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REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

ON............ 12 April 2002 ....

.... [redacted] ....

Sec. Research Graduate School Committee

ERRATA

Chapter 1
Page 1-6

Paragraph 3, 3rd line: "in turn" for "inturn"

Chapter 3
Page 3-12

Paragraph 2, 10th line: "Indeed" for "In deed"

Chapter 5
Page 5-19

Formulas at the bottom of the page to be replaced by:

The set of Alternatives is denoted as A $a_i \in A,\ i = \overline{1,k}$

The set of Criteria is denoted as C $c_j \in C,\ j = \overline{1,l}$

The evaluation of each alternative is given by the vector $c(a_i) = (c_1(a_i),\ldots c_l(a_i))$

Chapter 5
Page 5-20

Two top formulas to be replaced by:

The value of a criterion $c_j(a_i) = f(W_j S_j(a_i))$

where, W_j is the weight for the criterion c_j
and S_j is the score for c_j

The weight of a criterion $W_j = f(P(c_1,c_1),\ldots P(c_l,c_l)),\ j = \overline{1,l}$

where,

P is the preference between $c_x, c_y,\ x,y = \overline{1,l}$

Chapter 6
Page 6-5

The top half of the page to be replaced by:

The set of Alternatives is denoted as A $a_i \in A,\ i = \overline{1,k}$

The set of Criteria (variables) is denoted as C $c_j \in C,\ j = \overline{1,l}$

The evaluation of each alternative is given by $a_i = \sum_{j=1}^{l} (s_{ij} w_j)$

Where, s_{ij} is the score for criterion c_j
for an alternative a_i, and
w_j is the weight for criterion c_j

The outcome of the decision is the highest evaluation for an alternative.

The weights for the criteria in the decision situation are determined by the collective set of preferences to those criteria.

The weight of a criterion $W_j = f(P(c_1, c_1) \ldots P(c_l, c_l)),\ j = \overline{1,l}$

where,
P is the preference between c_x, c_y, $x, y = \overline{1,l}$

Using Decision Maker Personality as a Basis for Building Adaptive Decision Support System Generators for Senior Decision Makers

By

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ABSTRACT

This dissertation is the artefact of the of a Doctoral research project undertaken to evaluate the proposition that decision-makers' personality preferences can be used to provide active decision support to senior decision-makers in organisations. The research project was undertaken as a series of steps, under the *concept-development-impact* model of information systems research. The comprehension of the past body of work in the related disciplines, the selection appropriate theories from the past work to substantiate the detailed hypothesis, conducting experiments to clarify and confirm the validity of using personality as a means of distinguishing between criteria preferences of decision-makers, the determination of a suitable architecture in which criteria preferences of individuals may be incorporated in to formally expressed decision models, building a computer-based system to illustrate the feasibility of the architecture and finally evaluating the ability of the system to adapt to practical situations were steps in this work.

Although decision support system research has not given it much consideration, many organisational and individual decision making studies have shown the importance of the decision-makers' personality to the decision process. Within this project *different personalities* are aligned with the 'types' of the Myers-Briggs Type Indicator, a commonly used and validated personality instrument. *Criteria Preferences* are obtained through weight allocation to decision variables, using a pair-wise comparison method. A specific emphasis is placed on decision tasks that lack in structure. Extracted criteria preferences are held as profiles, that are refined with usage through artificial neural networks. Profiles are organised into a hierarchy within a decision support system generator, based on the level of abstraction of the preferences. As an illustration of the conceptual proposal, a system named ADAPTOR was built. This system was then used to evaluate the efficacy of the proposition.

In the early stages of the research, it was shown that a quantifiable difference does exist between different personality types when assigning criteria preferences. Through the use of profile hierarchies, it was possible to a build system that successfully abstracted situational and personality data. The efficacy of the system in practical scenarios could not be confirmed through short-term studies. It is proposed that that aspect will need further longitudinal investigation.

This thesis has not been submitted for the award of any other degree or diploma in any other tertiary institution. No other person or person's work has been used without due acknowledgment.

[redacted]

Priyanka Paranagama
August, 2000

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To my wife, Thushara who supported me through times when the will to complete seemed faint. Thank you for providing enough distraction to make life interesting while providing the encouragement to complete. The thesis is the culmination of the road shown by my parents and their aspiration to see me succeed in life. Thank you for all the support and encouragement.

This study could not have been a success without the cooperation of the many willing research participants. It is fitting to acknowledge the contribution made by fellow researchers, academics, journal and conference referees who have provided valuable input to make my research project a success. Thank you to my work colleagues who have continually encouraged me to complete the dissertation.

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Chapter 1

Introduction

Decision support systems (DSS) has been recognised as an important branch of the information systems discipline since the nineteen sixties. While the intentions of initiating such a branch were clear at the time, its definition has been the subject of constant evolution. In Gorry and Scott-Morton's (1971) seminal paper, they illustrated the need for supporting *non-structured* decisions made by senior (strategic) managers. However, how this support is provided has been the subject of contention. It was envisaged that decisions lie on a continuum from *structured* to *unstructured*. Computer support for structured decisions was considered routine and programmable. Dealing with the unstructured was considered the domain of human beings. Lying between these two extremes are a range of decisions termed semi-structured, which may be increased in their structure or formalism for better decision-making. Decision support systems are a special category of systems that can help in this *structuralisation* process. Essentially, these are corporative systems where the structured components are handled by the computer-based system while the unstructured components are handled by the human decision-maker. In this interaction, the system is seen as an assistant rather than a replacement to the person.

Definition of DSS beyond the above has been difficult. A number of researchers have provided various perspectives (Keen, 1980; Klein and Methlie, 1995; Manheim, 1988; Power, 1997; Sprague and Carlson, 1982, Stabell, 1983). Studying the various perspectives, it is clear that the definition cannot be limited by technology; DSS are primarily targeted at individuals; improving the effectiveness of decision making is the major goal; and decision support systems aim to influence the decision making process.

Initially, the intentions of DSS were sought to be realised through two major paradigms. The first espoused that *ad-hoc DSS* should be built to suit each individual decision situation (Keen, 1980), while the other believed that a range of tools should be made available to the decision-maker in the form of *DSS generators* (Carlson, 1983). In this second perspective, the decision-makers had to use these tools in whatever way they thought fit to help in the decision making process. These systems are termed *passive DSS*.

Passive DSS were based on the belief that no decision-making process is better than any other. However, researchers such as Stabell (1983), believe that there should be some specification of how to use the facilities to form a good decision process. Managers alone cannot be expected to systematically improve their decision making thorough the use of DSS. Stabell was of the opinion that it was important to build DSS that are congruent with existing decision behaviour of individuals, while still providing a normative framework within which to make decisions.

The involvement of the system (without explicit instructions from the user) in the decision making process is seen as a way of guiding the decision-maker towards a better decision by providing a normative framework (Manheim, 1988). Manheim advocated building systems that maintain a dynamic model based on the problem solving approach of the user. This model is used to complement the user in the decision making process, while still respecting the primacy of the user. A system that utilises this mechanism is considered an *active DSS* (Carlsson and Walden, 1999). Such active support may also be useful in decision-making as conservation of effort has been repeatedly illustrated to be a major influence in human decision-making (Todd and Benbasat, 1992). If the system is capable of taking over some decision-making functionality, the effort required to be expended by the decision-maker may be reduced.

1.1 Rationale and purpose of the study

In this thesis, I propose a distinct way of building active decision support system generators. The active capability of systems based on this proposal use the personality profile of individuals as a means of approximation.

Though the focus of DSS has changed with the evolution of the discipline, research has shown that the usage patterns of decision support systems are far from initial expectations. Contrary to beliefs that they are tools that should be used 'hands-on' to augment managers' decision making in unstructured situations, most decision support systems are used for a purpose other than intended, mainly by intermediaries (Keen, 1980). Recent knowledge shows that decision support systems are being used primarily by middle-level managers with 'resource allocation' type of problems. Therefore, it is plausible to assume that the discipline has developed at a position further down the organisational hierarchy than what was envisaged by pioneers in the discipline. Though this form of decision support remains a legitimate arena for the discipline, it is important that we refocus on supporting key decisions in organisations made by more senior managers. This doctoral research project is aimed at taking a step towards this direction.

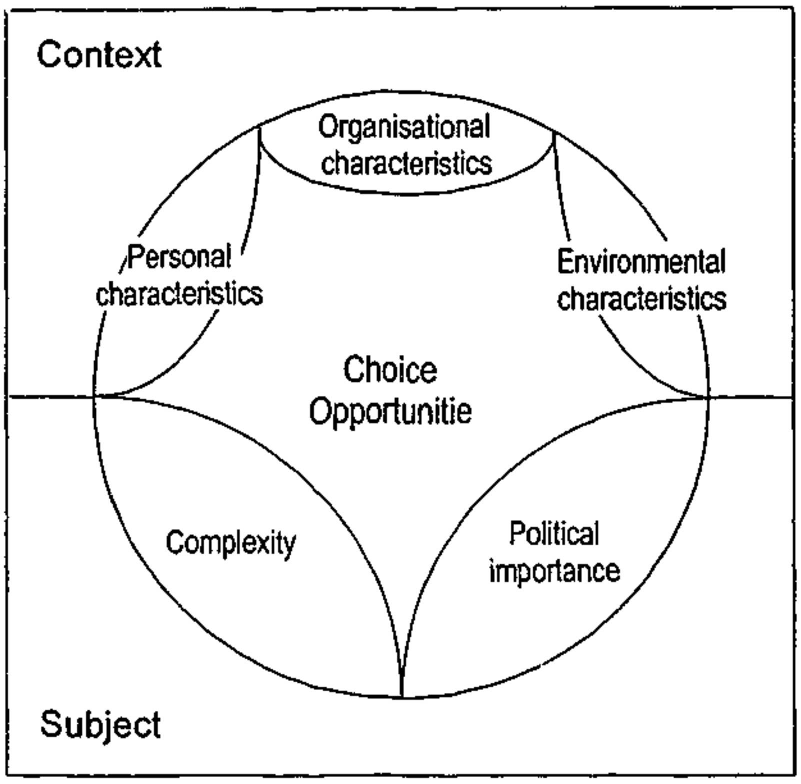


Figure 1.1: Koopman and Pool (1994) model of Choice Opportunities

Koopman and Pool (1994) present a model of decision making in organisations (Figure 1.1). This model is similar to the Four-Force Model proposed by Rowe and Boulgarides (1992) and many other organisational decision making models. In these models, personal characteristics of the decision-maker are constituents in the *context* of decision making along with organisational characteristics and environmental characteristics. The context of decision-making is distinct from the subject matter (*task*), as it forms the parameters within which the decision is made. These influences in the context affect the leeway that is available to make a choice. The normative approach to the study of decision-making assumes that decision-makers will select the optimal choice where all possible alternatives are known and evaluated in a quantitative manner. However, studies of managers and their decision-making behaviour show that they are not always searching for decision alternatives that optimise a stated set of objectives. The choice activity is said to be 'quasi-rational' or 'bounded-rational' (Hammond *et al.*, 1975; Simon, 1960). Analytic activities are combined with intuitive processes. The violation of principles of rational choice within decision-makers is systematic and can vary with individuals (Slovic, Fischoff and Lichtenstein, 1976). Orville C. Brim *Jr. et al.* (1962) articulate that choice is an interaction between three types of variables: *situational variables*, *personality variables* and *interactional variables*. *Abilities*, *beliefs*, *attitudes* and *motives* are among the personality variables they identify. These have exposed the limitations of the normative model of decision-making as it is clear that the cognitive and perceptual limitations and the personality traits of the decision maker play an important role in choice activities.

The importance of addressing cognitive limitations of human decision-makers in the decision support system development process has been highlighted in the research of Arnott (1994). The influence of personality in decision-making and its implications to decision support systems has not been investigated to any useful extent. This has prompted researchers such as Koopman and Pool (1994) to call for further research into the relationship of personality and decision-making. This research project aims to undertake this task so that useful conclusions can be reached for the decision support systems discipline.

My contention here is that if personality is shown to be an important part in choice behaviour, consideration of the decision maker's personality should be a part of any tool that aims to support decision-making, in addition to the traditional aim of optimising objective functions. This may be even more important at higher organisational echelons as individuals at those levels have the mandate to make decisions that depend heavily on personal satisfaction than any stated organisational objective (Koopman and Pool, 1994). In fact, Scott Myers's (1966) study of a large number of managers has shown that managers' motivation is highest when self-actualisation was a goal. They can give direction to the organisation, utilising their experience represented in their personality, to enrich the choice process.

It has been shown that psychological forces such as personality may in fact help towards achieving original decision making objectives rather than working against them (Harrison, 1987). This is also compatible with the management perspective which illustrates that senior managers work toward satisfying their personal agendas (Isenberg, 1984; Kotter, 1982; Mintzberg, 1975). Decision-makers at lower organisational levels have to work within given constraints, keeping organisational goals and objectives as the primary criteria. The use of individual personality at lower levels can be detrimental to the organisational mission if the decision-maker's persona is not congruent with the organisation.

When faced with a decision situation, individuals attempt to classify it based on their value system. The goals for the current process are derived from this value system. The goals are then translated into decision rules, which inturn are imposed in the decision making process (Svenson, 1990). In forming the value system of a person, consequences of previous decisions are very important. Svenson believes that most of our lives may follow logically from past decisions and present circumstances.

In considering personality differences between decision-makers it is important that we define how these differences may be used in practical applications. The issue is to identify whether this approach is used:

1. to provide a different style or layout to the interface,

2. to perform a certain amount of information filtering, or

3. for the purpose of trying to achieve decisions that are congruent with the individualistic characteristics of the user (decision-maker).

Artificial intelligence (AI) and other user modelling literature (for example McTear, 1993) have been concerned with the first two aspects while little attention has been given to the third. Arguably, from a decision support systems perspective the third aspect is the most important as we have to maintain the decision focus of systems development efforts. DSS are by definition, computer based systems that support individual decision makers. Hence, achieving personalised goals are within the scope of developing such systems.

Thus, to support decisions of senior managers in organisations, we should devise a method of incorporating decision-maker personality in decision models. Decision models traditionally represent the attributes of the problem and the objective functions so that components can be manipulated to optimise the stated objective functions. Decision models, of course, have been one of the most important facets of decision support systems from the inception of the discipline. However, the models that the discipline is familiar with mostly cater for quantitative, mathematical representation of the decision situation (Brookes, 1985, Olson, 1996). Therefore a challenge posed to this research work is to devise mechanisms to incorporate qualitative constructs such as personality into a suitable formally represented decision model.

1.2 Scope and limitations

This research project is organised into several distinct stages. These stages can be aligned with the aforementioned rationale. Although it is envisaged (from the study of past research) that personality of decision-makers is an important element in decision-making, how those characteristics can be utilised in a quantifiable manner is not clear. Hence, the first step would be to investigate and confirm the existence of such a relationship between decision-makers' personality characteristics and their decision preferences. In performing this task, it is important to stress that the personality of an individual can be described in varied forms (as explained in Chapter 2). Within the scope of a doctoral research project, it is impossible to consider a multitude of such forms. To overcome this problem within this project, a thorough review of personality literature prior to any experimentation was included in the scope. As a result of this review, the Myers-Briggs Type Indicator was selected as the mechanism of classification of personality types (based on Jung, (1923)).

This project primarily concerns senior managers in organisations. Sample selection for experiments is also biased towards this population segment. Gaining commitment from very senior managers for time consuming experiments is a difficult task. Hence sample sizes are necessarily small. To overcome this weakness it is important that utmost care is given to the design of experiments and the analysis of data resulting from those experiments. The use of multiple methods of data analysis including statistical analysis and use of Neural Networks for triangulation is an aim in this research project.

If a relationship can be identified between the decision preferences and personality of individuals, the next step is to propose a method of using that relationship in decision support systems. This project proposes a generic multi-criteria decision-making framework for the use of decision-maker personality preferences in decision support system generators. This framework addresses the issues of adaptation to individuals and personality types over time, as well as the provision of active decision support by measuring the consistency of decision-making. How profiles of individuals are built and maintained is a major focus of proposing this framework.

The viability of this framework is then illustrated by implementing a system that is based on it. Although the framework is independent of particular decision models, the implementation is limited to two types of decisions: binary and multiple-alternative situations.

