face validity and stability across decision targets.

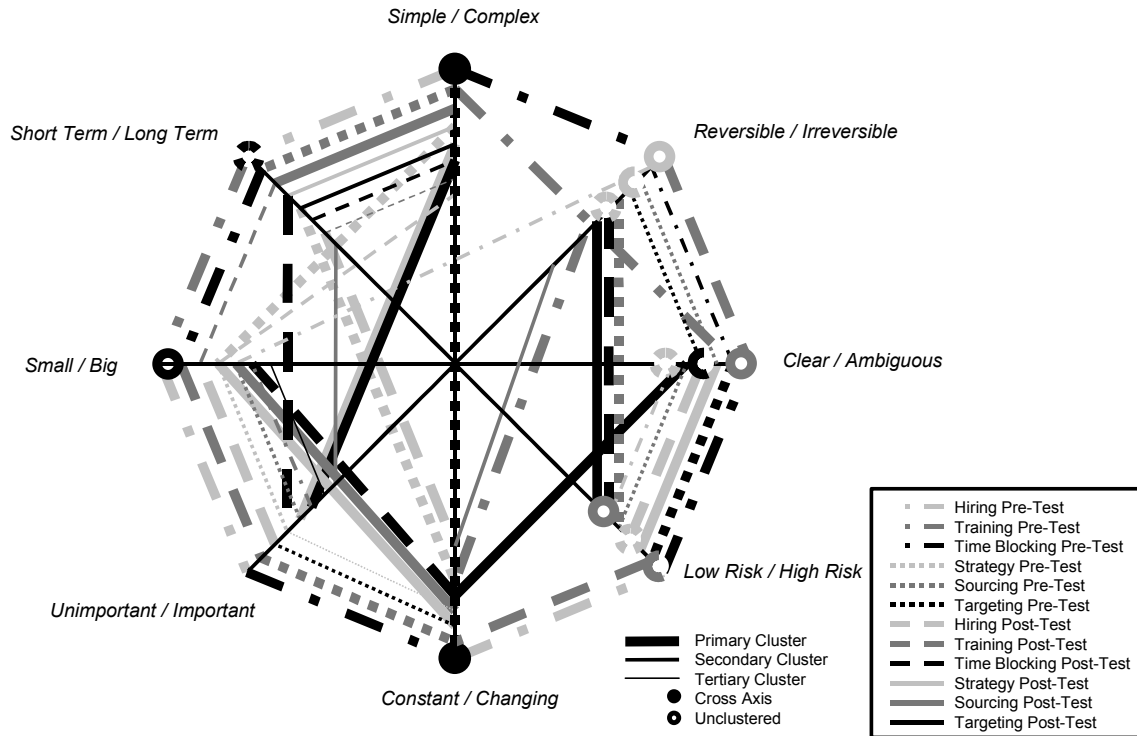
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<sup>19</sup> In this study, all participants attending the final session were able to complete the posttest questionnaire prior to departure. However, there was one participant, who for emergency reasons, needed to leave just prior to the final session and did not receive the posttest questionnaire. Because of the small sample size, it was decided that the inclusion of this participant’s posttest responses was important. Therefore, the questionnaire was immediately sent electronically to the missing respondent. This questionnaire was electronically returned within a week and carefully inspected for abnormalities. None were detected, so these data were added to the full data set without further note.

<sup>20</sup> There is a continuing debate over the role of factor analysis in research. “Many researchers consider it only exploratory, useful in searching for structure among a set of variables or as a data reduction method” (Hair, Anderson et al. 1998, p. 91). Those with this perspective do not set any a-priori constraints on the estimation or the number of factors extracted. “For many – if not most – applications, this use of factor analysis is appropriate” (p. 91). In other situations the researcher is interested in testing an a-priori structure, based on theoretical or prior research. The methods used in this exploratory section do not provide the necessary precision for formalized hypothesis testing.

*Cluster Results*

The goal of cluster analysis is to identify from a set of data the groups of variables that relate. Subjecting the field study data to cluster analysis results in a grouping of similar semantic differential scales<sup>21</sup>. Since the data are stratified by the target decisions, six different cluster solutions can be crafted for each decision concept in each data set (pretest and posttest). The resulting twenty-four<sup>22</sup> cluster solutions are summarized by dendrograms. By identifying the closest clustering variables on these dendrograms; identified as the primary, secondary, and tertiary; a more compact summary can be developed. The summary spider chart for the “decision characteristic” concept is shown in Figure 5. The eight semantic scale axes are arranged to minimize the distances between the closest neighboring variables. This process conveniently reduces the clutter and reveals the underlying structure.

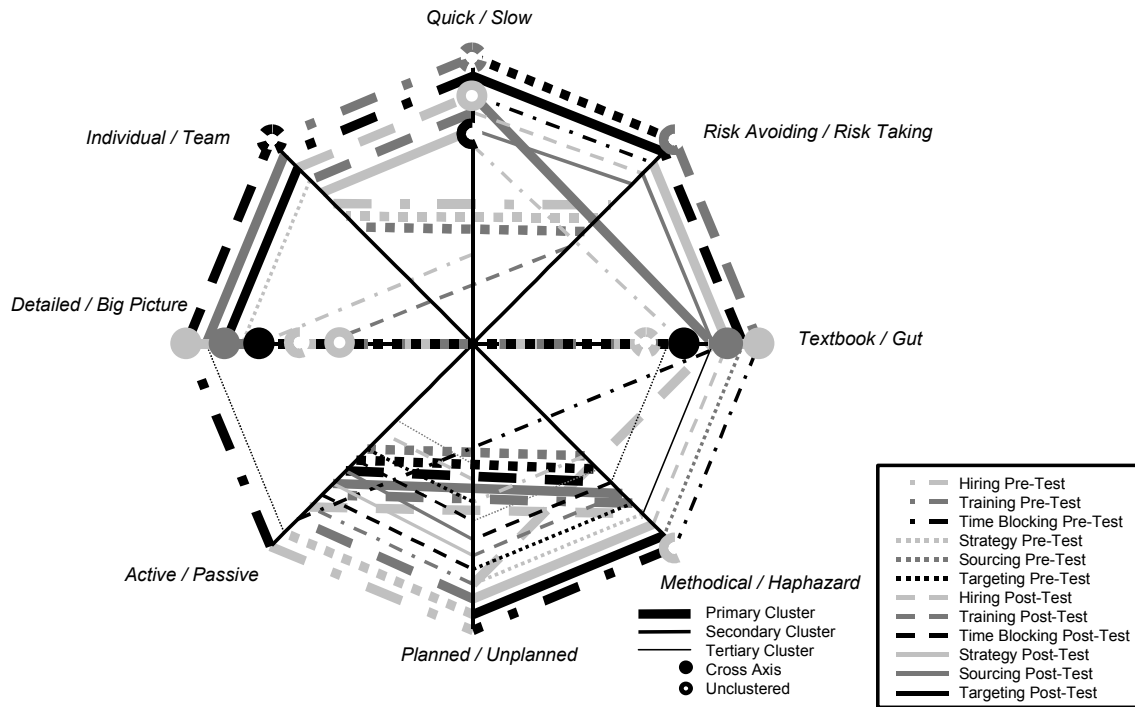


**Figure 5: “Decision Characteristic” Concept – Cluster Analysis Summary**

<sup>21</sup> Using the Ward linkage algorithm (Ward 1963). The Ward linkage algorithm is designed to optimize the minimum variance between clusters.