In the final stage of this project the capabilities of the system are evaluated through practical application. The underlying principle of adaptation to individuals based on their personality characteristics is the major focus here. As the emphasis is on supporting senior managers, it is essential that that population segment appreciate the benefits of this method of decision support. Hence, an attempt is made to evaluate the decision support method in realistic situations. However, as the objective is to measure the adaptive capability, the long-term use of the system is important. This is especially true when evaluating the capabilities of adaptation to personality types, as that requires the use of the system by a number of individuals belonging to the same type. A doctoral project has to balance that need with the available timeframe. Hence, only evaluation of the capability of adapting to individuals is undertaken within the scope of this project.

Stated briefly, this research project will attempt to establish a reliable relationship between the personality of an individual and the decisions that the person makes; use that relationship as the basis for the construction of an adaptive decision support system for senior managers and investigate whether such systems are capable of capturing the dynamism of decision situations through modelling the situation and the personality of decision makers. It should be noted here that this is not an attempt to provide solutions to problems based *only* on personality of the decision-maker. Personality is viewed as a vehicle for partial adaptation of the system to its user so that active decision support can be provided.

1.3 Research Questions

In keeping with the research steps described above, the project is aimed at investigating several distinct research questions. These questions are listed below. The first two questions are regarded as preliminary questions that will be answered through the study of past literature.

Qa. What theory/theories provide an adequate basis for the articulation of decision-maker personality for decision support?

Qb. What is the personality assessment tool that resembles the selected theory and can be used in a computerised implementation for managerial use?

The major research questions that are to be answered through empirical research work are as follows:

Q1. Is there a relationship between the personality and the decision criteria preferences of a decision-maker?

Q2. How can the distinct criteria preferences of individuals belonging to different personality types be used as the basis of building an architecture for decision support systems that adapt to individuals?

Q3. How can a prototype computer-based system be built to implement the Adaptive Decision Support System Generator Architecture?

Q4. Is the implemented decision support system generator (ADAPTOR) capable of incrementally adapting to individuals' decision making preferences based on their personality?

1.4 Methodology

In keeping with the scope, the research work is undertaken as in several steps. Each step has a different focus. Collectively, these steps contribute to the objective of investigating the usefulness of decision-maker personality as a basis for adapting decision support systems generators to individual decision-makers.

The research project is undertaken within a positivist paradigm. However, as the steps have different foci, they also have different methods of achieving the objectives. This leads to the use of a broad selection of research techniques within the project. As a precursor to empirical activities, a wide-ranging review of past research was undertaken. Like most other work in the decision support, the literature review in this project was drawn from a number of disciplines including psychology, decision-making and decision support systems. The review of literature was used as a means of generating firm hypothesis that can be tested through empirical activities.

The first empirical stage was to establish a quantifiable relationship between personality types and decision preferences. A differential study design was used in this stage to evaluate the differences between the distinct personality types. This step was seen as *basic research* as the results of this study may be used in a variety of applications that are different from the intentions of the current research project.

The systems development research technique was seen as the appropriate candidate for the next steps of proposing a framework for using personality in decision support systems and implementing a system that is based on that framework. Systems development is an *applied* research activity as the results (and artefacts) are of potential immediate practical use.

The last step in the project was to investigate the usefulness of the concept. As external validity of the work is the major concern at this stage, a case study approach was seen as superior to other approaches. This stage was also considered *applied* as the aim is to refine the concept leading to better immediate practical benefit. Hence, the evaluation of the concept is a descriptive research activity.

The steps of the research method show that the complete project conveniently fits into the *concept-development-impact* model of information systems research (Nunamaker, Chen and Purdin, 1991). While most information systems research borrows the *concept* from reference disciplines, this research project performs concept evaluation work within the project.

Work related this research project was presented at various national and international forums as the project progressed through the above stages. These forums included the International Conference on Decision Support Systems, the conference of IFIP Work Group 8.3 (Decision Support Systems), the Hawaiian International Conference, Australian Human Computer Interaction Conference (OzCHI), International User Modelling Conference and the Australasian Information Systems Conference. These related publications are listed in Appendix A.

1.5 Outline of the dissertation

As already discussed, this doctoral research project is addressed as a number of distinct stages. The structure of the dissertation is also organised to follow this step-wise process.

In Chapter 2, I present my evaluation of past research works that are useful to this project. The selection of a personality articulation method is an aim studying past literature. The use of individual differences in decision-making, the research body on active decision support systems, relevant decision support system frameworks, and the nature of decision models are subjects investigated within this chapter. The chapter concludes with the expression of hypotheses that are to be tested in this project.

Chapter 3 is devoted to understanding research paradigms and techniques, and the subsequent selection of techniques that are relevant to this project. An overview is presented on the scientific method and the two main paradigms of positivism and interpretivism. Then, I discuss the range of research techniques within the positivist paradigm selected for this project, leading to the justification of the selections.

The first empirical stage of the research work, the investigation of the relationship between personality types and decision preferences, is discussed in Chapter 4. The steps of designing, implementing and analysing the results of the differential study are described in detail. Analysis of data is performed both through statistical methods and with the use of neural networks.

In Chapter 5, I articulate an architecture for adaptive decision support systems that is based on the results of the differential study. The chapter begins with the description of the requirements that such an architecture should satisfy. Then the architecture is presented, followed by the detailed description of the components.

Chapter 6 is devoted to describing an implementation based on the architecture presented in Chapter 5. After the introduction of the technology platform used, how each architectural component is implemented is detailed. The nature of the implementation is illustrated with screen-shots of the actual artefact, ADAPTOR.

The impact of the adaptive system developed in the current project is the focus of Chapter 7. The method of performing the case studies, along with the findings is presented. Particular emphasis is placed on the impact of the concept of adapting decision support systems based on the decision-makers personality.

The conclusions reached from the composite project, consisting of a number of distinct stages, are presented in Chapter 8. The implication of these findings to the decision support systems discipline is discussed with the future research possibilities. The problems and limitations of this project are also discussed.

Chapter 8 is followed by the list of references used in this dissertation.

The dissertation also consists of a series of appendices consisting of the experimental instruments used, contains detailed results of the analysis of data and the user manual for ADAPTOR.

Chapter 2

Developing Hypotheses

This doctoral research project was aimed at investigating several specific research questions. These questions relate to steps that should be fulfilled before a claim can be made on the feasibility and success of using personality as a basis for adapting decision support system generators for senior decision-makers.

This chapter critically reports the past work in related disciplines that are useful in investigating the research questions and establishing firm hypothesis that could be tested through research. The survey of relevant past work also sets the context under which the research was carried-out. Hence, not all stages of the project require the articulation of hypothesis. This is especially true of the questions that are to be answered as a precursor to the main research questions. The preliminary questions, Qa and Qb, are answered through the review of literature. The results of that investigation are presented at the conclusion of this chapter in addition to the hypotheses that are to be tested in the latter stages of the project.

Since this project is multi-disciplinary in nature, the literature presented also draws from a wide range of disciplines. The works presented in this chapter relate to the most relevant material from those disciplines in investigating the research questions.

The first part of this chapter is devoted to investigating preliminary research questions:

Qa. What theory/theories provide an adequate basis for the articulation of decision-maker personality for decision support?

and,

Qb. What is the personality assessment tool that resembles the selected theory and can be used in a computerised implementation for managerial use?

2.1 Situationism versus personalogism

Personalogism (study of person), compared to situationism (study of situation), is a perspective which has historically lost favour in organisational behaviour research. Much of the criticism of personalogism is attributed to assertions made by Mischel (1968). Other researchers have quoted Mitchell's (1979) statement in the Annual Review of Organisational Behaviour to illustrate conceptions in this area:

> We will find throughout this review that personality traits appear as predictors of attitudes (eg. involvement) motivation (eg. expectancies) and leadership (eg. behavioural styles), but the central focus of that research is usually motivation, attitudes of leadership and not personality.
>
> This secondary role seems justified and necessary. If Mischel's arguments are correct then we will be better served by continuing in the direction we are heading. Personality variables probably control only a minor percentage of variance in behaviour when compared to situational factors.
>
> (Mitchell, 1979)

Many arguments in this debate have been construed on the basis of percentage contributions of personality and situational factors to a given situation. However, Weiss and Adler (1984) show that these percentages can be affected by many other possibilities in experimental situations. Among such possibilities are the range of personality variables used, level of criterion abstraction and imposed constraints on behaviour. They warn against discarding personality as a valid area of study in organisational behaviour and highlight the need for more research in this area. They show that a considerable body of literature in areas such as goal setting, leadership and study of level of aspiration point to the influence of personality. In building DSS, such areas are relevant to us. Weiss and Adler stress the importance of *interactionism* in the study of personality in organisational contexts as against the study of personality in isolation.

Schneider (1983) presents a useful review of interactionism. Proposed as an alternative to emphasis on situations and traits, interactionism holds that situations are constructed through personalities and that personalities are in-turn a function of situations. Interactionists argue that people selectively confront situations and environments that are congenial to them. As individuals promote and foster environments sympathetic to their beliefs, those environments are just a conception of the people in them. Such situations would cease to exist separately to the people. Thus, it is difficult to study either of them in isolation. Unlike the negative view held by situationists on research into stability of personality characteristics across situations, interactionists take a more positive approach.

Interactionists propose the concept of *coherence* as opposed to the traditional notions of absolute and relative consistency. Coherence is defined to be predictable behaviour not because an individual will always behave in the same manner, but because the manner in which the individual is inconsistent is consistent across situations; the inconsistencies are characteristic of the individual (Magnusson and Endler, 1977; Schneider, 1983). This view of predictability-by-situations is currently well accepted in personality research (Revelle, 1995).

As a corollary to this discussion, researchers have suggested that the *strength* of a situation is an important determinant of the usefulness of personality aspects as predictors of behaviour. Strong situations have well accepted means of response and therefore less chance of variation between the responses of different individuals. Situations that do not have such strength are better suited to prediction through personality constructs (Mischel, 1977). We anticipate the utility of the findings of this research project to be in supporting senior managers in organisations. The decisions to be made at this strata of the organisation generally fall into the 'ill-structured' decision category. Therefore, personality can be expected to have a greater predictive powei in supporting senior mangers than for other decision-makers.

In this research project, we intend using individual differences as a basis for DSS design. A system incorporating the ability to adapt to decision-makers depending on their personality is expected to be an outcome of the project. Although such use of individual differences will indicate that we rely on the predictive power of personality constructs, the final outcome will rely more on coherence. This is because such systems are expected to 'learn' the behaviour patterns of individual decision-makers over time. In fact these systems may provide an opportunity to observe coherent behaviour through constant adaptation to inconsistencies. Reliance on absolute or relative consistency may be limited to being a means of first approximation. The 'profiles' maintained for individual decision-makers will be aligned with decision scenarios so that it is possible to infer situation or domain specific tendencies. Since these systems will allow the definition of the situation and modification of basic profiles by the decision-maker, we not only take a personality approach, but also consider the situation. Although we review the personality aspects independently to the situation for ease of understanding, when a system is implemented, personality profiles will be aligned with situations. Thus, it can be seen to agree with the basic principles of interactionism.

2.2 Personality in DSS

The literature seems to be confused with the distinction between DSS and MIS (Management Information Systems) when it comes to assessing the worth of user characteristics in designing systems. There are fundamental differences between these two types of systems that relate to the domains in which they operate and their orientations, which make a common approach to individual differences irrelevant (Gorry and Scott-Morton, 1971). These deficiencies notwithstanding, since Huber's (1983) landmark attempt to document the case for using cognitive style as a basis for DSS and MIS design, very little attention has been given to this issue, although there has been few attempts to evaluate the worth of individual differences in designing systems (Alavi and Joachimsthaler, 1992; Ramamurthy, King and Premakumar, 1992).

A major work in the area, Huber's 1983 paper, drew two conclusions: (1) the literature available at the time on *cognitive style* was an unsatisfactory basis for deriving operational guidelines for MIS and DSS designs, and (2) further cognitive style research was unlikely to lead to operational guidelines for MIS and DSS designs.

2.2.1 Individual differences

The use of such terms as *cognitive style* and *personality* is common in references to individual characteristics in the information systems discipline. Often, these terms are used interchangeably without much regard to their underlying assumptions. When evaluating the worth of using individual differences in DSS design, it is important to define which individual aspects are being considered. Huber (1983) considered cognitive style only. Cognitive style according to Simon (1960) is the 'the characteristic, self-consistent mode of functioning which individuals show in their perception and intellectual activities'. This is primarily an internal construct that describes the process by which individuals arrive at conceptions. Response to uncertainty, cognitive complexity, need for achievement, risk-taking propensity, intelligence, task familiarity, dogmatism, gender, locus of control and education are some of the other individual differences that have been identified as important in decision-making (Alker, 1971; Huber, 1983; Ramamurthy et al., 1992).

Ostensibly, the term *personality* incorporates most of these different aspects. Personality refers to both how other people perceive an individual and to the inner constructs that provide a characteristic behaviour pattern to an individual (Hogan, 1991). Personality psychologists define a *public* personality that can be described using common trait terms such as talkative, enthusiastic and kind. These terms represent an individual's observed past behaviour and are expected to be predictors of future actions. *Private* personality on the other hand relates to the explanation of observed behaviour. We, as decision support systems researchers, are not interested in explaining behavioural manifestations at this stage, although explanation of behaviours can be important in evaluating system use (Elam, Jarvenpaa and Schkade, 1992). Our major concern is the use of individual differences to build systems that will provide decision support that is compatible with the individual's requirements. Therefore, we may be able to use personality defined in terms of *traits* as our basis for understanding individual differences. Trait theories, championed by Allport (1937), are also used as the dominant form of personality assessment (Buss, 1989; Ozer and Reise, 1994; Wiggins and Pincus, 1992). It should however be mentioned that personality is by no means a broad consensus area in psychology. Three other classical schools of personality theory (psychoanalysis, behaviourism and humanism) compete with trait theory as the basis of understanding individual differences.

2.2.2 Individual differences and decision-making

use individual differences as the basis for DSS design, first a viable relationship should be established between those differences and decision-making. This task is not as straightforward as it seems, as this is an area with a considerable body of literature, but with little cohesive or conclusive results. Harrison (1987) asserts that the fundamental psychological force affecting human decision-making is the decision-maker's personality. Newell and Simon (1972) articulate that the problem space will be defined by the knowledge that an individual brings to a situation. Therefore, the perception of the problem or the decision situation will essentially differ between decision-makers. Simon and Hayes (1976), Kahneman and Tversky (1979) and Fischhoff (1983) give credence to this assertion. The introduction of cognitive biases to a decision situation by decision-makers is an example of the effect of personal characteristics.

However, these views are not universal. Although the presence of the like of cognitive biases is commonly accepted, inconclusiveness of the results in studies that try to establish firm links between decision-makers and decision-making is obvious. Ramamurthy *et al.* (1992) reports on a classic case of this inconclusiveness: Henderson and Nutt (1980) showed a strong relationship between cognitive style and decision-making. However, other studies have shown the contrary - little or no effect of cognitive style on decision-making (McKenney and Keen, 1974; Nutt, 1986). On similar lines, McGhee *et al.* (1978) conclude that personality characteristics show little ability to describe or predict information processing in humans. McInish (1982) in trying to establish a link between locus of control and risk taking in individuals, hypothesised that people with internal-scoring would opt for higher risks. His experiments proved otherwise. Other researchers have shown that risk behaviour may not be explained with personality characteristics, but could vary depending on the circumstances (Slovic, 1962). In studies directly relating the personalised use of computerised tools to individual characteristics, the results have not been much different. Alavi and Joachimsthaler (1992) show that improvements of only 10 to 15 percent can be obtained through incorporation of psychological factors, as against 20 to 30 percent increases when considering user-situational factors. There is also other literature that claim that personality traits and cognitive styles depend on experience and expertise in the task domain (Mischel, 1980; Sage, 1981). Ramamurthy et al. (1992) have experimentally shown that experience and expertise are not important for DSS effectiveness.

These contradictory results have led to the conclusion that although individual characteristics are a factor in decision-making, there is no firm relationship between the individual characteristics of decision-makers and the decisions that they make. If there is any indication of a link, they are very weak and do not provide a sufficiently firm basis that can be used in practical situations (Liang, 1986; Zmud, 1979).

As Huber (1983) points out, the lack of conclusive results can be attributed to several reasons. Problems with the design of research experiments may be one of the major factors. Most experiments consider only single facets of personality and only a single decision situation. Hogan (1991) shows that 'behaviour may be situationally specific at the level of a single act but cross-situationally stable when correctly aggregated'. Thus, what may be lacking is longitudinal studies that try to aggregate individual behaviour accurately. Failure to do this has resulted in emphasising the importance of situational factors (Bowers, 1973; Hogarth, 1989; Jacoby and Hoyer, 1989). However, this emphasis is clearly a result of the failure of the individual differences approach and not necessarily a well established research result.