<sup>22</sup> There are six (6) different decision targets on each of the pretest and posttest questionnaires, testing the two decision concepts (“decision characteristic” and “decision approach”). The total number of cluster solutions that can be generated from these data is  $6 \times 2 \times 2 = 24$ .

The same procedure is performed on the “decision approach” concept data to generate Figure 6. Using these visual presentations, the complexities of these data and the identification of the true underlying structure might be revealed.



**Figure 6: “Decision Approach” Concept – Cluster Analysis Summary**

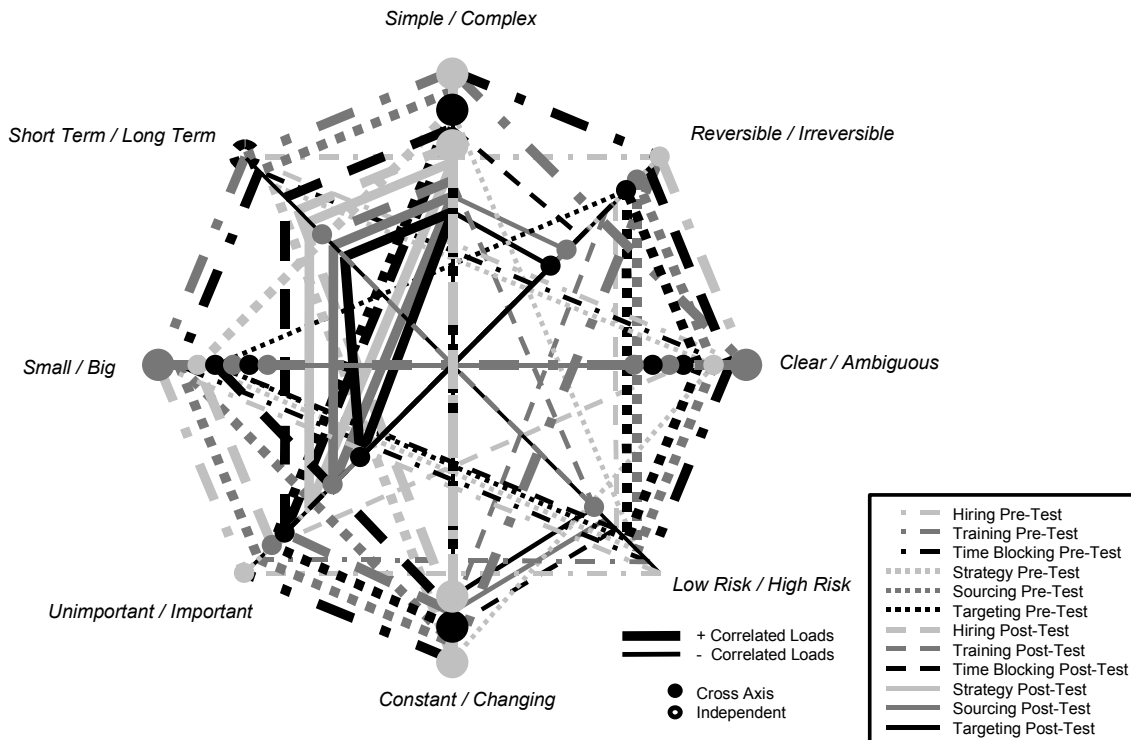
*Factor Results*

This technique has a long history of use in analyzing semantic differential results. The developers of the semantic differential technique, Osgood et al. (Osgood, Suci et al. 1957), promoted factor analysis as the technique of choice for their seminal work. The factor analytic technique explores the data set to find a reduced structure. The resulting solution summarizes the data in a form that makes the theory easier to communicate.

A series of exploratory factor analyses are performed on the experimental field study data set<sup>23</sup>. A spider chart for the “decision characteristic” concept, Figure 7, is used to summarize the compiled factor analytic results. Arranging the eight semantic axes so that the distances between related factor loads are minimized, crafts this spider chart.<sup>24</sup> The thicker lines represent the positive factor loading variables, while the thinner lines represent negative loading. The different line types represent the different decision targets.

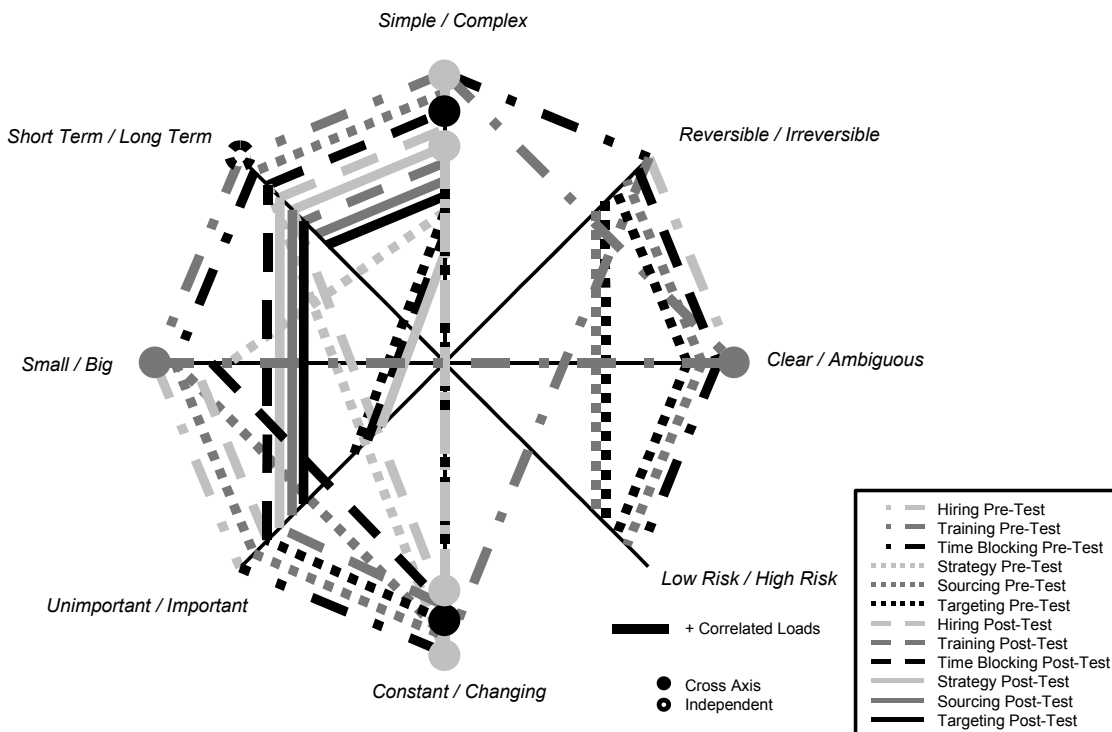
<sup>23</sup> Using the procedure described by Hair et al. (Hair, Anderson et al. 1998, p. 94-135), a series of common factor analyses are performed on the experimental field study data set. The objective is to factor analyze the semantic differential scales for each decision target. This is called R-type factor analysis in literature, and it involves the process of analyzing the correlation matrix for a set of variables to extract the underlying dimensions. This procedure is performed using a standard algorithm available in the MiniTab™ software package.

<sup>24</sup> The spider charts were originally developed in color to draw a clearer distinction between the different target concepts. Unfortunately, the format of this document allows only a black and white rendition, which makes identification of the related scales difficult. Therefore, the raw factor analytic results are included in Appendix R.



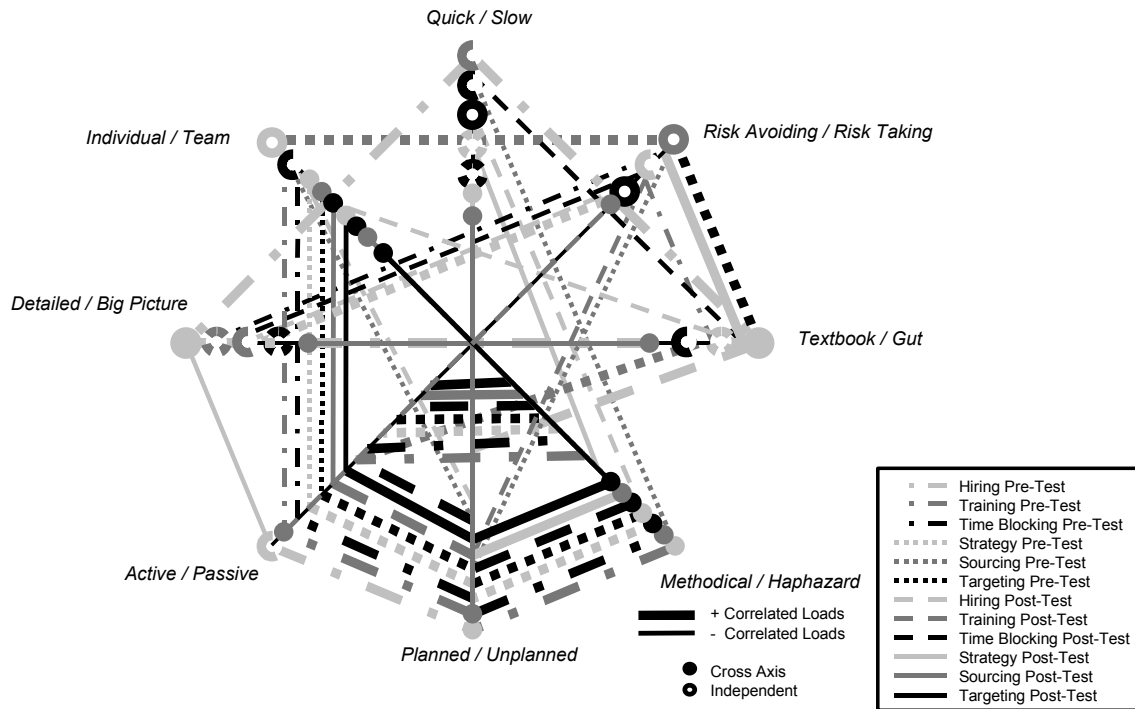
**Figure 7: "Decision Characteristic" Concept – Factor Analysis Summary**

Since there is a hypothesized theoretical polarity to the semantic differential scales, the intent is to only identify positive loading variables. Removing these negative-loading relationships from Figure 7, results in the clearer structure illustrated in Figure 8. These results will be explored further in the discussion sections.



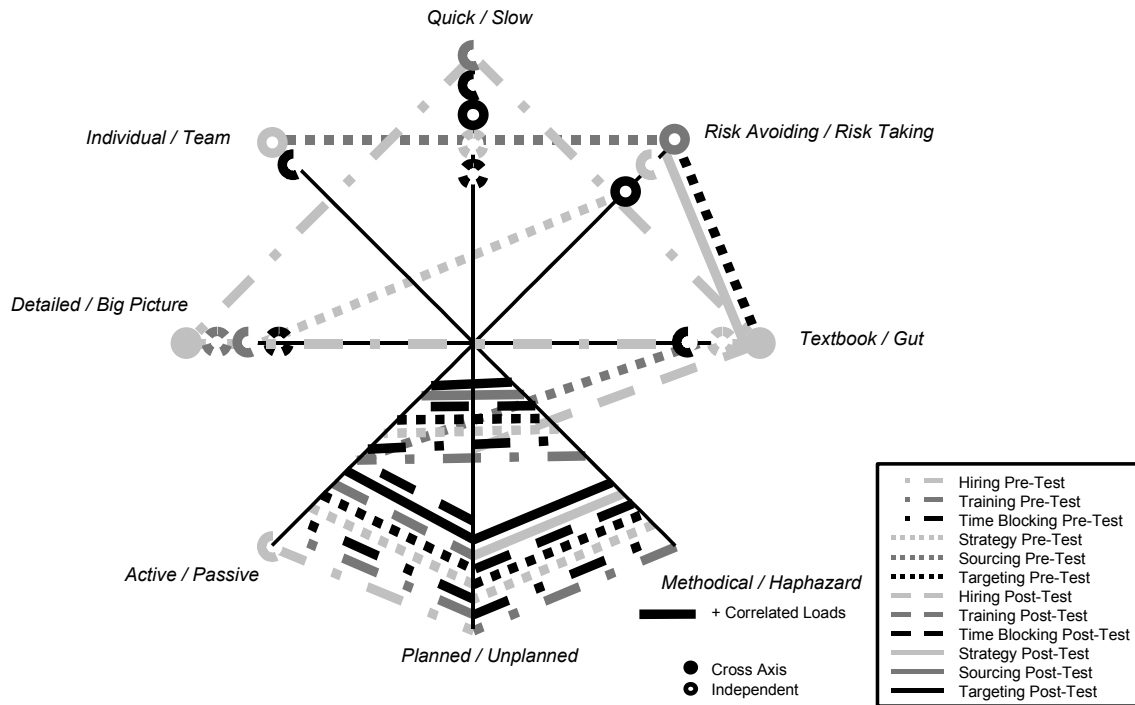
**Figure 8: “Decision Characteristic” Concept – Restricted Factor Analysis Summary**

Performing the same procedure on the “decision approach” concept results in the Figure 9 spider chart. It should be noted that the spider charts for the “decision approach” concept are significantly sparser than the “decision characteristic” concept. This is due to the large number of single loading, or independent, factors in the analysis.



**Figure 9: “Decision Approach” Concept – Factor Analysis Summary**

Restricting the analysis to only the positively loaded factors results in Figure 10.



**Figure 10: “Decision Approach” Concept – Restricted Factor Analysis Summary**

#### FURTHER ANALYSIS: STRUCTURAL EQUATION MODELING

Previous sections have alluded to many of the experimental field study’s findings. These findings are made more explicit in this section. First, the analysis is advanced using a special technique called structural equation modeling. This additional analysis provides theoretical support and suggests modifications to the theories proposed in the statement of research objectives

#### Special Technique - Structural Equation Modeling

The structural equation modeling process is completed in two steps: defining the hypothetical model structure, and then evaluating the empirical data “fit” to the hypothetical model. In this study, the model structure is theoretically derived for both the “decision characteristic” and the “decision approach” concepts. Each variable in the model is conceptualized as a latent variable measured by several semantic scales as indicators. The latent variables are defined as the dimensions in the semantic space models. Although the models appear relatively simple, structural equation modeling calculations focus on analyzing the covariance structure, which can be quite complex. Thus, a number of statistical packages have been developed by researchers to ease this complexity burden. In this study, the commercial software package AMOS (Analysis of Moment Structures) is used.