Zmud (1979) highlights the importance of incorporation and control of contextual variables in research design, claiming that failure to do so 'will result in ambiguous, inconsistent and possibly meaningless findings.' Wright (1985) reports on Svenson's (1983) speculation on the need for the study of cross-situational consistency of rules in individual decision-making. This may result in the articulation of general principles used by decision-makers when facing different situations (Payne, 1982). Effectively, these would lead to individual differences in contingent decision behaviour. This approach to the study of situationism is obviously important as the study of situationism without reference to personality makes little sense (Weick, 1979). Situations are manifestations of the surroundings as perceived by individuals. These perceptions are shaped by personality characteristics of the individual. As Stubbart (1989) notes with an interesting implication for DSS (as it aims to support managerial decision-making), 'if minds propel entrepreneurship, then managerial cognition about key ideas lies at the centre of a strategic management process.' Hence, the more pronounced the call for the investigation of situationism, the more important it is to understand personologism. This goal, however, still seems elusive.

2.2.3 Assessing individual differences

Our aim in considering individual differences is the use of them to build practical decision support systems. If these systems intend to provide support that is compatible with the decision-maker's personality, they should be able to extract decision specific knowledge as well as the expectations implicit in the decision-maker's personality. The need to understand mechanisms that are capable of articulating personality characteristics of the decision-maker is therefore clear.

Personality psychology has a long tradition of study into personality assessment. As with personality theories, the assessment techniques are aligned with different schools of thought. For example, revealing hidden and unconscious personality structures to predict 'abnormal' behaviours is the aim of assessment in the psychoanalytic school; in the humanistic approach, an attempt is made to capture individual differences in terms of 'growth, health, mastery, and development' (Hogan, 1991). Among this plethora of approaches, trait theories are by far the most prominent approach in contemporary personality assessment (Funder, 1991; Tellegen, 1991; Wiggins and Pincus, 1992). Within the trait approach, again an area which abounds with controversy, the *five-factor model* (FFM) is the framework with the most consensus. McCrae and John (1992) illustrated the superiority of the five-factor model as follows:

> .... In the 1980s, however, researchers from many different traditions were led to conclude that these factors were fundamental dimensions of personality, found in self-reports and ratings, in natural languages and theoretically based questionnaires, in children, college students, and older adults, in men and women, and in English, Dutch, German, and Japanese samples (John, 1990). All five factors were shown to have convergent and discriminant validity across instruments and observers, and to endure across decades in adults (McCrae and Costa, 1990).
>
> (McCrae and John, 1992)

This confidence has been shared and illustrated by many other researchers such as Goldberg (1990 and 1993), Ostendorf (1990), Yang and Bond (1990) and Trapnell and Wiggins (1990). The 'big-five' factors identified by this model are: I - Extraversion, II - Agreeableness, III - Conscientiousness, IV - Neuroticism and V- Openness. These five factors have been observed to be present in many of the popular scales of personality measurement such as Personality Research Form (PRF), Freiberg Personality Inventory (FPI), Eysenck Personality Inventory (EPI) and NEO-Personality Inventory (NEO-PI) (Borkenau and Ostendorf, 1989; Ostendorf and Angleitner, 1990). The FFM has been applied in clinical assessment to identify personality disorders (Costa, 1992; McCrae, 1989), in psychotherapy (Miller, 1992) and in linking health outcomes to personality factors (Smith and Williams, 1992). The model has also been linked to various psychopathological syndromes (Buss and Chiodo, 1991). The FFM has also shown to be deficient in two major areas: 1. The high level, aggregated nature of the factors cause the loss of detail that is needed for description and prediction; and 2. The model is not a complete theory that is capable of explaining behaviours and therefore is limited to description (Mershon and Gorsuch, 1988; Wiggins, 1992). Ozer and Reise (1994) raise an issue related to the first concern. Some personality constructs have been shown to consist of many sub-components. These sub-components may be better predictors of behaviour than the relevant general construct. In addition to the loss of detail, this also poses a problem of modelling the relationship between the sub-components and the general construct.

Another common application of personality assessments has been in the area of industrial and organisational psychology. In this sphere, assessments are regarded as of immense practical usefulness in career choice or career counselling, environmental fit of personnel and personnel selection (Hogan J. and Hogan R., 1986). The most widely used personality measurement instrument, the Minnesota Multiphasic Personality Inventory (MMPI), has been used to select applicants for jobs that need specific temperaments (Hogan, 1991). Other tools such as the Myers-Briggs Type Indicator (MBTI) have also been used with reported success in similar applications. This has led Hogan to conclude that when appropriately designed to suit a specific application, structured personality measures can be of practical benefit. It should also be noted here that MMPI was developed for the study of mental illness of hospital patients. A revised version of this inventory (MMPI-2) has been used mainly in the assessment of psychopathological conditions (Butcher et al., 1991).

Other issues to consider when studying personalty measurement include the stability of measurements and the differences between ratings by strangers and acquaintances. Research shows that predictions provided by acquaintances have greater accuracy than those given by strangers about general personality characteristics. However, when evaluating situation-specific behaviour, the estimates given by the two groups are less deviant (Wiggins and Pincus, 1992). Stability of personality measurements poses an interesting dilemma for personality research. As Funder and Colvin (1991) manifest, 'research has focused on the consistency of behaviour. Intuition focuses on the consistency of personality.' It is also clear from research that some characteristics are more stable than others and that personality in adults may be more stable than in children (Costa and McCrae, 1988). A personality measurement scale may also be a good measure of a general psychological construct, but may not be as good for predicting the behaviour of a given individual (Ben-Porath and Waller, 1992).

Another issue that may have implications for DSS is the distinction between types and traits. Personality psychology primarily deals with dimensional structures. This leads to a situation where the conceptualisation of constructs is inhibited, for the lack of definition whether a particular concept (such as extrovert) is a type or an extreme end of a dimension (Ozer and Reise, 1994). Although this issues lacks favour in orthodox personality research, the call for a typology has merit if it can provide a method of summarising (prototypes) multi-faceted dimensions of personality (Meehl, 1992). Instruments such as the MBTI has utility if a typology is agreed upon. However, as stated initially, personality assessment is a research area with profuse activity, but with questionable theoretical soundness in some of its developments (Ozer and Reise, 1994).

2.2.4 Using Individual differences in DSS

The foregoing discussion of the influences of personality on decision-making and personality assessment is not intended to be a comprehensive review of personality psychology. Its utility is in examining the claim that individual differences are useful in designing decision support systems. As a result of the review, a few pertinent observations on this proposition can be made.

Huber (1983) claimed that cognitive style literature is weak and inconclusive. The situation regarding the relation of decision-making and personality is not much different. When considering general personality, an added constraint is apparent. Unlike cognitive style, which is a single constituent of behaviour, general personality is a combination of a multitude of factors. Most literature deals with the relationship between a single component of personality and the effect that that component has on decision-making.

Even the studies that attempt to establish simple relationships display a range of deficiencies. The inability to control situational/interactional factors in experimental situations raise questions as to whether the positivist approach has merit in this domain. The contradictory results of different studies into the same phenomenon point to either a weaknesses in experimental design or the lack of stable relationships to observe. The general consensus is that faulty research designs have led to the present conclusions. True to Huber's assertions, very little progress can be seen in the past decade in either cognitive style or general personality literature that is of use to us. Even studies that directly deal with the importance of personal characteristics in the use of DSS have not produced conclusive results. Rather, they have added to the confusion in the field.

Even if firm co-relations are established, before practical utilisation, one more obstacle needs to be overcome. This is the availability of reliable personality assessment techniques; we should have means of classifying people into different personality types or different dimensions. The types versus dimensions issue is by itself contentious. The resolution of that issue will also have implications to the DSS developer in relating different formalisms of personality to given decision situations. The present emphasis in personality assessment is on dimensional constructs such as that proposed in the Five-Factor Model. Assessment techniques generally measure only a few dimensions. Whether the measurement of few constructs provide the necessary granularity for classifying decision-makers remains a question that needs further investigation. There would be little point in developing systems that suit only specific types of person (such as an *extrovert*). When only one specific characteristic is targeted, the effects of other characteristics on the decision situation remain uncontrolled. Therefore claiming success for the system will be similar to the purported success of the experiments on individual characteristics in decision-making. A measure of a 'holistic' personality would be much more useful in this respect. However, this should be balanced with the requirement for sufficient granularity.

Researchers claim that assessment techniques work best when they are designed to suit the specific domain in which they are used. The survey of literature shows that the vast majority of available techniques were designed for the domain of psychopathology. The central concept in designing these is the presence of a 'disorder' in the subject. However, as noted earlier, various personality assessment schemes have been employed with success in organisational situations, even when the scale has been developed for a different purpose. This gives us the hope that some scales are likely to predict decision behaviour of decision-makers. Identification of possible candidates for this role needs further investigation, as current literature does not appear to reveal any technique that has been built for predicting holistic decision behaviour. Possible adaptation of candidate techniques will need theoretical validation before they can be used in decision support systems.

There are few other factors that raise hope for using personality assessment scales to predict decision behaviour in DSS. If DSSs are to automatically adapt to different decision-makers to provide support that is compatible with them, they have to be able to assess the personality of the decision-makers. Arguably, this would be best achieved by having the system administer a personality assessment questionnaire. As previously discussed, research shows that assessments of strangers are no different to assessments provided by acquaintances when it comes to situation-specific behaviour. Therefore, a certain amount of confidence may be placed on the system to provide an unbiased measurement of personality of the decision-maker. Certain personality characteristics are regarded as more stable than others. If these characteristics are cross-situationally consistent, then a DSS can be provided with the facility of retaining an amount of 'personality knowledge' for future use.

2.2.5 The Myers-Briggs Type Indicator and decision making

One major outcome of the above discussion of personality and personality assessment is that care should be taken when instruments are selected for a particular purpose, the main criterion being the suitability to the selected activity. In our domain, we are trying to establish patterns of decision behaviour of senior decision-makers. The inappropriateness of instruments like the MMPI lie in the fact that they have been developed for psychopathological analysis and not for assessing 'normal' personalities. Though such instruments have been used in domains other than clinical psychology, it has been against the intensions of the instrument developers themselves (Graham, 1993) and therefore the validity for the purpose cannot be guaranteed. One instrument that has been developed for the specific purpose of assessing normal personalities is the Myers-Briggs Type Indicator (MBTI).

Constructed to operationalise Carl Jung's theory of personality types, the MBTI is the most commonly used personality inventory among 'normal' subjects, according to both academic and professional literature (Guthrie, 1993; Moore, 1987; Murray, 1990; Zemke, 1992). Jung (1923) believed that people have distinct patterns and preferences in their personality and that human behaviour is not random. He described four functions of how people perceive and generate judgements about data. Perceiving is the way of becoming aware of surroundings, while judging is the way of arriving at conclusions about the things perceived. *Sensing* and *intuition* are according to him, ways of perceiving. Sensing people prefer precisely formulated data and endeavour to be realist, whereas intuitive people prefer less 'hard', general data with ambiguities. Judgement is performed either in the *thinking* or the *feeling* mode. Judgement through thinking is said to be formal, logical and use generalisations and abstractions. Feeling is less formal in arriving at judgements, value laden and emphasises the human aspects. Jung's theory states that people will develop a dominant mode of perception and judgment, although they poses the ability to use the less dominant mode when needed. He called these less dominant functions the 'shadow' functions. The four functions were further classified into either extroverted or introverted attitudes. Like the previous four functions, people can demonstrate both kinds of attitudes, although there will be a dominant and a shadow function. Jung described personality 'types' based on the dominant modes of behaviour.

Myers and Briggs constructed the MBTI to extract Jung's dominant dimensions, while adding a fourth dimension to the theory (Myers and McCaulley, 1985). This fourth dimension describes a preferred method of dealing with the world. Some people are action oriented and strive for closure in their activities, while others prefer to maintain openness to new developments. These two extremes are named *perceiving* and *judging*. The MBTI is a forced-choice format questionnaire which measures these two styles in addition to the basic dimensions of Jung's theory. The scoring method of the MBTI articulates the dominant preferences of individuals, thereby classifying them into one of the sixteen possible 'types'. Therefore the MBTI is different to most other instruments as it does not measure 'traits'.

Other than its suitability to assess 'normal' personality, Jung's type theory delivers few other advantages to us by using it to establish a relationship between decision-maker personality and decisions that are made by them. Jung's dimensions of personality were presented to describe a holistic view of a person.

One criticism of past experiments in our domain has been their inability to control the effect of independent behaviour factors. If we use Jung's theory, that problem can be overcome, as there is no need to control such variables. A 'holistic' personality is also more useful for machine implementation as that will facilitate the development of systems that are capable of adapting to personalities and not parts of personalities. As mentioned in the discussion above, 'types' versus 'trait' is a contentious issue in personality research. Types are arguably more useful for our purpose as customising to a discrete entity is more convenient than customising to a number of continuous scales.

It is clear that using the MBTI as an instrument to establish personality preferences of decision-makers, has got merit in the DSS domain. Thus the validity of MBTI becomes an important issue for our research. Important determinants of validity of a personality inventory are the validity of its scales and the suitability of the internal structures of items in each scale. The MBTI has been shown to provide distinct scales which are congruent with its theoretical basis (Tzeng *et al.*, 1984). The internal consistency measures are comparable to that of longer scales such as the MMPI (Murray, 1990). Stability of scales is said to endure over long periods of time (Levy, Murphy and Carlson, 1972; Nauss, 1972). In studies that compared MBTI dimensions to that of other common personality inventories, the general conclusion has been that MBTI scales are valid (McCrae and Costa, 1989; Murray, 1990). Some researchers however, regard typologies such as that created by MBTI as a mere simplification of reality (Gangestad and Snyder, 1991; Mendelsohn, Weiss and Feimer, 1982). A large body of empirical data also exists to support the claim of 'types' in personality (Myers and McCaulley, 1985). We are unable to resolve these conflicting ideas. Since there is sufficient evidence of discriminant validity between types, we see them as useful constructs for our purpose.

Another criticism of the MBTI is its inability to measure the strength of 'shadow' functions. It has been shown that some individuals show equal preference to both ends of a single dimension, such as thinking and feeling (Girelli and Stake, 1993). A related factor is the scant evidence available for the true dichotomous nature of scales in the MBTI. Most researchers report on the failure to establish that there are sharp discontinuities close to the mid-point of each scale (McCrae and Costa, 1989; Hicks, 1984). This has led to the introduction of scoring methods such as the use of Item Response Theory, to overcome the deficiency (Harvey and Murray, 1994). Again, though we appreciate this deficiency, computer systems that are built can be expected to provide cues to such closeness of preference and therefore evaluate both resulting types. Another encouraging fact is that 'highly developed' samples such as chief executive officers of companies have demonstrated truly dichotomous preferences (Rytting, Ware and Prince, 1994). As our target audience is senior managers, similar patterns of preferences can be expected. Doubts have also been cast on the ability of the MBTI to operationalise Jung's theory of types, although it measures four independent dimensions of normal personality congruent with the five-factor model (McCrae and Costa, 1989). McCrae and Costa propose that the positive association of external data such as job preferences are a result of the MBTI scales being convergent with the dimensions of the FFM. This is in itself is important as the FFM has been accepted to epitomise the fundamental dimensions of personality (McCrae and Costa, 1990).

The MBTI has been used in management applications to select people, build effective teams and for personal skills development (Bayne, 1990; Coe, 1992; Guthrie, 1993; Moore, 1987). It has also been employed in an interesting range of applied research in education (Cooper and Miller, 1991) nursing administration (Freund, 1989), strategic decision-making (Haley and Stumpf, 1989) and evaluating information system design principles (Nutt, 1986) among others. Even those critical of some aspects of validity of the MBTI acknowledge that it is pertinent in some applied settings such as in predicting characteristic style of behaviour of individuals (Boyle, 1995). With important implications to our research project, Haley and Stumpf (1989) have initiated a research program that attempts to illustrate a link between cognitive biases in decision-makers and their personality types based on Jungian theory. Their conclusions indicate that a plausible relationship does exist. They also propose that in spite of situational factors, personality types as measured through the MBTI, are an important determinant of strategic decision processes. As Jung's types are based on preferences to data and judgments, the classification intuitively belongs in our domain of supporting managerial decision-making; individuals can be expected to exercise different strategies, resulting in different outcomes, when making decisions. As Moore (1987) reports, senior decision-makers are also more agreeable to assessing their 'type' than other psychological indicators.