Having established the theoretical basis for the structural model, the fit with the empirical evidence needs to be assessed. The sample size is not sufficient to test each decision target individually, so it is decided to aggregate all the pretest decision targets into a single data-file, and similarly aggregate all the posttest decision targets. Fortunately, this is not a major problem. If the theoretical model is correct, the relationships that exist between semantic scales should be consistent across decision targets. Alternatively, the covariance structure should not be significantly altered by this aggregation. If the theory is incorrect the empirical data will fail to show the hypothetical relationships and the results will indicate a poor fit. These procedures result in an independent pretest and posttest data-file, to be used for testing and confirming the theoretical relationships identified. Some additional relationships need to be defined that are not a part of the theoretical description. These relationships are between the additional terms included in the model to account for measurement error. For the “decision characteristic” concept it is argued, based on post questionnaire discussions, that the measurement errors are correlated.

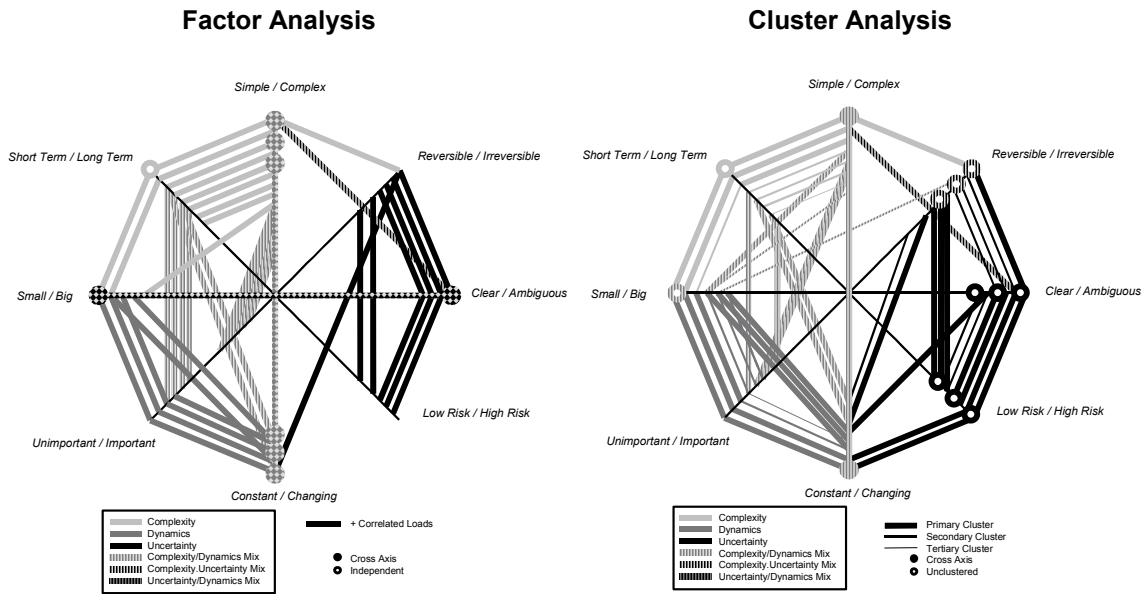
Structural equation modeling begins with a hypothetical “path” model describing the relationships between the dependent and independent variables. These relationships are then transformed into a series of equations. The



procedure requires a slight redefinition of the problem. Although the dependent variables remain the semantic differential measurement scales, the independent variable is now described in terms of the model’s proposed latent variables. What are the model’s proposed latent variables? These are simply the variables represented by the labels on the semantic space, the three dimensions for the “decision characteristic” concept and the four dimensions for the “decision approach” concept.

*“Decision Characteristic” Structural Equation Modeling*

By visually analyzing the results from the factor and cluster analysis, Figure 8 and Figure 5 respectively, an underlying structure seems to appear. Carefully re-coloring the connection relationships between the semantic differential scales, an enhanced image of the semantic space is created. This enhancement is illustrated in Figure 11, showing a visibly defined three-dimensional structure for the “decision characteristic” concept.



**Figure 11: “Decision Characteristic” Concept – Enhanced Structure**

Labeling the dimensions in this semantic space requires the intuition gained in prior research. However, the grouping of the semantic scales follows directly from the re-coloring process. Figure 12 imposes the groupings and provides a possible labeling convention. Specifically, the three semantic dimensions defined for the “decision characteristic” concept are complexity, uncertainty, and dynamics.

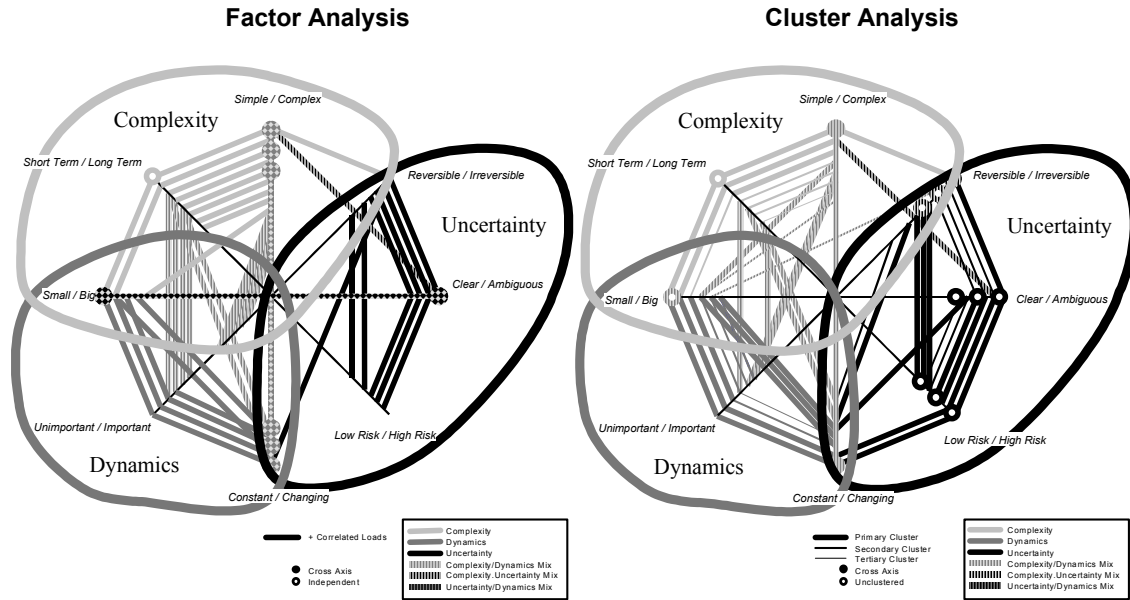


Figure 12: “Decision Characteristic” Concept Suggested Semantic Space

From this graphical analysis, the theoretical three-dimensional semantic space for the “decision characteristic” concept is derived. In Figure 13, the dependent variables are indicated along the spider axes, while the independent variables are defined as by the three-dimensional groupings. The labels on the three groups form the defining terms in the concept’s theoretical semantic space.

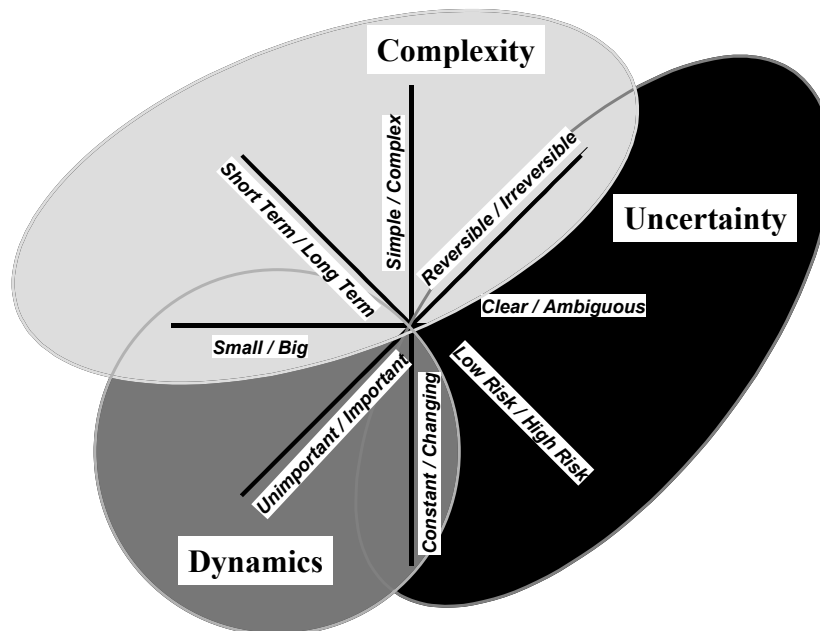
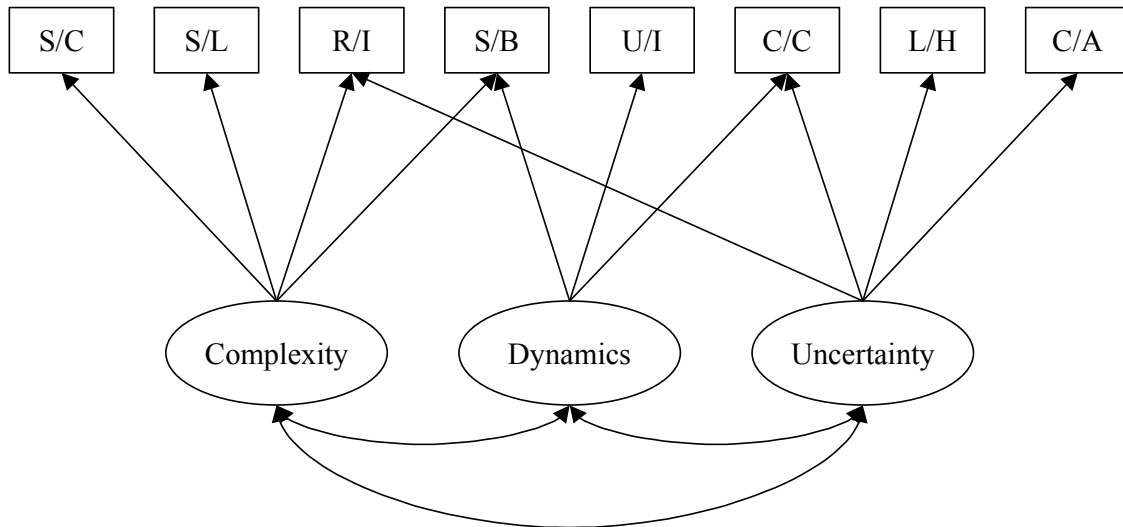


Figure 13: “Decision Characteristic” Theoretical - 3D Semantic Space

The labels in Figure 13 represent the independent variables and are re-specified as the latent variables in the path diagram, presented in Figure 14. These latent variables are not directly observable but are measured indirectly by the independent variables, which are called “indicator” variables in the structural equation modeling. The path

diagram describes the proposed causal relationships formally. This path-diagram in structural equation modeling represents a constrained theoretical formulation that contrasts the previous exploratory factor analytic techniques. Thus, this model represents a hypothesis that can be subjected to a series of rigorous tests to assess how it fits empirical data.



**Figure 14: Path Diagram for the “Decision Characteristic” Concept**

To determine if the model should be accepted, a number of specialized statistical tests have been developed. AMOS reports 25 different goodness-of-fit measures; however, no standards have been established regarding which measures are the most critical. Most structural equation modeling methodologists recommend the use of several measures to judge fit. Garson (1999) recommends the chi-square, AGFI, TLI, and RMSEA, while Kline’s (1998) list references the chi-square; GFI, NFI, or CFI; TLI; and the SRMR. Hair et al. (1998) recommend using one or more measures from the following three general categories; 1) absolute fit measures, 2) parsimonious fit measures, and 3) incremental fit measures. This later recommendation is used in this study.

Two absolute fit measures are selected for model evaluation, the “Goodness-of-fit index” (GFI) and the “Root mean square error of approximation” (RMSEA). Both measures are developed to measure the degree to which the overall model predicts the observed covariance matrix. The GFI is a non-statistical measure ranging in value from 0 (poor fit) to 1.0 (perfect fit) and represents the percent of observed covariances explained by the covariances estimated in the model. By convention, the GFI should be equal to or greater than 0.90 to accept the model. The RMSEA is a statistical measure representative of the goodness-of-fit estimated for the population. Values ranging from 0.05 to 0.08 are acceptable.

The parsimonious fit measures relate the goodness-of-fit of the model to the number of estimated coefficients required to achieve the reported level of fit. The analogous statistic in regression analysis is the adjusted  $R^2$ . Only a single parsimonious measure is discussed in the results for the hypothetical models. The “Normed Chi-Square<sup>25</sup>” is the ratio of the chi-square statistic divided by the degrees of freedom. This measure provides two ways to assess the appropriateness of the hypothetical model. If this measure falls below a lower threshold of 1.0, the model is capitalizing on chance by “overfitting” the data to the model. The upper bound is set somewhere between 2 and 3, representing the limit to where the model truly represents the data.

The incremental fit measures are designed for use in comparing models, often comparing the hypothesized model with the null model<sup>26</sup>. In this study, the Adjusted goodness-of-fit index (AGFI) and the Tucker-Lewis index (TLI) are highlighted. The AGFI adjusts the GFI by a ratio of the hypothesized model’s degrees of freedom to that

<sup>25</sup> The “Normed Chi-Square” is reported as the “discrepancy/df” in the AMOS output.

<sup>26</sup> The null model is some realistic model that all other models should be expected to exceed. By convention this model is usually a single construct model with all indicators perfectly measuring the construct. This form of the null model is used in the computation of the incremental fit measures.

of the null model. The second measure, TLI, is a comparative index based on the chi-square statistic and penalizes the model for too many parameters. Thus, it can be described as an incremental fit indicator with an adjustment for parsimony. Both the TLI and AGFI have recommended lower limits of 0.90, however, since they are comparative measures this limit is not firm.

If the overall model is judged acceptable by these goodness-of-fit measures, each of the constructs can be evaluated separately. This is done in two steps. The first step is to examine the indicator's loading for statistical significance. In this case, "P-values" of approximately 0.10 are identified as significant. Then an examination of the construct's reliability and variance extracted is made. Values of approximately 0.70 for reliability and 0.50 for variance extracted are indicators of acceptability (Hair, Anderson et al. 1998, p. 623).

The structural equation modeling assessment of fit for the pretest "decision characteristic" concept is reported in the following tables. These tables highlight in bold the selected overall goodness-of-fit measures, the construct's p-values, and the construct's reliability and variance extracted values. To obtain information on other measures available from structural equation modeling Hair et al. (1998) is recommended.

The empirical data collected in this study seem to support the model relationships as illustrated in Figure 14. A brief summary of these results is included in Table 1 for the pretest data and Table 2 for the posttest data.