Thus, the use of the Myers-Briggs Type indicator is proposed to establish 'types' of personalities. 'Types' will be viewed as a convenient way of conceptualising the interactions of the independent scales of the instrument. We hypothesise that individuals belonging to different types, as established by the MBTI, will have different preferences when making decisions.

The hypothesis arising out of the above findings is presented at the end of this chapter.

2.3 Active decision support systems

Traditional decision support is based on notions borrowed from operations research and organisational behaviour (Gorry and Scott-Morton, 1971). Systems design principles have also had an influence on the way DSS have been addressed (Sprague and Carlson, 1982). This orientation has led to DSS being tools that respond to standard requests with pre-programmed routines. The major support elements are in providing data and modelling capabilities. These traditional decision support systems are labelled as *passive* DSS (Keen, 1987) or *vehicle/toolbox* DSS (Angehrn, 1993). The concept of *active* decision support has been proposed as an extension of traditional decision support approaches. Active decision support differs from these early approaches as a cognitive focus is sought. Active

DSS attempts to provide augmented support that goes beyond what the decision-maker explicitly requests from the system (Manheim, 1988).

The current research project attempts to build an adaptive decision support systems generator that provides support that is congruent with the personality preferences of the decision-maker. A system is considered adaptive if it is capable of autonomously changing behaviour because of environmental change (Shaw, 1993). Adaptive DSS fall into the domain of active decision support systems.

In an active DSS, the components that react to user commands are enhanced with system-activated components that display learning behaviour with reference to previous behaviour of the decision-maker. Active decision support has emerged from many streams of research which aimed to provide this augmentation to traditional support, as shown in Table 2-1 adopted from Fuller (1996).

Table 2-1: Primary Streams of Active DSS Research (After Fuller, 1996)

Research Stream	Reference Work
Expert Systems as ADSS	Colby (1975) Carbonnel (1980) Miller (1984)
Autonomous Processes	Manheim (1989) Mili (1989) Castillo, Dolk and Kridel (1991) Manheim, Srivastava, Vlahos and Tseng (1991)
Idea Stimulation	Kremar and Asthana (1987) Nierenberg (1987) Raghavan and Chand (1989) Raghavan (1991) Carlsson (1995) Brannback (1995)
Problem elicitation and Structuring	Pearl (84)

Mili (1989) discusses DSS components that act as a 'critique' that 'watches over the shoulder' of the decision-maker. This approach is based on knowledge-based technology. Jelassi, Williams and Fidler (1987), proposed a similar concept of *triggers*, based on knowledge-based technology as a means of identifying and exploiting opportunities in organisations. Kreamar and Asthana (1987) proposed another scheme based on activation of triggers. The system they proposed raises key questions that are intended to stimulate new ideas in decision-makers.

Others have emphasised the need to support the 'right-brained' activities of decision-makers. They point that unstructured decision situations faced by senior decision-makers require support that is creativity oriented and is suited to specific styles of decision-makers. Young (1982) proposed a set of functional components that can form the basis of systems that provide 'right-brained' decision support. Functional components he articulated include:

- Information retrieval
- Filtering and pattern recognition
- Extrapolation, inference and logical comparison
- Modelling

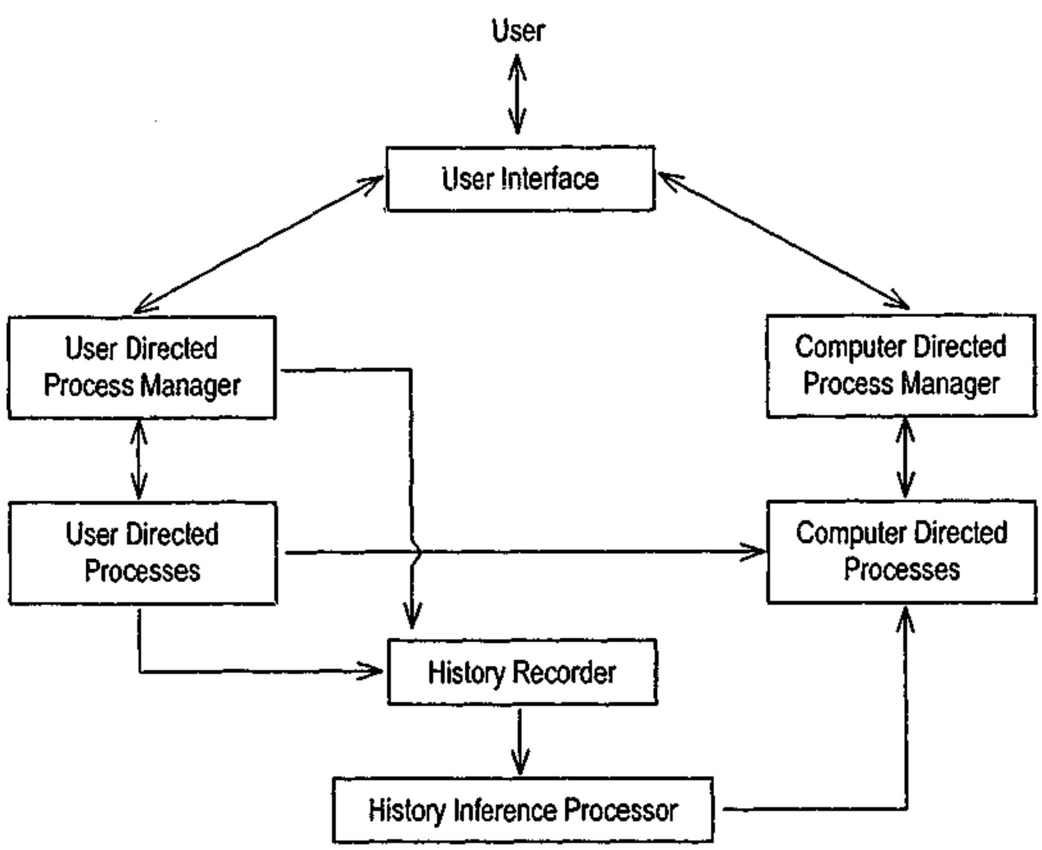


Figure 2.1: Architecture for Active DSS (after Manheim, 1988)

Use of general policies and behaviours is one of his information retrieval strategies; constructing taxonomies of domain objects is used as a means of filtering and pattern recognition. These strategies are relevant to the current research project, as the attempt is to 'learn' from general behaviours, so that adaptation can be achieved for specific instances.

Manheim (1988) articulated a general architecture for symbiotic DSS, which incorporated components leading to active decision support (Figure 2.1). In this architecture, 'traditional' decision support is provided by *the User-Directed Process Manager.* The ability of the system to actively participate in the decision making process rests on having a good understanding of the decision making process of the user, having normative criteria for judging the decision making process and having strategies for improving the process. Understanding of the decision making process is gained through the *History Recorder* and the *History Inference Processor.* The History Recorder logs user commands and the output in response to those commands. The Inference Processor evaluates the recorded decision making history to identify patterns. If a pattern is identified, the *Computer Directed Process Manager* activates a routine that is associated with the pattern. Manheim's scheme for the Inference Processor includes a general processing model that is based on human problem solving. The Inference Processor has been identified as a candidate for neural network technology. Other researchers have shown that what is required is a neural network approach to cognitive science, rather than an expert system approach or other similar technique used in many other active DSS research (Dolk and Kridel, 1991).

Active, extended support is considered by researchers (for example Carlsson, Kokkonen and Walden, 1999) to be important to serve knowledge workers in organisations, the target population of the current research project. DSS components that were only considered as *tools* in traditional decision support are considered to be active participants in the decision making process in the active DSS paradigm. Active components may monitor the decision making process so that inconsistencies and weaknesses are identified and the communicated to the decision maker; autonomously initiate activities based on the context of the current instance, and be creative in generating and stimulating new ideas (Raghavan and Chand, 1989). These goals of active decision support is congruent with the needs of knowledge workers in performing their decision making tasks (Mintzberg, 1973).

Most proponents of active decision support suggest the usefulness of expert systems, neural networks and other technologies based on artificial intelligence, in conjunction with traditional DSS technologies, in making systems 'active'. Although the distribution of tasks between human decision making and computer-based tools is not as well defined in active decision support as in traditional decision support, it is still possible to implement active systems that do not violate the principles of decision *support*. The intention is not to replace the creativity of human decision making in unstructured decision situations, but to enhance the creativity through the augmentation of cognitive capability. In doing so, it is also possible to effectively use the advances in software and computational technology.

2.4 Some useful decision support frameworks

There have been attempts to address the decision support issue from many different perspectives. The reviews by Stabell (1987) and Raghavan and Chand (1988) provide details of many of these perspectives. The frameworks that have been proposed to support decision-making are also clustered around these perspectives. Our aim in this project is to develop an architecture that is capable of supporting a support system generator. This generator should provide facilities to assist many specific decision situations. A level of active support is also envisaged. Therefore, frameworks that cut-across some of the perspectives mentioned above may need to be understood. This section is devoted to the study of some of these useful frameworks.

Bonczek, Holspapple and Whinston (1981) define seven facets of human decision making. According to them, the level of support provided by an automated decision support system (DSS) is measured on the degree of effectiveness in supporting these seven facets. The interaction between the facets is also a major concern. Decision making using an automated tool is considered a man-machine interactive system. In this interactive environment, the human decision-maker assumes the role of an information-processor that requests and receives help from an automated information-processor. The automated component (DSS) comprises three components: the *language* component, the *problem processing system* and the *knowledge* component that stores knowledge about the problem domain (Figure 2.2).

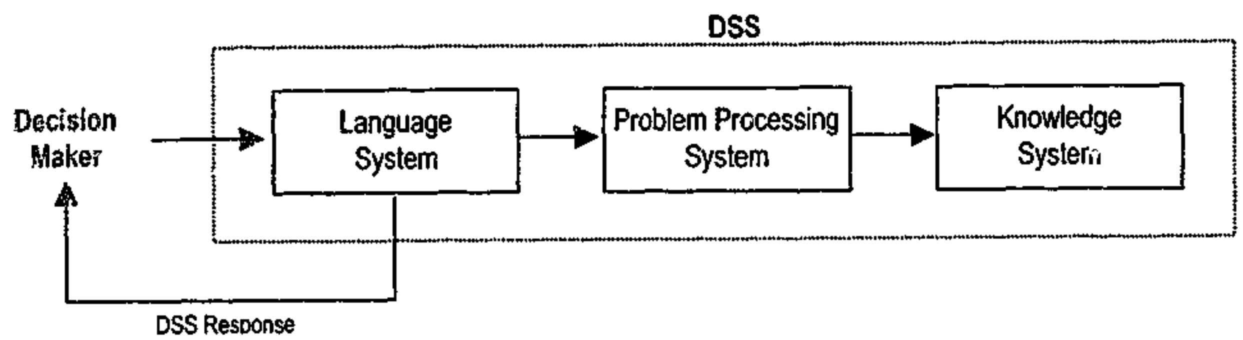


Figure 2.2: Bonczek, Holspapple and Whinston (1981) Architecture

Information collection for a particular decision situation can be done in two ways: from the human decision-maker or the knowledge component. In the interaction between the decision-maker and the problem processor, the language component plays an important role. Perception of the decision situation is assisted by representations available in the language component and the problem recognition routines available in the processor. The access to information stored in the knowledge component will depend mainly on the database management abilities of the system.

The problem-processing component maintains various models for decision making. The availability of these models is conveyed through the language system. Bonczek, Holspapple and Whinston envisage two extreme levels of capability for decision support systems. One is the explicit statement of the model to be used by the decision maker. The other extreme will see systems that are capable of building a model by itself from basic data (such as inputs and outputs from the model) that is given by the decision maker. This capability is enabled through domain knowledge stored in the knowledge base.

While emphasising the requirements for built-in knowledge and models, this framework establishes some of the necessary requirements for adaptable decision support systems.

Another useful conceptual model of decision support is presented by Raghavan (1984). The focus of this model is the support of a complete decision making process. Such a decision process will include activities that range from identification of a need for a decision to the selection of a particular decision outcome. This model considers the need for supporting dynamic factors in a decision process such as interruptions, and resumptions. Consistent with the focus on the process, the framework emphasises the need to keep independent of particular decision situations. The aim is to provide a generic set of facilities that can be tailored to fit specific decisions as the need arises. Raghavan and Chand (1988) report a list of important generic support requirements that are presented through this model:

- Support planning, organising and the execution of complex and inter-related tasks that constitute decision-making.
- Maintaining the details about intermediate decisions and their inter-relationships.
- Capturing the details surrounding each decision-point including justification and contingencies.
- Supporting flexible process sequences during decision making.
- Offering a repertoire of problem structuring strategies that includes problem migration and reformulation.
- Supporting interruption and resumption.
- Offering various kinds of sounding boards and machine personalities for problem structuring, brainstorming and critical analysis of the problem from different perspectives and promoting convergent and divergent thinking.
- Supporting active elicitation through various kinds of conversation/dialogue models/strategies.
- Supporting the development of problem-specific data bases and knowledge bases as the problem-solving process progresses.
- Simulating decisions and studying their potential consequences.

- Supporting multiple words/ contexts for exploring alternate scenarios.
- Providing various schemes for choice reduction.
- Ability to instruct the system about structured activities for repeated executions.

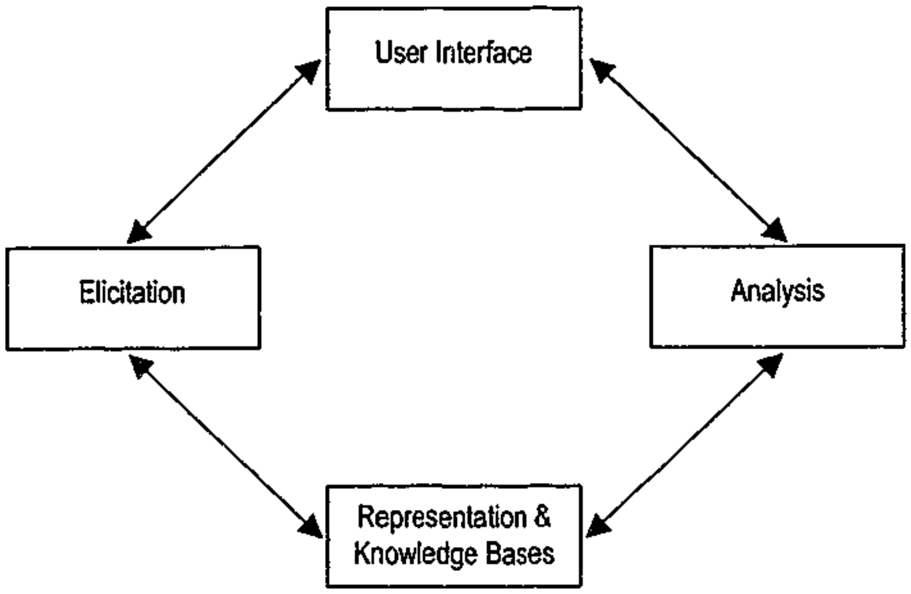


Figure 2.3: Raghavan's (1984) Framework

Raghavan's framework consists of four components (Figure 2.3). The *user interface* is the communication channel between the decision-maker and the automated tool. The control of the decision process with interruptions, resumptions, and process sequencing is achieved through this channel. The *elicitation* component is responsible for producing the required dialogue to extract decision knowledge from the user and also provide feedback through suggestions. The *analysis* component is concerned with consistency analysis, constraint satisfaction, sensitivity analysis, simulation and also critiquing agents and triggering daemons. Models for problem solving and representation, data bases and knowledge bases are the responsibility of the *representation and knowledge base* component.

While the above two frameworks establish basic conceptual requirements, the framework presented by Sprague and Carlson (1982) provides a more comprehensive practical arrangement for decision support. This framework is introduced in detail in chapter 5. However, it is useful to comprehend the requirements for a decision support system as proposed by Carlson (1983) at this stage.