<b>Solution</b>					<b>Goodness-of-fit</b>	
			<b>Estimate</b>	<b>P</b>	<b>Measure</b>	<b>Value</b>
S_B	<--	Complexity	0.22	0.231	<i>overall</i>	
S_L	<--	Complexity	0.69	<b>0.000</b>	<b>absolute fit</b>	
S_C	<--	Complexity	1.00		GFI	<b>0.96</b>
R_I	<--	Complexity	0.30	<b>0.116</b>	RMSEA	<b>0.07</b>
					<b>parsimonious fit</b>	
R_I	<--	Uncertainty	0.51	<b>0.008</b>	Normed Chi-Square	<b>1.60</b>
C_A	<--	Uncertainty	1.00		<b>incremental fit</b>	
L_H	<--	Uncertainty	1.02	<b>0.000</b>	Tucker-Lewis index	<b>0.73</b>
C_C	<--	Uncertainty	0.77	<b>0.000</b>	Adjusted GFI	<b>0.89</b>
					<i>measurement</i>	
C_C	<--	Dynamics	0.19	0.299	<b>Complexity</b>	
U_I	<--	Dynamics	0.26	<b>0.003</b>	Reliability	0.41
S_B	<--	Dynamics	1.00		Variance Extracted	0.18
					<b>Dynamics</b>	
					Reliability	0.51
					Variance Extracted	0.28
					<b>Uncertainty</b>	
					Reliability	<b>0.67</b>
					Variance Extracted	0.35

\* **Bold values achieve recommended levels**

**Table 1: Pretest "Decision Characteristic" Concept – Structural Equation Modeling Summary**

**Solution**

			<b>Estimate</b>	<b>P</b>
S_B	<--	Complexity	1.74	<b>0.018</b>
S_L	<--	Complexity	0.87	<b>0.000</b>
S_C	<--	Complexity	1.00	
R_I	<--	Complexity	-0.77	<b>0.000</b>
R_I	<--	Uncertainty	-0.14	0.561
C_A	<--	Uncertainty	1.00	
L_H	<--	Uncertainty	0.74	<b>0.008</b>
C_C	<--	Uncertainty	-0.18	0.334
C_C	<--	Dynamics	0.19	0.299
U_I	<--	Dynamics	1.00	
S_B	<--	Dynamics	-1.60	<b>0.031</b>

\* **Bold values achieve recommended levels**

**Goodness-of-fit**

<b>Measure</b>	<b>Value</b>
<b>overall</b>	
<b>absolute fit</b>	
GFI	<b>0.96</b>
RMSEA	<b>0.06</b>
<b>parsimonious fit</b>	
Normed Chi-Square	<b>1.47</b>
<b>incremental fit</b>	
Tucker-Lewis index	<b>0.90</b>
Adjusted GFI	<b>0.89</b>
<b>measurement</b>	
<b>Complexity</b>	
Reliability	<b>0.75</b>
Variance Extracted	<b>0.51</b>
<b>Dynamics</b>	
Reliability	<b>0.68</b>
Variance Extracted	<b>0.53</b>
<b>Uncertainty</b>	
Reliability	0.40
Variance Extracted	0.21

**Table 2: Posttest “Decision Characteristic” Concept – Structural Equation Modeling Summary**

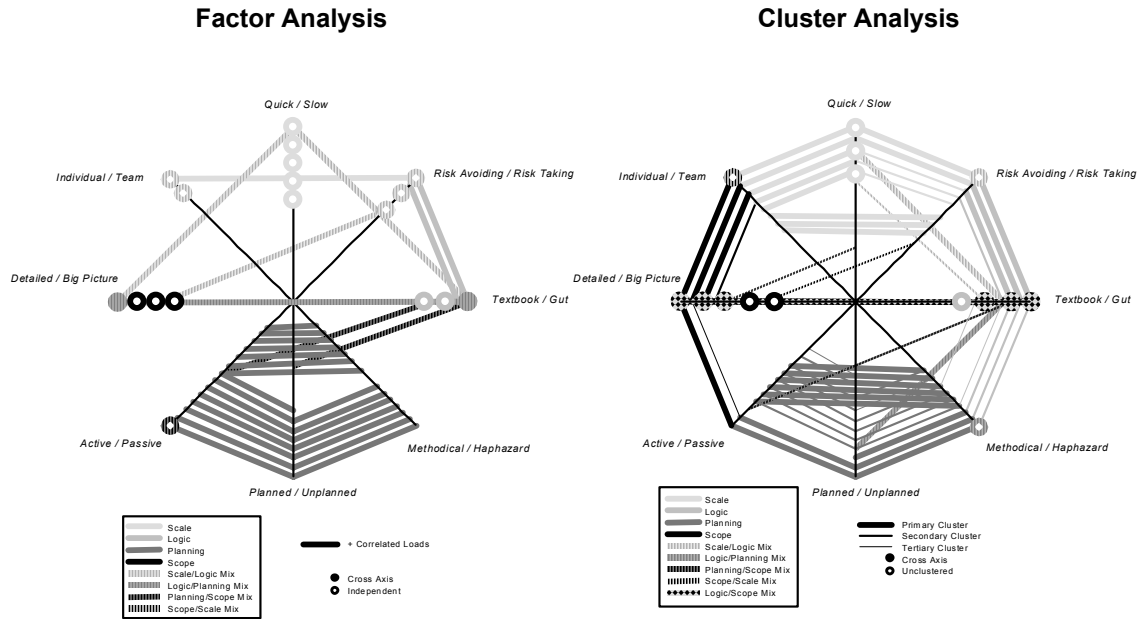
These results indicate that the model has an acceptable overall fit for the empirical data collected in this study.<sup>27</sup> Unfortunately, the fit of the model as a predictive measurement model is suspect. Several of the indicator variable coefficients are not significant, and the reliability and variance extracted indexes are too low for several of the dimensions. These problems may be indicative of non-normality, non-linearity, and an inadequate sample size in the data set. The results do, however, support the “decision characteristic” concept model’s feasibility and provide some indication that a more robust predictive model can be developed.

*“Decision Approach” Structural Equation Modeling*

In a similar procedure, the “decision approach” concept is reduced to a four-dimensional semantic space. Examining the results from the factor and cluster analysis, Figure 10 and Figure 6 respectively, an underlying structure is revealed. By carefully re-coloring the connection relationships between the semantic differential scales,<sup>28</sup> an improved image of the semantic space is produced. This improvement is illustrated in Figure 15, showing a clearly defined four-dimensional structure for the “decision approach” concept.

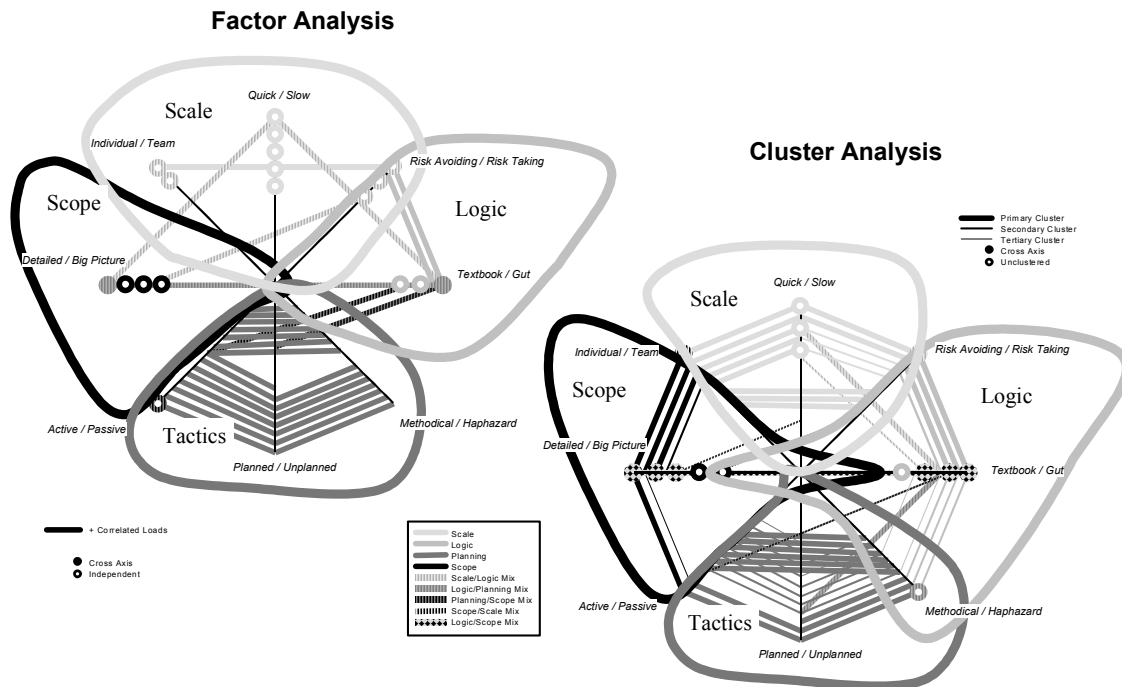
<sup>27</sup> Note that the bold values in Table 1 and Table 2 indicate acceptable levels of fit according to Hair et al. (1998).

<sup>28</sup> The re-coloring procedure is the same as was used to develop the “decision characteristic” concept.



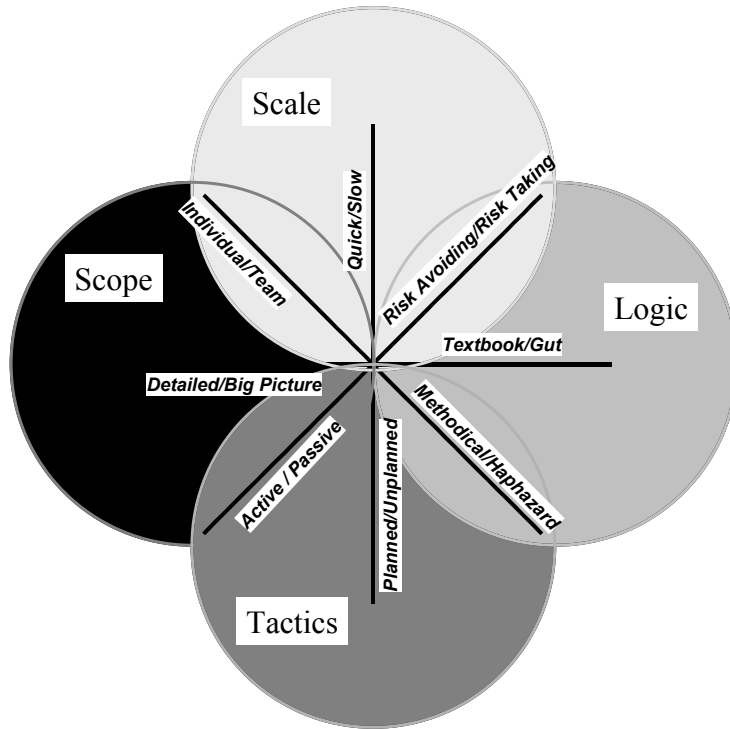
**Figure 15: “Decision Approach” Concept – Enhanced Structure**

The dimensions in this semantic space are labeled to communicate the intuition underlying the semantic space representation, and follow directly from the re-coloring process. This representation is presented in Figure 16. In this figure, the scale, logic, tactics, and scope semantic dimensions define the “decision approach” concept.



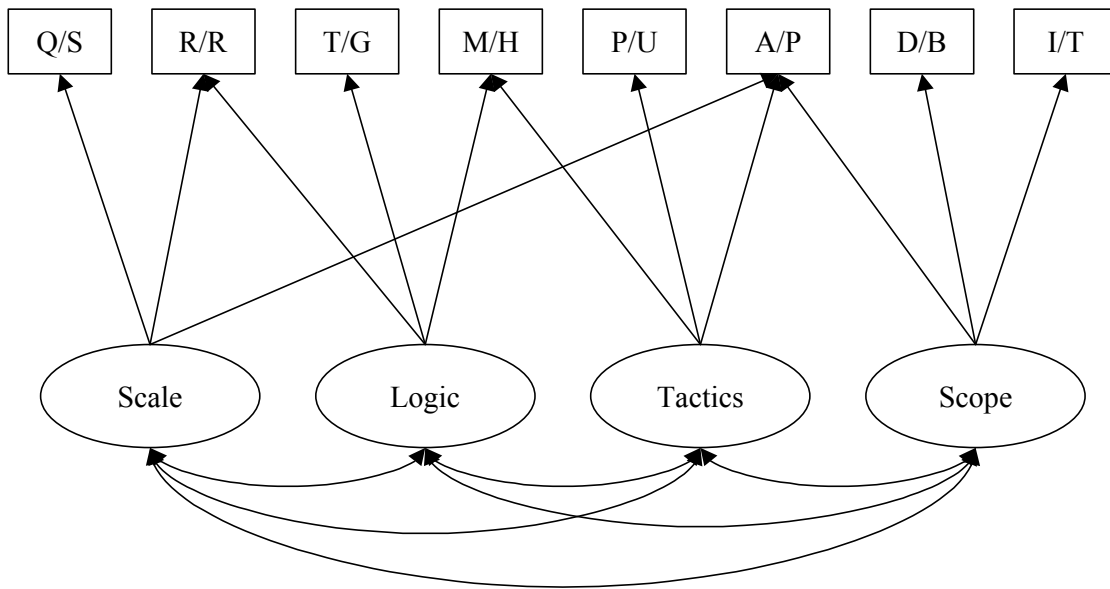
**Figure 16: “Decision Approach” Concept Suggested Semantic Space**

Combining the slightly different groupings identified in Figure 16, a single theoretical four-dimensional semantic space for the “decision approach” concept is derived in Figure 17. In this figure, the dependent variables are indicated along the spider axes, and the independent variables are defined by the four circled-groups. The labels on the four groups are defining dimensions in the concept’s theoretical semantic space.



**Figure 17: “Decision Approach” Theoretical - 4D Semantic Space**

The labels in Figure 17 are used as the labels on the independent variables, or latent variables, in the Figure 18 path diagram. These latent variables communicate the underlying theory and are not directly observable. Instead, specific combinations of the eight semantic scales represent the causal relationships for these latent variables. The path diagram formally describes the causal relationships. Thus, this model represents the hypothesis that the specified structure is a feasible representation that can be supported by the empirical data.



**Figure 18: Path Diagram for the “Decision Approach” Concept**

Support for a four-dimensional “decision approach” concept theory is offered by the use of structural equation modeling techniques. The empirical data collected in this study seem to support the model as illustrated in Figure 18. A brief summary of these results is included in Table 3 and Table 4 for the pretest and posttest data respectively.