Carlson bases his requirements on five observations of decision-making activity:

- Decision-makers have difficulty describing the process of making a decision. They often depend on conceptualisation methods like pictures and charts to explain or make a decision.
- Although explaining a decision process is difficult, the activities can be classified. The categories of intelligence, design and choice (Simon, 1965) can be used for this purpose.
- Decision-makers require memory aids to augment decision-making. They may be physical, such as memos, scratch paper, reports, or non-physical such as reminders from staff and mental rules.
- Each decision-maker may be unique. They have different styles, skills and knowledge. Therefore, many different decision making processes exist.
- Decision-makers prefer to have direct, personal control over decision making activities.

According to Carlson, the validity of these observations will increase with increases in the unstructuredness of a decision. To support these traits displayed by decision-makers, a decision support system should also provide alternate mechanisms to achieve similar requirements. The set of system requirements thus includes:

Representations to assist in conceptualisation and to provide a frame of reference for using the DSS. Representations could include tables, graphs and pictures. They assist in communication between decision-makers in addition to supporting conceptualisation of the decision situation.

Operations on the representations to support intelligence, design and choice phases in decision-making. The three phases can be used to describe all decision activities. The available operations may be used in more than one of these phases.

Memory aids to support the usage of the representations and operations. The memory aids could include databases, workspaces, links between different components of data, triggers that act as reminders or simple scratch-pad type notes.

Control aids to help the decision-maker control the representations, operations and memory aids. These control aids should facilitate the customising of a DSS to fit the style and requirements of a particular decision-maker. Control aids should also help the decision-maker learn from the DSS to get maximum benefits of the tool.

Representations and operations are the basis for the support system structure. Carlson asserts that a DSS should be designed as a set of representations that have associated operations instead of a set of operations which result in representations.

The Sprague and Carlson (1982) framework for decision support systems has three layers (Figure 4). The top layer is *specific DSS*. The other two layers consist of *DSS generators* and *DSS tools*. The bottom layer is a collection of tools that provide a wide range of facilities to construct and modify DSS generators. The tools could include graphics editors, database management systems, report generators and programming languages. The generators that are built using the tools should have three basic components: a dialogue management component, a data management component and a model management component.

2.5 Binary decisions

Binary decisions were investigated as a special type of decision in this research project as it was considered an important category for senior decision-makers. Binary decisions are decisions that have only two possible outcomes. Although this encompasses situations where a choice has to be made between two completely independent alternatives, the focus here is slightly different. Though selection out of two alternatives is binary, there is little difference between such a situation and selecting between more than two alternatives. Therefore a stricter definition of binary decisions limits the use of the term to describe situations where a given decision alternative is either pursued further or discarded. This situation can be easily understood in the context of the Mintzberg, Raisinghani and Theoret (1976) model of decision-making. They describe the authorisation routine as a typically binary process. Authorisation is the acceptance or the rejection of a particular outcome. They also illustrate other routines where binary decisions are made, such as screening where solutions are retained for further action or rejected immediately.

Binary decisions may occur as independent decisions where a particular course of action has to be evaluated (this may be more common in personal decision-making although also possible in organisational situations). A binary decision can also be a sub-decision of a larger decision-making process. Decision-making activities can be categorised into phases and routines. Mintzberg, Raisinghani and Theoret (1976) describe seven routines: recognition, diagnosis, search, design, screening, evaluation-choice and authorisation. Screening, evaluation-choice and authorisation in particular, can be sources of many binary decisions.

A binary decision, like all other decisions, will also have the phases of intelligence, design and choice.

In a well-defined decision, there are clear objectives, defined outcome alternatives and known probabilities. The decision-maker selects between the known alternatives. A binary decision invariably has known outcomes. It would thus be plausible to conclude that a certain level of definition exists in a binary decision situation. Such problems have traditionally been the subject of information processing approaches to decision-making. The representation of the problem and the decision-maker's perception of the problem are important attributes in the outcome and the process of such decisions (Covaliu and Oliver, 1995; Dixon and Moore, 1997; Hackathorn, 1981; Paivio, 1986; Shepard, 1966; Simon 1976b; Simon and Hayes, 1976). Hence, a framework that purports to support binary decisions should give high consideration to these two factors. This requirement is reinforced by the importance attached to *representation* in decision support frameworks (Sprague and Carlson, 1982).

Mintzberg, Raisinghani and Theoret (1976) also point out that two important decision routines where binary decisions are common, authorisation and screening, are rarely rational. Authorisation is done in a climate of uncertainty, where the authority lacks in-depth decision knowledge, is subject to time limitations and other inhibiting factors. The screening routine has been labelled as superficial as there is no systematic filtering of decision alternatives. Similarly, evaluation-choice is not systematic as the name implies. Convenience, and not rationality is the major concern. As with the support of many other decision processes, the objective of supporting a binary decision is to achieve a higher degree of rationality by avoiding emotions, politics, personality biases and cognitive limitations.

2.5.1 Representing binary decisions: Lewin's concept of force-fields

By allowing the decision-maker to exercise better control of the decision process, and reducing cognitive demand, we may reduce cognitive pressure due to time limitations. Ease of conceptualising the problem would also help towards this end. Information presentation formats have been shown to have an impact on the way decisions are made (Johnson and Russo, 1978; Slovic, 1972; Tversky, 1969). Familiar patterns of representation have a positive impact towards the efficiency of decision-making (Bettman and Zins, 1979). All these point to the importance of presentation of information and selection of representations in support of decision-making. We can conclude that a good representation method would help in supporting the cognitive capabilities of decision-makers.

Interactions with other people, bargaining and persuasion are all inherent characteristics of making decisions (Mintzberg, Raisinghani and Theoret, 1976). Sometimes there is also a need for justifying the process and the outcome. All these characteristics highlight the need to communicate the process to others. A decision support tool should facilitate this communication process. A good representation of a binary situation would also help towards this end.

Our aim in studying the concept of force-fields is to investigate its suitability as a representation of a binary decision scenario. Kurt Lewin's (1952) field theory provides us with the necessary basis for understanding force-fields in social behaviour. Although defined in a different context, in a different discipline, the concept of force-fields has wide ranging general appeal. While Lewin introduced the *field theory* in social science in a much broader framework, our focus here is limited to comprehending the notion of force-fields at a somewhat superficial level.

Field theory is a 'method of analysing causal relations and of building scientific constructs'. When possibilities of behaviour are dependent upon the concurrent status of several variables, we have the basis of field theory.

Group behaviour is constantly subject to change. The amount and type of change may vary with the circumstances. There may also be periods of time where there is relatively little change. In striving to understand change, lack of change and the resistance to change in group behaviour, Lewin says that there is a need to formalise tools. The concept of *quasi-stationary equilibriums* is presented in this context and is proposed as a system of analysis that allows the representation of social forces. The social context is represented by a force field, where the an 'activity' is occurring in an environment of social entities. The status of the activity is dependent on the totality of these entities. An important consideration here is the relative position of the entities within the field. This positioning, while defining the structure of the field, also establishes basic rules for movement of the entities within the field.

When we are dealing with change processes, the 'activity' represents the state of the totality of the force-field at a given instance. The activity can be equated to an equilibrium that exists between social entities that are promoting the change process, and entities that are opposing this change. Promoting entities are labelled 'driving-forces', while opposing entities are labelled 'restraining-forces' (Figure 2.4). At a given instance, the sum of driving and restraining forces will be zero. Therefore, the equilibrium is said to be stationary. However, Lewin concedes that quasi-stationary processes are not perfectly stable. The equilibrium can be shifted by the addition or change of forces in the field.

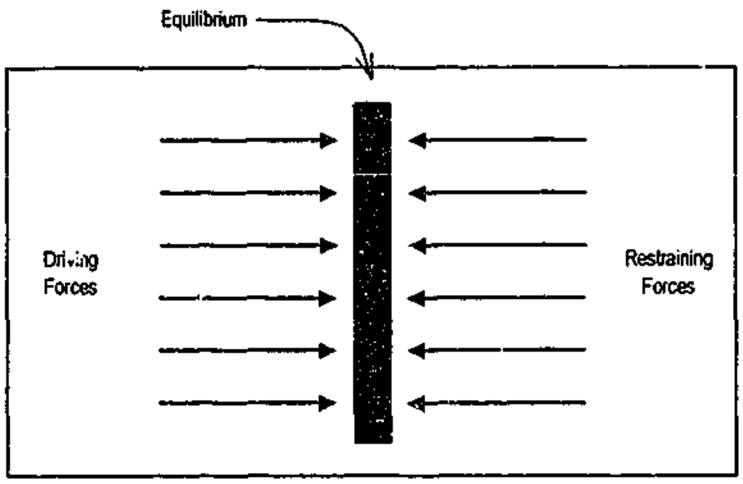


Figure 2.4: A Force-Field

Once the change process has been completed, the equilibrium will attain a new 'stable' position in the field. This new position may be different to the initial position, although stability implies the balancing of driving and restraining forces, *ie.* the sum of the forces will again be zero. To achieve a permanent shift in position, Lewin proposes a three-staged change process: unfreezing, moving and refreezing. Unfreezing involves forcing the group to break current values and prejudices. Once unfrozen, the desired change should be effected. On achieving the new status, the permanency is retained through 're-freezing' by instilling new or old values once again.

In a binary decision, there are only two possible outcomes. If we envisage one of the outcomes as the desired objective, we may have a set of forces that will promote that outcome. Another set of forces that will resist the attainment of that objective may also exist . Hence, we have a concept that is very similar to Lewin's social group context. Our decision outcome may be represented as an equilibrium that exists between driving and restraining forces. Lewin's notion of force-fields therefore has appeal to this work as a representation instrument.

2.6 Decision models

Decision-making has been the focus of a plethora of studies. Many different disciplines have contributed to the body of knowledge in decision-making. For example, micro economics, operations research, behavioural decision theory, psychological decision theory, social judgment theory, information integration theory are just a few disciplines that provide explanations of human decision-making. This knowledge is generally organised along several dimensions, although these dimensions may not be mutually exclusive. Different authors have used diverse axioms for classification (Eg: Keen and Scott Morton, 1978; Slovic, Fischhoff and Lichtenstein, 1977). We chose to use the axioms proposed by Abelson and Levi (1985).

Normative and descriptive models of decision-making are two of the easily understood common classifications of decision models. Normative models deal with how decisions *should* be made and are based on assumptions from a particular view of human rationality. Descriptive models on the other hand, deal with *how* decisions are actually made in practice and are based mostly on observed behaviour (Bell, Raiffa and Tversky, 1989). Barclay, Beach and Braithwaite (1971) contended that we should begin analysis with normative models and then gradually shift towards descriptive models, to overcome problems with describing human decision processes.

The classification along the *structure* versus *process* dimension is another major organisation of decision-making models. This distinction deals with whether a particular explanation is concerned with the *what* (structure) or the *how* (process) of decision-making.

2.6.1 Structural models

Structural models attempt to explain the relationship between the inputs and outputs of a decision activity. Mathematical formulae are sometimes used to explain these relationships. The study of structural models is closely related to the study of judgment (Hammond, McClelland and Mumpower, 1980; Slovic and Lichtenstein, 1971; Wallsten, 1980; Zeleny, 1976). Structural models can be further classified into two categories. The first category is often termed 'riskless decision models'. This type comprises decision models that do not consider risk and uncertainty as important considerations in decision processes (Hammond, 1966).

The second type, 'models of risky decisions', involves incorporation of risks and subjective probabilities into the decision process (von Neumann and Morgenstern, 1947). Social judgment theory (Hammond *et al.*, 1975) and information integration theory (Anderson, 1970) have contributed a large number of models of riskless decisions. Linear models are an important class of riskless structural models. Utility models such as prospect theory (Kahneman and Tversky, 1979), portfolio theory (Fishburn, 1977; Lopes, 1981; Pruitt, 1962) and subjectively expected utility (Slovic, Fischhoff and Lichtenstein, 1977) are examples of models of risky decisions.

Linear models need some elaboration here as they represent a large proportion of research and practice in decision-making and judgment. As discussed by Abelson and Levi (1985), they have been used in a range of decision activities ranging from medical diagnosis to managerial decisions. The attractiveness of linear models lie in their simplicity. Linear models facilitate the representation of the intuitively convincing concept of different importance of different attributes towards a decision. They generally include two types of factors: weights and attributes. Attributes are factors that should be considered in a judgement task. Weights are importance measurements for attributes. The composite value for a particular decision alternative is inferred by multiplying the attributes and relevant weights for all attributes. Such linear models have found uses in capturing decision-makers' judgment policies, as comparison mechanisms for decision-maker judgments, and even with replacement of the decision-maker (Dawes and Corrigan, 1974; Stewart and Carter, 1973).

The degree of fit between linear models and actual human judgment processes has been a subject of debate (Daws and Corrigan, 1974; Einhorn *et al.*, 1979; Hoffman, 1960). The major criticism of linear models has been their inadequacy to incorporate the human traits of using non-linear, compensatory processes when making decisions. However, linear models are still effective in identifying different attributes of a decision situation and capturing the non-uniformity of importance of those attributes (Abelson and Levi, 1985).

2.6.2 Process models

Process models of decision-making attempt to explain the activities that decision-makers perform to arrive at decisions. They focus on the dynamic factors and steps in a decision-making activity. Process models have become the dominant area in recent decision research for a number of reasons. Inadequate explanation of psychological processes by structural models (Dawes, 1975; Simon, 1976a) and the increased awareness of cognitive psychological concepts in the study of process models (Simon, 1976a; Taylor, 1976) have been two of the important reasons. However, other researchers have commented on the complementary nature of the two approaches of structure and process (Einhorn *et al.*, 1979; Svenson 1979).

Process models can be used to describe both *well-defined* and *ill-defined* decision problems (researchers have suggested that well-defined and ill-defined problems lie on a continuum with varying degrees of definition along the continuum. eg., Simon, 1960). Well-defined problems have clear objectives, defined outcome alternatives and known probabilities. The task of the decision-maker is to collect information so that a choice can be made between the known alternatives.

Research has shown the usefulness of applying information processing techniques for this type of problem. The decision-maker's perception and representation of the problem situation are significant influences on the decision outcome and the process (Simon, 1976b; Simon and Hayes, 1976). Another assumption in the study of these problems is that human decision-makers are imperfectly rational. This well documented assertion leads to the conclusion that we use heuristics in our choice activities (Bazerman, 1990; Dawes, 1976; Newell and Simon, 1972; Tversky and Kahneman, 1974). Information format and task complexity are believed to be the main determinants of the heuristics that humans employ. Important considerations include number of attributes, available time for processing, format and sequence of data presentation (Slovic, 1972; Wright, 1974; Tversky, 1969). The conjunctive rule, disjunctive rule, elimination-by-aspect rule are some of the many choice rules that have been presented as mechanisms of selection between alternatives (Abelson and Levi, 1985; Einhorn, 1970 etc.).

It has been shown that we may be using these choice rules in combination, not just as single rules at a time, with the ultimate goal being to achieve a plausible choice without unnecessary cognitive effort. Models of such combinatorial use of choice rules are numerous (Beach and Mitchell, 1978; Christensen-Szalanski, 1978; Montgomery and Svenson, 1976; Park, 1978).

As the number of available outcome alternatives increase, decision-makers generally reduce the amount of information search (Mills, Meltzer and Clark, 1977; Payne, 1976). The scope of information to be searched is determined by using more simple rules. A similar phenomenon has been observed when the number of attributes are increased (Svenson, 1979). When the number of attributes are increased beyond what is acceptable to the decision-maker, it has been observed that a choice may be made by considering only a few important attributes (Olshavsky, 1979). High information loads have been associated with reduced decision quality. Under time constraints, human decision-makers act to eliminate unfavourable alternatives by assigning disproportionate weights (Wright, 1974). When time constraints are imposed, alternatives are also classified into 'accept' and 'reject' categories for quick resolution of situation (Wright and Weitz, 1977). Safer alternatives are often sought under time-limited conditions (Hansson, Keating and Terry, 1974).

The format of information presentation can have similar effects on the methods that are employed by decision-makers (Slovic, 1972; Tversky, 1969). Sequential exposure to alternatives, leads to processing by alternatives, while the availability of attribute information for alternatives will facilitate processing by attribute. This has been linked to the way information is stored in human short-term memory (Johnson and Russo, 1978). We posses the capability to adapt to whatever the format of data presentation, however, more efficient processing has been observed if the presentation format is congruent with learned patterns of behaviour (Bettman and Zins, 1979).

Process models have also been presented for ill-defined decision situations. Unlike well-defined situations, in this type of problem, the objectives are less clear and the available outcome alternatives are generally not known. Clear research paradigms are also not forthcoming for these types of problems. This has resulted from the complexity and lack of observable cues in these decision tasks (Nisbett and Wilson, 1977; Schneider and Shiffrin, 1977). As Weick (1983) points out, defining multi-stage models for ill-defined problems is difficult by definition:

> One's next thinking step is conditioned on the outcomes of ongoing activities. The absence of procedural structure is also due to the nature of managerial problems. Since they are typically indefinite, one-of-a-kind, and lack a clear-cut solution, such problems do not lend themselves to proceduralisation.
>
> (Weick, 1983)

Nevertheless, many attempts have been made to articulate process models for these problems. Possibly the most influential of these models is the trichotomy presented by Simon (1960, 1965). According to this model, all problem solving can be classified into three phases - *intelligence*, *design* and *choice*. Intelligence is the scanning of the environment, looking for situations that need decisions. The second phase, design, is the inventing, developing and evaluation of possible solutions to the problem. The choice phase is the selection of a particular course of action from the available set of alternatives. The fundamental transition mode between the phases is normally sequential, although Simon concedes the possibility of sub-problems, and therefore, the model can be viewed as recursive as well as iterative.

This model is congruent with Dewey's (1933) assertion that we solve problems by defining the problem, developing alternatives and then selecting the best possible course of action. Empirical studies have also validated the existence of phases in decision-making (Ackerman, 1970; Bower, 1970). Witte (1972) in his study of 233 decision processes, concluded that, although distinct phases may exist in decision processes, they are not easily distinguishable and they may not follow a sequential progression.

Though most of these models purport to be describing ill-defined decision situations, there is little essential difference between them and normative models such as that of Friedman (1957). Studies show that individuals do not always act systematically and sequentially as these models require. Several attempts have been made to describe ill-structured decision processes in a more 'realistic' manner. The model proposed by Mintzberg, Raisinghani and Theoret (1976) is one of the most comprehensive of these and provides a good basis for use in automated decision support attempts.

2.7 Findings from past research

Through the survey of past work it was identified that although there are many candidates for the articulation of personality, the Myers-Briggs Type Indicator provides the most practical framework for this research project. It was hence decided that the MBTI would be used for the assessment of decision-maker personality. Therefore, Q1 can be translated into the following hypothesis:

H1: Individuals with different personalities (based on the their MBTI) will attach different importance to decision attributes in a given decision situation.

The testing of this hypothesis is explained in chapter 4 of this dissertation.

Research questions Q2 and Q3 relate to how the results of the testing of H1 can be put to practical use in a decision support system generator. The author is of the view that hypothesis need not be stated for these two questions as they will be answered through the systems development paradigm. These questions are addressed in chapters 5 and 6 respectively. The background material required for implementing the findings of Q1 were discussed within this chapter.

Q4 is a logical extension to Q2 and Q3. If it is possible to successfully build systems in the process of investigating Q2 and Q3, it is important that the success of that implementation is tested. Since the aim is to build adaptive systems, the capability of any resulting system to adapt to individuals is important. Chapter 7 of this dissertation is dedicated to describing the attempt at testing that capability.

Chapter 3

Research Method

Careful examination of the research questions for this project shows that it is composed of three distinct stages:

1. Establish relationship between personality types and the criteria preferences of individuals belonging to those types,

2. Build a computer-based decision support system generator capable of adapting to individuals based on their personality type, and

3. Validate the ability of such systems to adapt to individuals based on their personality.

This is typical of information systems research projects. The stages are compatible with the *concept-development-impact* model described by Nunamaker, Chen, and Purdin (1990). The attempt is to use *personality* as a basis for providing managerial decision support, a concept that is new to the decision support systems discipline. The basic hypothesis of a relationship between personality and decision preferences of individuals has been formulated through literature analysis of relevant reference disciplines. Though such hypotheses generation from secondary sources is a valid scholarly activity, it is clear that the hypothesis alone would not justify the use of the concepts as a basis for a new method of decision support (see Shanks, Rouse, and Arnott, 1994 for a discussion of *scholarship* in information systems). Therefore, this research project is not totally dependent on secondary data. That hypothesis will be tested as a pre-requisite for the systems development stage. Systems development is undertaken to demonstrate the viability of the use of personality as a basis of decision support systems design. The efficacy of the system in providing personalised support will be investigated in the final (impact) stage of the project. The three stages may require very different research techniques. Before proceeding to identify the candidate techniques for each stage, it is prudent to understand the philosophies behind research methods. Such an approach would assist us in selecting the most appropriate techniques.

Valid research in the academic community is conducted conforming to the *scientific method*. The scientific method is a set of conventions that is used to generate knowledge.

It is distinguishable from other sources of knowledge such as authority, tradition, rationalism and common sense for several reasons. Science is a combination of both rationalism and empiricism (Graziano and Raulin, 1993). For a method to be accepted as scientific, it has to be empirical in nature and replicable. However, it should be understood that what is regarded as 'scientific' is conditioned by the culture that propagates it. The conventions followed by the academic community are widely accepted as arising from western culture. Although other forms of knowledge generation has often been considered as 'pseudo-science', some epistemologists argue that these forms may in fact be more appropriate for the study of human or social phenomena (Hirschheim, 1985). Information systems, and specifically decision support systems are largely human interaction systems. When conducting research in these disciplines, the researcher should be mindful of this narrowness of our conception of science and use the most appropriate tools and techniques available. Conforming to our current understanding of science indicates that we agree to several common assumptions, whichever discipline we claim to belong:

1. A true physical universe exists.
2. While there is randomness and thus unpredictability in the universe, it is primarily an orderly system.
3. The principles of this orderly universe can be discovered, particularly through scientific research.
4. Our knowledge of the universe is incomplete, and new knowledge can alter current knowledge. Therefore all knowledge is tentative.

(Graziano and Raulin, 1993)

These assumptions lead to the goals of all scientific activities: to explain, predict and control phenomena (Gay and Diehl, 1992). The goals of this research project are no different. We are attempting to build a theory on the predictive power of personality so that it can be used to better support senior decision-makers. Data and theories are both aspects of science. Which of them come first is dependent on the personal preferences of the scientist. To produce coherent scientific knowledge both these aspects are essential. The maximum value of both approaches can be reaped when they are used in combination (Burns and Dobson, 1981). Depending on the starting point, research can be termed *induction* or *deduction*. When data or observations are collected first, that data is used to produce theories or explanations. Sufficient quantities of data can help make generalisations. This type of research falls into the *induction* category. The reverse of this process occurs when researchers attain specific conclusions based on generalisations. This is termed *deduction*. Refinement of theories often take place in the deduction stage of a research project. The first stage of this research project will attempt to build a theory based on observations of the decision-making behaviour of individuals. Therefore it is taking an inductive approach. The second and third stages are geared at measuring the implications of this theory in the process of decision support through the use of computer-based systems. Therefore we will be looking at further improvement of the theory or development of a new theory, with decision support as a goal. This trace back to specific application is an example of deduction. When building theories, it should be kept in mind that they can never be proved; they can only be disproved. Some data may support the theory. Other data that only partially conforms to the theory causes that theory to be refined. The concept of testability is important in this context as if the theory cannot be tested, then it cannot be disproved (Burns and Dobson, 1981).

Another important classification of research defines whether it is *basic* or *applied* research. Some researchers view these as being extremes of the same continuum (Gay and Diehl, 1992). Basic research is conducted for the purpose of building and refining theories. How such theories may be used in practice is not of particular concern with this type of research. This type of activity is generally undertaken to understand general principles of behaviour. Applied research is more concerned with using that understanding in practical situations. It is concerned with testing and evaluating theories so that they can be applied to solve problems in society and business. Information systems as a discipline attempts to improve the practices of organisations and individuals. Therefore research in the discipline generally falls into the latter category (Shanks *et al.*, 1994). In this doctoral project, aspects of both basic and applied research can be seen. The primary concern is the provision of better decision support to senior decision-makers. This can be classified as applied research for better methods of decision support. However, as a pre-requisite to that, the relationship between personalty and decision making is sought to be established.

This is closer to the basic research end of the continuum as it is an attempt to study a general principle of human behaviour. A theory establishing such a relationship may also be used to solve other practical problems in decision support and other disciplines.

The purpose of the research also provides a way of classification. While it is convenient to view research as having a single purpose, often projects consist of many purposes. Some studies attempt to explore a new topic to gain a greater understanding of the area. This kind of research may stop short of developing theories and only go so far as to formulate questions for future investigation. This type of research is termed *exploratory* and deals with the 'what' question of research. A researcher has to approach exploratory research with an open mind as they are subject to change of direction as more is learnt about the topic. Other research is undertaken to describe in detail a known phenomenon. Such research is termed *descriptive* and addresses the 'how' question. Research attempting to articulate relationships and many other types of social research is descriptive. The third variety of purpose for a research project is explanatory. With explanatory research, the attempt is to understand 'why' something happens the way it does. This follows description, as by this stage what happens is already known.

There would not be an explanatory phase in this project as 'why' there might be a relationship between personality and decision making is not within the scope of our discipline, although psychologists may see benefits in such explanation. The first stage of the project may be placed somewhere between exploratory and descriptive research. It is exploratory, as it is an attempt to investigate the relationship between personality and decision-making. If there is a relationship, then the focus is on what form that relationship takes and how it manifests. This is descriptive research. This is typical of many research projects where the distinction between exploration and description is not obvious (Neuman, 1994). The second stage of the project can be described best by adopting the systems development research approach (Nunamaker *et al.*, 1990) as it does not conveniently fall into any of the three categories explained above. The last stage is descriptive as an attempt is made to describe the usefulness of the decision support method proposed.

3.1 Logical Positivism and Interpretivism

Research activities within the information systems discipline are seen as following to one of two different paradigms: *logical positivism* and *interpretivism* (Luthans and Davis, 1982). Logical positivism is often mistaken to be *the* scientific method. In the context of information systems research, it is important to understand both paradigms and the alternative techniques that they offer. This is an implication of information systems being a more social science discipline than a physical or natural science discipline. What is interesting in is not technology *per se*, but the application of technology (Keen, 1987). According to Avison and Fitzgerald (1991), '...much research in information systems is not concerned with scientific method (although some - particularly aspects in formal methods and software engineering, structured methods and data analysis) but is concerned with human activities, and may therefore be more in the realm of social science methods'. Even though this implies that scientific method is not compatible with social science, investigation of methods used in social science show that they subscribe to a much broader definition of the scientific method where both positivism and interpretivism coexists. This is typified Collins's (1989) assertion that 'modern philosophy of science does not destroy sociological science; it does not say science is impossible, but gives us a more flexible picture of what science is.' Neuman (1994) presents a discussion of the paradigms within this broader 'science' and the philosophies underlying them. We choose to follow his approach to the discussion.

Positivists believe that reality consists of predetermined regularities. These regularities can be discovered through research. The concept of regularity is important as it provides the basis for logical deduction and prediction. This regularity is assumed to be constant over time. A goal of positivism is to minimise the effect of biases in the research process and the reporting of research. The researcher has to be detached from the research and has to maintain objectivity at all times. Hence, positivists often resort to quantitative research. They try to gather precise measurements of events. The world is seen as objective and hypotheses testing through the analysis of numbers is the preferred approach. Empiricism is a cornerstone of positivism; observable facts are of more value than other forms such as ideas and beliefs. This is because facts can be observed through the senses of humans or instruments that enhance the senses and can be shared with others. Rational individuals will agree on the same facts. If there are disagreements over things observed, it may be due to improper observation. This leads to a shared understanding of the empirical world.

Human activities are simplified into convenient quantitative measurements by positivists. The positivist view of humans is referred to as *the mechanical model of man*. Under this model, individuals are seen as rational beings whose behaviour is conditioned by external events. A cause is expected to have the same effect on all individuals. This leads to the positivists belief of causal laws. It should be noted that these causal laws are probabilistic and therefore do not conform to determinism. Although under these assumptions the behaviour of a given individual cannot be predicted for all situations, probabilistic measures of the likelihood of a certain behaviour pattern can be presented. The relationships between various objects or social phenomena are expressed as abstract formulae. The process of deduction allows the explanation of specific situations through the application of causal laws.

Positivism asserts that all mature sciences should conform to the same basic principles. Any apparent differences are believed to be caused by the immaturity of other disciplines (as against physics, the most advanced science) and the variances of the subjects under investigation. The pursuit of truth through the accumulation of knowledge is advocated in positivism. 'Explanations of social life are true when they have no logical contradictions and are consistent with observed facts' (Neuman, 1994). In addition, replicability is a major issue with positivism. Replication acts as a way of maintaining truth. Any new relationship advocated by a researcher is open to be replicated by others. For a causal law to be generally accepted, it should be demonstrated to hold with multiple studies. Objectivity and honesty in research is ensured through this acceptance of a common set of values.

Interpretivism is the study of meaningful social action. It advocates the study of people and their behaviour within a context. Interpretivists believe that actions of individuals may not have complete meaning divorced from the environment in which the individual operates. Interpretivism has its origins in *hermeneutics*, among others (Neuman, 1994). Hermeneutics refers to the interpretation of text based on a complete understanding of the context in which it was produced. It involves understanding beliefs, values, assumptions, and motivations of the originators of the document. This is evident in the interpretivists belief that the social world can only be interpreted through the perspective of the people being studied. 'Individual motives are crucial to consider even if they are irrational, emotion-laden, and contain facts and prejudices' (Neuman, 1994). Thus, the conclusions are not limited to what can be observed. Interpretivists focus their attention to the study of humans as other beings generally lack the capacity to attach meaning to their behaviour.

Researchers following interpretivist approaches often spend long periods observing and getting acquainted with their subjects. They focus on small numbers of individuals, preferring to do in depth analysis rather than the positivist approach of generalisations on large groups of subjects. Interpretivist generalisations are very limited. The data that interpretivists gather mainly belong to the qualitative variety. Hence, the dependence on statistics is much less. They do not view the world as consisting of objective social reality irrespective of the people who create and interpret it. Reality is conceived internally by people. Thus, it is a subjective reality, leading to possible different interpretations of the same experience by individuals. The goal is not to uncover causal laws that explain common external realities. Though there may be regularities and patterns of behaviour, it is not because of external controls, but because of shared meaning through social interaction by individuals. The interpretivist researcher is interested in discovering these shared meanings. The place of common sense in interpretivism is important. Common sense is seen as an alternative to the positivist laws. Positivists assert the accuracy of their theories through replication. Interpretivists on the other hand, posit that their research is accurate 'if it makes sense to those being studied, and if it allows others to understand deeply or enter the reality of those being studied' (Neuman, 1994).

As we see, positivism and interpretivism have distinct philosophies underlying them. The goal of value free, objective research is alien to the interpretivist as they see it as an impossible goal. Even when positivists claim that their scientific method is free from value, it is implicit that the value system of the positivists gives meaning to the context. Another main discrepancy between the two paradigms is the issue of replicability. Positivists believe that research should be replicable to be valid. However, it is clear that due to the influence of a plethora of factors, human beings may not behave in the same manner in different situations. Therefore, the goal of replicability is rarely achieved in social research. Research involving information systems confounds this situation in that new systems change the environment into which they are introduced.

The literature review on personality and its influence to decision making, leading to the first stage of this research project, indicated that there are many contradictory results. Some researchers have indicated that that may be due to deficiencies of conducting research. Positivism being the dominant research paradigm in psychology, has been the framework under which much of this research has been conducted (Shanks *et al.*, 1994). Therefore, it indicates a degree of mismatch between the phenomenon being studied (human personality) and the research paradigm. However, psychologists are well aware of these deficiencies:

> These human restrictions do not imply that the scientific approach to studying human behaviour should be abandoned. Within the limits imposed by having human subjects, psychologists do apply the basic attributes of scientific method so that their findings are objective, reliable, replicable and quantifiable as possible, employing the hypothetico-deductive approach and controlling extraneous variables and systematically manipulating, under defined conditions, the independent variable in question. Even the hardboiled sciences are not totally objective since subjectivity is involved in the very choice of a problem as worthy of investigation and in the discussion of results.
>
> (Burns and Dobson, 1981)

The positivist paradigm is followed in this project for the same reasons of obtaining objective, reliable, replicable and quantifiable results. However, especially considering the arguments in interactional psychology, still there is an argument for the use of an interpretivist approach to the first stage this study. This argument is balanced with the need for generalisable results. The interpretivist approach is not concerned with generalisable results, it advocates the detailed study of a small number of subjects. The results of such studies would only be relevant to the context in which they are performed. The goal of this research project is to produce decision support systems that adapt to individuals based on their personality. Therefore, we are searching for generally applicable rules. Such rules belong in the domain of logical positivism. Though positivism is selected as the dominant paradigm, it is acknowledged that interpretivism has much to offer in this domain of research.