<b>Solution</b>					<b>Goodness-of-fit</b>		
			<b>Estimate</b>	<b>P</b>	<b>Measure</b>	<b>Value</b>	
I_T	<--	Scale	0.80	0.265	<b>overall</b>		
Q_S	<--	Scale	1.00		<b>absolute fit</b>		
R_R	<--	Scale	1.13	0.184	GFI		<b>0.97</b>
					RMSEA		<b>0.06</b>
R_R	<--	Logic	0.24	0.317	<b>parsimonious fit</b>		
T_G	<--	Logic	1.00		Normed Chi-Square		<b>1.37</b>
M_H	<--	Logic	0.08	0.455	<b>incremental fit</b>		
M_H	<--	Tactics	1.00		Tucker-Lewis index		<b>0.92</b>
P_U	<--	Tactics	0.60	<b>0.000</b>	Adjusted GFI		<b>0.91</b>
A_P	<--	Tactics	0.67	<b>0.000</b>	<b>measurement</b>		
A_P	<--	Scope	-0.09	0.242	<b>Scale</b>		
D_B	<--	Scope	1.00		Reliability		<b>0.81</b>
I_T	<--	Scope	-3.29	0.179	Variance Extracted		<b>0.59</b>
					<b>Logic</b>		
					Reliability		0.59
					Variance Extracted		<b>0.48</b>
					<b>Tactics</b>		
					Reliability		0.33
					Variance Extracted		0.23
					<b>Scope</b>		
					Reliability		<b>0.85</b>
					Variance Extracted		<b>0.67</b>

\* **Bold values achieve recommended levels**

**Table 3: Pretest “Decision Approach” Concept – Structural Equation Modeling**



Solution					Goodness-of-fit	
			Estimate	P	Measure	Value
I_T	<--	Scale	0.29	0.159	<i>overall</i>	
Q_S	<--	Scale	1.00		<b>absolute fit</b>	
R_R	<--	Scale	0.65	<b>0.006</b>	GFI	<b>0.97</b>
					RMSEA	<b>0.08</b>
R_R	<--	Logic	0.35	<b>0.059</b>	<b>parsimonious fit</b>	
T_G	<--	Logic	1.00		Normed Chi-Square	<b>1.74</b>
M_H	<--	Logic	0.01	0.946	<b>incremental fit</b>	
M_H	<--	Tactics	0.56	<b>0.000</b>	Tucker-Lewis index	<b>0.87</b>
P_U	<--	Tactics	0.50	<b>0.000</b>	Adjusted GFI	<b>0.88</b>
A_P	<--	Tactics	0.53	<b>0.000</b>	<i>measurement</i>	
A_P	<--	Scope	-0.18	0.187	<b>Scale</b>	
D_B	<--	Scope	1.00		Reliability	0.41
I_T	<--	Scope	0.73	<b>0.000</b>	Variance Extracted	0.22
					<b>Logic</b>	
					Reliability	0.37
					Variance Extracted	0.19
					<b>Tactics</b>	
					Reliability	0.33
					Variance Extracted	0.24
					<b>Scope</b>	
					Reliability	0.62
					Variance Extracted	0.36

\* **Bold values achieve recommended levels**

**Table 4: Posttest “Decision Approach” Concept – Structural Equation Modeling**

The results indicate that the “decision approach” concept model has an acceptable overall fit for the empirical data collected in this study. However, when analyzing how well the indicators measure each construct or semantic dimension, the results are less hopeful. Noting that several of the indicator variable’s coefficients are not significant, and the reliability and variance-extracted indexes are below the acceptable level for a majority of the dimensions, the predictive powers of the model are questionable. These observations may be indicative of non-normality, non-linearity, and an inadequate sample size in the data set. Even with these difficulties, support can be given to the “decision approach” concept model as a feasible representation of the empirical data. This analysis provides some strong evidence that a more robust predictive model can be developed using this framework.

#### REMARKS

The analysis provides support for the two hypotheses. First, the reduction made from the eight semantic differential scales to the three dimensions defining the “decision characteristic” semantic space is supported by both the cluster and factor analysis results. Similarly, these analyses support the reduction of the “decision approach” concept to four dimensions. The significance of this support cannot be validated using statistical techniques; however, finding the a-priori dimensional structures in the empirical data does provide credibility beyond raw intuition. The refinement made in isolating the measurement of these dimensions is a major advancement over previous efforts. By utilizing multiple decision targets, the external validity of these models is enhanced. It can now be postulated, with some confidence, that these models will remain valid when applied to other specific business decisions.

Additional support is provided by the structural equation modeling results. These results suggest that a predictive model may be possible. Unfortunately, the data set used in conducting this analysis does not conform faithfully to the data requirements established in the theoretical literature.<sup>29</sup> Therefore, it is premature to draw strong

<sup>29</sup> For additional information see (Wang and Willson 1996; Hair, Anderson et al. 1998; Loehlin 1998).

conclusions regarding the causal relationships. Weaker conclusions can be stated in the form of support for the two models identified. The structural equation modeling analysis supports the validity of the two concept models by confirming their existence as members of a feasible set.<sup>30</sup> Thus the models are not “proven” unique using structural equation modeling; they are only supported by the technique’s confirmation.<sup>31</sup>

### CONCLUSIONS AND FUTURE RESEARCH

Theoretically, this study establishes a descriptive foundation upon which a reliable predictive theory can be built. Where the study has failed to provide rigorous proof, it has provided extensive exploratory direction for future research. The semantic models represent complex hypotheses that are difficult to test. Even with the limited data, these models hold up remarkably well under the various testing methodologies. However, further data collection, analysis, and refinement are necessary. The prospect of developing a predictive model that can link the characterization of decisions with the approach people take toward those same decisions, is an objective not reached by this effort. However, the seeds have been planted to make such an endeavor a promising prospect.

In applied work, the ability to profile individual and group perceptions is a valuable tool for valuing interventions that claim to change these perceptions. Management training is typically such an intervention. How do you measure the value of training programs that teach the intangibles? It is relatively easy to measure the change in specific skill performance: but how do you measure the results of a training program that changes people’s internal paradigms? A business war game exercise is this type of management training program. The methodology developed in this study provides the much-needed instrument.

This research develops and tests the use of multidimensional semantic spaces to represent the perceptual characterization of decisions and approaches to those decisions. The resultant is a common language and a visual communication tool that can be used by both practitioners and researchers. The application is made to a business war game exercise; however, there is ample indication that the methodology is applicable to any intervention that claims to change people’s paradigms.

A major area of future investigation comes from the interest in the categorization of decisions. How can instruments like the decision dimension models help in this categorization? The profiles developed in this study provide raw information regarding decision maker’s perceptions of decisions. The intuitive advantage of an unbiased measurement instrument over a path based theoretical taxonomic classification scheme is clear. However, the prospect of using both the descriptive intuitions gathered from field studies and the prescriptive guidance provided by a taxonomic theory is extremely attractive.

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<sup>30</sup> Hair et al. (1998, p. 591) suggest that obtaining an acceptable level of fit using structural equation modeling does not assure the researcher that the optimal model has been found. “Numerous alternative models may provide equal or even better fits.” They continue by stating “the strongest test of a proposed model is to identify and test competing models that represent truly different hypothetical structural relationships.”

<sup>31</sup> In fact, research has suggested that the techniques developed for assessing structural equation models have a “confirmation bias,” which tends to confirm the model’s fit to the data (Robles 1996).

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