3.2 Research techniques

This doctoral research project includes several stages. Although there may be a single end-purpose, each stage has its own objectives and relevance. Hence, when referring to a 'method' for this project, we refer to a broad set of techniques; not a single technique. The term 'technique' in this context is analogous to 'approach' as used by Galliers (1992): '[they] are a way of going about one's research'. Galliers goes onto distinguish between approach and method, where a method is a way of systematising observations. The challenge for any researcher is to select the most appropriate techniques within the paradigm they conduct their research. Selection of a paradigm indicates that the researcher agrees with all the underlying assumptions, at least for the purpose of the research project. Thus, the results of a study should be interpreted through this framework, conscious of the limitations. It is however possible to conduct the same research using both competing paradigms enabling a more comprehensive understanding of the phenomenon being studied. Such pluralism in paradigms will also require pluralism in techniques.

Many information systems scholars have proposed sets of research techniques that they believe are relevant to our discipline. Galliers (1992) summarises some of these attempts. He also placed each technique in either the positivist or the interpretivist paradigm. Shanks *et al.* (1994) proposed a framework that they claim to be more useful in placing research techniques. They conceive a continuum between strict positivist and interpretivist techniques. Some techniques, according to them, could be used in either paradigm. Hence, they could be placed between the extremes of the continuum. It should be understood that there are techniques that belong close to an end of this continuum. Such techniques have little utility for research in the opposing paradigm. Since this project takes a positivist approach, techniques such as subjective/argumentative study and phenomenological study are not considered as useful. The discussion below is limited to possible candidate techniques within the positivist paradigm.

3.2.1 Experimental research

The basis of experimental research bears a very close resemblance to the principles of positivism. When conducted well, experimental research articulates reliable cause-effect relationships. While widely used in natural sciences, experiments are also common in social sciences, psychology being one of the disciplines to subscribe to experimental research regularly (Neuman, 1994). The objective of experimental research is to observe the effect of independent variables on dependant variables. The independent variable is the factor that causes the behaviour, while the dependant variable is the outcome. Experimental research process starts with a hypothesis that states the expected causal relationship (Gay and Diehl, 1992). The causes and outcomes of experiments are defined operationally in order to be measured quantitatively. Experiments are conducted in a controlled environment so that possible alternative influences other than the influence of considered independent variables are eliminated. The degree of control and the well-defined nature of experiments make it possible to be replicated easily. There are many ways of trying to limit the influence of such control variables. Random selection of samples, selection of samples based on known characteristics and control groups are strategies that could be employed for this purpose (Leary, 1991; Shanks *et al.*, 1994). Although there can be variations, typically, experiments are conducted on at least two groups: the experimental group and the control group. The experimental group is subject to a treatment related to the hypothesis. Other than this treatment, both groups are considered identical. The researcher wields control over the whole exercise. An attempt is made in experiments to quantify exact relationships between variables. Statistical measures are used for this purpose. In keeping with the principles of the positivist paradigm, statistically significant relationships are considered to be generalisable to populations.

Although such generalisation is the main goal, many researchers point to deficiencies in laboratory experiments in achieving that goal. Many laboratory experiments are carried out using students as subjects, limiting the true generalisability to practical applications (Shanks *et al.*, 1994). This is a threat to external validity. The balance between control and realism is another issue of concern (Gay and Diehl, 1992). Laboratory experiments can be manipulated to such an extent that all resemblance to the real situation that it is supposed to represent is lost. Similarly, there are many questions about internal validity of laboratory experiments. In some experiments, it is acknowledged that curbing the effect of control and unknown extraneous variables is a problem. In deed, this is seen as a major weakness of information systems related laboratory experiments (Jarvenpaa *et al.*, 1985).

Field experiments have been proposed as a way of overcoming some of the deficiencies in laboratory based experiments. Field experiments also are labelled as *quasi-experiments* or *natural experiments* (Millar and Crabtree, 1994). The artificiality of laboratory settings are replaced in such experiments with real situations in the field. However, some degree of control is lost in the process as it may be impossible to control all extraneous factors in a field situation. Random assignment of subjects is also difficult in field experiments. Thus, internal validity has to be compromised for external validity (Sommer and Sommer, 1991).

Single subject experiments are a special form of experimental study where a within-subject approach is taken. This form is sometimes considered superior, as there is loss of information in the summarisation process in the between-subject approach. Such summarisation is required for group comparison procedures in multiple subject experiments, as group differences are the main object of study. Generally, a control group is not present in a single subject experiment. However, causal relationships may be established because of the ability to control confounding factors and independent variables. Single subject experiments therefore have good internal validity. This form of experiment is often used to evaluate the effectiveness of treatment programmes in clinical psychology and other disciplines (Gay and Diehl, 1992).

3.2.2 Correlational research

Collection of data to ascertain whether a relationship exists between two or more naturally occurring variables is termed *correlational research* (Leary, 1991). The strength of the relationship is also a matter of investigation and is expressed as a correlation-coefficient. The correlational research process may begin with a hypothesis regarding a relationship between variables. For each subject in the sample, measures are quantified for each variable under investigation. Like in experimental research, variables should be operationally expressed to permit quantification (Graziano and Raulin, 1993). In addition, the quantification of variables should at least conform to an ordinal scale. If a strong relationship exists between variables, the coefficient will be close to 1.00. If there is no relationship or a weak relationship, the coefficient will be close to 0.00. If the relationship is an inverse one, then the scores will range from 0.00 to -1.00 A greater predictive ability is provided by variables that have strong relationships.

Correlational research may be employed to gain insight into a relationship so that it can be further investigated using experimental and causal-comparative studies. It may also be employed to establish relationships so that the behaviour of one or more variables can be predicted using another. The variable that provides the basis for the prediction is referred to as the *predictor* while the variable being predicted is called the *criterion*. The threshold value for an acceptable relationship depends on the purpose of obtaining the data. If the relationship was investigated for exploratory reasons or hypothesis testing, the statistical significance of the correlation coefficient is important. However, if it was investigated for predictive purposes then the coefficient itself becomes the important measure. Statistical significance is employed as a way of eliminating chance relationships. While acceptable coefficients for different purposes vary, generally, figures in the order of 0.60 or 0.70 are acceptable for group prediction and figures in the order of 0.80 are needed for individual prediction. However, for some activities such as personality measures, coefficients in the order of 0.70 are regarded as valid (Gay and Diehl, 1992).

A correlation between variables does not necessarily imply that one causes the other. If we are to conclude that one factor causes the other, three conditions have to be satisfied: co-variation, directionality, and elimination of extraneous variables (Graziano and Raulin, 1993; Leary, 1991). Co-variation is the only condition that is investigated genuinely in correlational studies.

3.2.3 Causal-comparative and differential research

Both causal-comparative and differential research have the same basic procedures in conducting research, although there may be a difference in purpose. In causal-comparative research, an attempt is made to identify the cause of an effect that has already been observed to be different between groups (Gay and Diehl, 1992). As both the cause and effect exist before the experiment, such research is also called *ex post facto* research. The reverse of this process, identifying different causes and then observing the effect it has on some variable is classified by some researchers as causal-comparative as well (Gay and Diehl, 1992). Others refer to this reverse process as differential research (Graziano and Raulin, 1993). Differential research is therefore concerned with investigating the effect some group difference has on a variable of interest.

It should be noted that the group difference has already occurred and is not under the control of the researcher. The researcher only measures independent and dependent variables. This characteristic distinguishes differential or causal-comparative research from experimental research. In experimental studies, the researcher has the ability to manipulate the independent variable. Experimental research and differential research are similar in that both attempt to establish cause-effect relationships. Differential and correlational research also have some similarities. Neither of them provides manipulative power to the researcher. However, correlational research does not attempt to identify cause-effect relationships. Causal-comparative and differential investigations involve two or more groups with one independent variable, while correlational investigations involve one group and at least two variables within the group. Another difference is that differential research involves comparison while correlational research deals with correlation (Gay and Diehl, 1992; Graziano and Raulin, 1993).

Like with most types of research techniques, the variables involved in a causal-comparative or differential research situation should be operationally defined. Such operational definition should permit the differentiation between the groups involved in the study. Good definitions will permit the results to be generalised to the respective population to which the group members belong. Groups may be differentiated on either a qualitative or a quantitative dimension. Random selection of samples within the targeted populations is advocated. To obtain useful conclusions, the effect of extraneous variables should be controlled. Therefore, in sample selection, care should be taken to select subjects who are identical in all respects other than the independent variable. There is a need to collect background information on the subjects so that it may be possible to correct or explain some inequalities in the results. Proper comparisons between groups may be done only if the same measuring procedures are applied to all groups. By having common measurement procedures, we reduce the effects of *confounding* (Graziano and Raulin, 1993).

Causal-comparative and differential research have immense utility where experimental procedures cannot be carried out either for practical or ethical reasons. When there is a need to study effects of group differences that have already occurred, such as gender, it is impossible for the researcher to manipulate distinguishing variable. In other research settings, it would be unethical to manipulate certain characteristics such as neurophysiology of people or child development. In such instances, researchers use groups of subject who have acquired the required distinguishing characteristics for some other reason not related to the research. Causal-comparative and differential research are often employed as precursors to experimental studies. They provide a method of identifying variables that need further investigation under experimental conditions.

This type of research also has limitations. Since the group differences have occurred before the study, there is no strict manipulation and control as in experiments. Random assignment of subjects to groups in the sample selection process is also difficult in causal-comparative studies. Therefore, the results should be interpreted cautiously. The relationship observed may not be as it seems on the surface, because of the effect of unknown extraneous variables. Thus, the results may point only to a relationship that may not be a causal one: 'cause-effect relationships established through causal comparative research are at best tenuous and tentative. Only experimental research, which guarantees that the alleged cause, or independent variable, came before the observed effect, or dependent variable, can truly establish cause-effect relationships' (Gay and Diehl, 1992).

3.2.4 Case studies

Case studies are extensive investigations of single instances, individuals, or a larger unit. They have a defined scope of investigation and a temporal dimension. Hypothesis for case studies are aimed at identifying contingencies:

'on what variables seem to go together' (Graziano and Raulin, 1993). They generally fall into the category of field research as the phenomenon may be observed in its natural environment, although some case studies are conducted in abstract settings. The amount of constraints imposed on the situation is not controlled by the investigator to the same extent as in other types of research discussed earlier. This facilitates unhindered observation of the case of interest. It also provides a degree of flexibility to the researcher to tailor the research process according to the realities of the situation. However, a greater responsibility is imposed on the researcher to preserve the research environment, in the absence of strict laboratory conditions as in experiments. It is important that the researcher wins the trust of the subjects. Yin (1989) provides a set of characteristics that a case study researcher should posses. In some case studies, the researcher is a passive observer who does not affect the natural behaviour of subjects, while in others the researcher takes the role of a participant-observer. Participatory-observation is used as a way of reducing unnatural behaviour by subjects. Although there is a conscious attempt to reduce intervention, it should be noted that case studies are carried out in a more constrained environment than other types of naturalistic research. Unlike in other research techniques discussed, case studies do not naturally lend themselves to statistical analysis. If statistical analysis is to be performed, largely qualitative data has first to be coded in some manner. Statistics employed will be limited to simple procedures such as the mean and standard deviation (Graziano and Raulin, 1993; Sommer and Sommer, 1991).

Case studies have utility in obtaining insight into new phenomena that are not very well understood. Thus, it can provide a basis for more constrained studies. It may also be employed to investigate the practical utility of relationships discovered by conducting laboratory-based studies. Case studies provide an opportunity to investigate a larger number of variables than possible with other techniques. However, it is not possible to generalise observations in a small number of case studies to populations. Even in single case studies, the results are subject to interpretation and perceptions of the investigator. When gathering data, the subjects themselves can act as filters of facts. Reliability of case studies may be improved through cross-verification using many subjects. Another reason for reduced generalisability is the sample selection process for case studies. Generally, rigorous techniques in sample selection are not applied as in laboratory experiments. There may be many instances where the researcher has no control over selection of a case. There is a possibility of the subjects behaving differently because of the knowledge that they are being observed. It is also not possible to confirm causality using case studies as there is no control of alternative explanations (Galliers, 1992; Graziano and Raulin, 1993; Shanks *et al.*, 1994; Sommer and Sommer, 1991).

Although *statistical generalisation* is not possible with case studies, it should be noted that *analytic generalisation* can be claimed. When performing analytical generalisations, the empirical observations are compared with a defined theory. If the observations are congruent with the theory, analytic generalisation is assumed. If two or more case studies support the given theory, replication may also be claimed (Yin, 1989).

3.2.5 Systems Development

Nunamaker *et al.* (1990) justify why systems development is a valid form of research in the information systems discipline, although it should be supplemented with other forms of research. Shanks *et al.* (1994) show that systems development may be regarded as a form of action research. Nunamaker *et al.* present their method as a 'super-method'. Systems development is discussed here as another *technique* that is relevant to this research project. Much of the discussion presented here follows Nunamaker *et al.*'s (1990) description of systems development as a research activity.

According to them, systems development is a five-step process that includes concept design, constructing the architecture of the system, analysis and design of the system, building the system, and observing and evaluating the system. Some of these steps do not directly involve an engineering approach; an artefact may not result from each stage. They simply form the groundwork to provide a useful context to artefact development and may include the use of some of the other research techniques such as laboratory experiments. Concept design is one such phase. In concept design, the researcher proposes research questions relevant to the domain. The primary concern is putting forward a novel solution to some problem. Systems development is undertaken as the usefulness of this concept may not be tested in another manner. Developing a system architecture is the next step. How the concepts proposed earlier may be translated to system components is the concern of this phase. The architecture is supposed to provide a 'road map' for system construction. The components of the system and their interactions are specified. How the functionality of the system meets the requirements of the proposed concept should also be explained. The next step, analysis and design of the system, involves taking an engineering approach. The researcher should understand the functional requirements of the system. The design specification is a more detailed plan than the architecture developed before. Detailed design of databases, data structures and process requirements are performed. It is usual to evaluate several different design options.

Actual systems development takes place in the next stage of systems development. The design selected in the previous stage is now converted into an artefact. In research settings, the artefact developed is referred to as a prototype as it may lack the finesse of a commercial product. However, in order to evaluate the system in practical settings, it may be necessary to refine the prototype. Such systems development demonstrates the ability to implement the concepts proposed, in addition to providing a vehicle for evaluating the practical value in solving the intended problem. Evaluation may also result in the prototype being refined to better achieve the objectives. The evaluation takes place in the next stage of the research process. This stage involves testing whether the system meets the requirements specification. More importantly, the impact of the system in solving the intended problem is investigated. Theory testing and refinement is done in this stage and may employ other research techniques such as laboratory experiments and case studies. This step-wise systems development research approach is not a sequential one; it may involve iterations through the steps until the requirements have been satisfied. When defining an information systems research technique in the context of this project, constructing the architecture of the system, analysis and design of the system and building the system will form the core of the technique.

3.3 Selected research techniques

Shanks *et al.* (1994) advocate informed decisions when selecting research techniques. The relevance of the research, the paradigm (framework), purpose, research cycle are factors that the researcher should consider. As explained at the beginning of this chapter, this doctoral project has three distinct stages that conform to the *concept-development-impact* model for information systems research. Each stage has a position along each dimension discussed previously. Table 3-1 summarises these dimensional positions. The task is to select the most appropriate research technique for each stage keeping the goals of the project in mind. The research method for the project would therefore be a composite of all the selected techniques. It is worth noting here that the complete project is conducted under the positivist paradigm for the reasons explained previously. Therefore, only techniques belonging to the positivist paradigm have been considered.

Table 3-1: Dimensional positions of research stages and the selected research techniques

Stage	Paradigm	Relevance	Research cycle	Purpose	Technique
1. Establish relationship between personality types and decision preferences	Positivist	Basic	Induction	Exploratory-Descriptive	Differential
2. Build computer-based DSS generator capable of adapting to individuals based on	Positivist	Applied	Deduction	Systems Development	Systems Development
3. Investigate ability of such systems to adapt to individuals based on their personality	Positivist	Applied	Deduction	Descriptive	Case Study

In the first stage, we attempt to observe the differences in decision outcomes of individuals belonging to different personality types, according to the Myers-Briggs type indicator. Hence, it is not an attempt to establish a causal relationship. Personality type differences between individuals naturally occur. The researcher cannot manipulate subjects' personality type. Hence, laboratory experiments do not suit this stage. Case study research may enable the observation of decision outcomes of individuals, but the requirement is for generalisable results with predictive power. It is not possible to make inferences for populations based on a small number of cases. Therefore, case studies are also considered inappropriate.

Both correlational and differential research appear to be strong candidates for this stage. Although causal-comparative and differential techniques have much in common, we prefer to use the term differential research as we are not attempting to establish the cause of observed differences in decision outcomes. Essentially, what is being investigated is the reverse process. Careful examination shows that differential research has a higher degree of suitability for this stage over the correlational technique. Although independent variables are not manipulated in both techniques, in correlational research, measures of at least two variables are obtained from each subject in a single group. Classification of people on the Myers-Briggs indicator results in more than a single group. The aim is to perform a comparison between the different types and not obtain a correlation between variables. For comparison, differential research is more useful. With correlational research, the measures obtained for variables are generally continuous. However, personality types are discrete values. The decision outcomes are also expected to be discrete in nature. Thus, differential research is selected as the technique for investigating the relationship between personality types and decision outcomes.

The second stage of the research program is the construction of an artefact capable of adapting to individuals based on their personality type. Such an artefact will permit the demonstration of the ability to embody personality information in a decision support system and the ability of the system to adapt to individual decision-makers based on their personality. The *proof-by-demonstration* philosophy is adopted here. The research technique is systems development.

The final stage of the doctoral project is the investigation of the efficacy of the system in providing the envisaged functionality for decision-makers. This is the theory refinement process. The main activity in this stage is measuring the success of adaptation achieved by the system. This would require various measurements over a considerable length of time. Greater practical utility of the systems' functionality can be advocated if the system is tested under real life conditions; 'real' decision-makers and 'real' decisions. Laboratory experiments can be a candidate for this purpose as it may be possible to test the system's capability under controlled conditions. However, controlled conditions limit the reality of the situation. Since the interest is in adaptation to individual personality, abstract situations are of little value. The strength of experiments is in identifying causal relationships. It is not required to investigate causal relationships in this stage. Thus, laboratory-based experimental research is considered unsuitable as the major research technique for this stage. Causal-comparative and correlational research have no relevance either.

Case studies permit the capture of rich information about the phenomenon being studied. In the theory refinement stage, generalisations and predictions are not of major concern. Conducting a limited number of case studies therefore would permit the investigation of the efficacy of the system in 'real' decision making situations, without hindering the validity of the results. The small number will also permit thorough investigation. Case study research is therefore relevant to this stage.

However, it could be argued that single-subject field experiments are an equally relevant form of technique for this stage. This is because, the use of the system may be seen as a treatment, and measurements obtained over time can be considered as the measurement of the dependent variables in a time-series design. While this is true, the manner envisaged to perform this research allows very little control over confounding factors. It is not possible to articulate causal relationships in such circumstances.

Therefore, the case study technique is selected as more appropriate, while acknowledging the relevancy of single-subject field experiments. Use of case studies in the theory refinement process may be viewed as a part of action research. Since there may not be iterations or a complete cycle, this stage cannot be considered as 'true' action research.

The overall research method for this doctoral project consists of differential, systems development and case study techniques (Table 3-1) and should be seen in the context of the *concept-development-impact* model.

Chapter 4

Personality and Decision Preferences

4.1 Hypothesis

The research question pertaining to this stage is whether there is a relationship between the personality and decision preferences of a decision-maker (Q1). This translates to the following hypothesis:

H1: Individuals with different personalities will attach different importance to decision attributes in a given decision situation.

Operationally expressed, this hypothesis can be explained as individuals belonging to different personality types, according to the Myers-Briggs Type Indicator, will have distinct criteria preference models using pair-wise comparison of decision attributes. The independent variable is the personality type defined according to the MBTI. Values for this variable are not a result of any experimental treatment, but a naturally occurring phenomenon (at least for the purpose of this experiment). The dependent variable is the criteria preference model of an individual. This model is expressed as the set of comparisons of all the decision attributes in the given decision situation. However, the interchange of the independent and dependent definitions of the variables is also possible since the personality type does not have a true independent nature.

4.2 Method

4.2.1 Subject Selection

Consent was sought from 359 senior executives to participate in this research study. As explained earlier, the research is aimed at better supporting senior decision-makers. Personality preferences are also said to be more developed in groups such as senior executives in organisations. This selection of individuals was targeted as they had participated in previous research and had indicated willingness to participate in future research activities. Forty consent-seeking letters were returned without reaching the addressees, mainly due to change and turnover of positions. A total of sixty-one gave their consent to participate in the research study. Thirty-nine of these individuals actually participated in the study.

Since the results of the study would not be generalised to the total population, probability sampling was not required. The scope of generalisation is expected to be senior managers in organisations. There was also no possibility to recruit a probability sample from all senior executives. Therefore a purposive non-probability sample was considered appropriate. The method of subject selection was voluntary and can result in sample bias. Since our independent variable is the personality type, the voluntary method may lead to an uneven distribution of personality types as some types may be more inclined to respond to the request to participate. However, since the personality type is measured as part of the experimental procedure, it is not considered as an impediment (Srivastava, 1995).

Previous studies conducted using the MBTI were investigated to gain an understanding of possible distributions of the types. This was undertaken as a way of safeguarding against unworkable type distributions. Figure 4.1 shows a summary of such studies. The focus in this table is on the *thinking-feeling* and *sensing-intuitive* dimensions of the MBTI. The first three columns are samples of managers from Australia, the United Kingdom and the USA respectively. The fourth column represents the complete Australian population. Although considerable variation is seen between the different samples of managers, it is clear that ST and NT types show overall dominance. The Australian management sample is heavily biased towards these two groups. The type distributions for the present study are therefore expected show similar bias. It is anticipated that at least the two dominant groups may have enough subjects to allow successful analysis.

Type	Aus Mgmt	UK	USA	Aus Pop
ST	51	53	39	37
SF	3	14	19	37
NF	7	10	18	12
NT	39	23	24	12

Figure 4.1: Possible percentage type distributions (Sources: Guthrie, 1993; Moss, 1989)

Parallel to the recruitment of the above subjects, consent was sought from some senior staff of a large University to participate in a pilot study. Although it is conventional practice to conduct the pilot study with a sub-sample of the target population, it was clear that that would be difficult given the number of accessible individuals in the target population. Even though the pilot sample consisted mainly of academics, some had previously held senior management positions while others were presently performing management roles. The main purpose of the pilot study was to test the experimental instruments and analysis techniques. Twelve individuals responded to the pilot study.

4.2.2 Study Design and Instruments

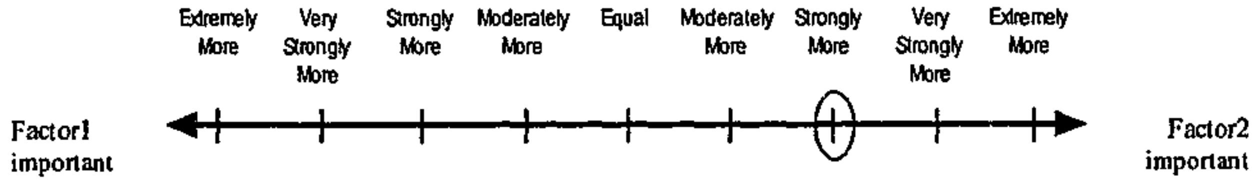
This is an attempt to observe the differences in decision preferences of individuals belonging to different personality types, according to the Myers-Briggs type indicator. It is not an attempt to establish a causal relationship. Personality type differences between individuals naturally occur. The researcher cannot manipulate subjects' personality type. As shown in the research methods chapter, the differential research technique has a higher degree of suitability for this stage over the correlational technique and laboratory experiments. Classification of people on the Myers-Briggs indicator results in more than a single group. The aim is to perform a comparison between the different types, not to obtain a correlation between variables. For such a comparison, differential research is more useful. With correlational research, the measures obtained for variables are generally continuous. However, personality types are discrete values. The decision preferences are also expected to be discrete in nature. Thus, differential research was selected as the technique for investigating the relationship between personality types and decision preferences. The modality for conducting the study was remote, through mail.

Subjects who gave their consent to participate in the study were mailed a package containing all the necessary material. This package included an instruction letter, a demographic questionnaire, an MBTI personality questionnaire (Form G, the current standard form) and a description of a hypothetical decision situation which the subjects had to study before indicating their decision preferences (see Appendix A for copies of the instruments).

The decision situation was constructed to provide sufficient unstructuredness so that there was room for individual creativeness in the decision preferences. As discussed earlier, task strength may be an important determinant when imposing ones personality on a decision situation. However, the task could not be totally ill-structured as that would result in a wide range of preferences that may not be comparable with other responses. Hence, the scenario selected was a decision to purchase a house, which most people are familiar with, but novel enough to provide some unstructuredness. The number of times subjects had purchased a house and how recently they had done it were queried as part of the demographic information.

A set of six decision attributes were provided to the subjects after the study of many sources of information regarding purchase of houses. It was mandatory for the subjects to compare these six attributes and indicate their preferences using a scale similar to Saaty's (1980) scale as illustrated in Figure 4.2. The subjects had a chance to add a further four attributes if they felt necessary (see Appendix B). This allowed a basic set of preferences that could be used for analysis. If a sufficient number of subjects added other common attributes, those could have been included in the analysis. This was viewed as a means of providing further freedom to the participants to express their individual preferences.

If there are two factors *Factor1* and *Factor2*, and you believe that *Factor2* is strongly more important than *Factor1* when deciding whether or not to buy the house, a circle should be placed as below.



The following pages provide you similar scales for each pair of factors. Place a circle on the scale to illustrate your opinion. Make sure that you keep the decision in mind when doing the comparison.

Figure 4.2: Illustration of attribute comparison scale and instructions to the subjects.

The demographic information sheet consisted of eight questions in addition to four questions which related to participants' desire to receive results of this project. The first two demographic questions inquired the subjects' organisational position and the number of hierarchical levels between the Chief Executive Officer (CEO) and the respondent. These were placed for sample justification purposes. The homogeneity of the sample of senior managers is an important determinant of external validity of this study. Age, gender, educational qualifications and annual income of subjects were inquired as these were identified as possible extraneous factors. The next two questions related to their familiarity with buying houses. These were needed as the task they were performing involved buying a house. Task familiarity has often been identified as one of the major determinants of decision-making (MacKay, Barr and Kletke, 1992). Hence, task familiarity could also be regarded as a possible confounding factor. If the sample was relatively homogeneous on all these factors, then the focus can be on the variability of decision preferences based on personality types.

The Myers-Briggs Type Indicator current standard form, Form G, consists of 126 questions related to eight dimensions. The internal consistency and reliability of this instrument has been validated on numerous populations (Myers and McCaulley, 1985).

4.2.3 Measures and Analysis Method

Since all participants were required to perform pair-wise comparison of the basic set of six variables, 15 measures resulted for each person $((n^2-n)/2)$. These were labelled *F1*, *F2*, ... *F15*. Each of these measures is a number between 1 and 9 representing the preference labels (*Extremely more....Equal....Extremely more*) on the comparison scale. No additional comparisons were used as subject responses did not include any additional common attributes. The responses to the MBTI personality questionnaire were scored using the MBTI Form G Hand-scoring templates. A four-letter type and a preference score for each dimension were obtained for each individual. Thus, eight preference scores were available. These were labelled using the MBTI dimensions they represent: *E*, *I*, *S*, *N*, *T*, *F*, *J* and *P*.

The analysis procedure is required to test the hypothesis that individuals with different personalities will attach different importance to decision attributes. Thus the independent variable is the naturally occurring personality type, measured with the MBTI. The scores for the eight possible MBTI extremes are regarded as intermediate variables that help define the type. This is congruent with the view that the four-letter type combination is more useful than the actual scores for dimensions (Myers and McCaulley, 1985). The dependent variables are the results of pair-wise comparisons, F1 to F15.

Testing the hypothesis involves investigating how the personality type of an individual affects the dependent variables. Univariate analysis will only provide insight into whether there is a relationship between personality types and a given pair-wise comparison. The operational definition of the hypothesis stipulated the criteria preference model as the unit of interest. To perform a test of the hypothesis, the differences between the criteria preference models of subjects belonging to different personality types should be measured. The criteria preference model comprises the collective set of pair-wise comparisons, F1 to F15.

This manner of investigation belongs in the realm of multivariate data analysis. Multivariate analysis is much more complex than standard univariate procedures and allows parallel analysis of a number of independent and dependent variables. Where univariate or bivariate analysis requires repeated application of a technique, multivariate methods allow a single analysis. Hence, the multivariate methods can be regarded as the 'general' model under which univariate and bivariate techniques belong (Tabachnick and Fidell, 1989).

Discriminant analysis was selected as the most suitable technique for testing this hypothesis. It facilitates the investigation of the relationship between one categorical variable and many metric variables. The major purpose of discriminant analysis is prediction of group membership; it is the reverse of multivariate analysis of variance (MANOVA). In MANOVA, the dependent variables are the metric variables and the categorical variable is the independent variable; in discriminant analysis, the metric variables are treated as predictors while the categorical variables are the dependents or grouping variables. Mathematically, both techniques are equivalent (Hair *et al.*, 1995; Tabachnick and Fidell, 1989). In this study, the personality type is categorical and therefore a grouping variable. Although pair-wise comparisons F1 to F15 can also be regarded as nominal variables, they are essentially ordinal metric. These form the predictor variables.

Multivariate discriminant analysis (MDA) generates a variate that discriminates between defined groups. The variate is a linear combination of independent variables. Discriminant scores are calculated for each individual in the sample by taking the sum of products of the discriminant weights and the value of all the variables. When the discriminant scores are averaged for all individuals within a group, that mean is known as the *group centroid*. In a two-group analysis, there will be two group centroids. The distance between the group centroids indicates the distance between the groups on the dimension being investigated.

The statistical significance of the discriminant function is generated by comparing the distribution of discriminant scores belonging to subjects of the groups. If there is only a slight overlap or there is no overlap, the significance is said to be good. If there is a large overlap the function has poor statistical significance.

Inferential statistics such as discriminant analysis are very sensitive to sample size. This hypothesis has to be tested with a relatively small data set. All assumptions that underlie the use of multivariate statistics should be strictly adhered to. Among these assumptions are the normality, linearity, exclusion of outliers, equal covariance and multi-colinearity of the data. Although larger samples can be robust to violations of these assumptions, small samples require that the analyst takes all precautions (Gay and Diehl, 1992).

As a cross-validation of the results obtained using discriminant analysis, it was decided to use Artificial Neural Networks (ANN) as an analysis technique. ANN are capable of producing good outcomes when handling inputs and outputs that have complex relationships between them. They are also tolerant to high noise levels in inputs (Treigueiros and Berry, 1991). ANN are regarded as universal approximators that can model any measurable function, including non-linear relationships. A neural network's inability to 'learn' is usually attributable to insufficient training, inadequate hidden units in the network architecture or a lack of a relationship between the input and the output (Hornik, Stinchcombe and White, 1989). They are also good at 'learning' with small training sets and dealing with missing data. The performance of ANN are however affected by network architecture. There is no clear theory on the design of a network, and analysts have to rely on a 'trial-and-error' mode of design. The ANN used for the analysis of results in this study was a back-propagation network.

The strategy adopted for the analysis of results for this research was to utilise the 'learning' capability of ANN to 'learn' the relationship between the personality type and the decision preferences of a person. If the neural network can be successfully trained on the data collected, it is an indication that there is a 'real' relationship between the personality type and decision preferences. The trained network can be used to predict the personality type of a person, given that person's decision preferences. The data set was divided into 'training' and 'test' categories, with approximately a 2:1 split. The actual personality types of these 'test cases' were known since they were obtained by administering the MBTI. This is semantically equivalent to discriminant analysis. If the network was capable of predicting the personality types with sufficient confidence, it would lead to the support of the hypothesis as there would be sufficient discriminant qualities between the personality types.

As inferential statistics model linear relationships and ANN can model any type of relationship, if both techniques of analysis produce comparable results, a conclusion can be drawn that the relationship between personality types and criteria preference models are linear.

4.2.4 Characteristics of the Participants

Thirty-nine individuals participated in the study. Sample characteristics were obtained using the demographic information provided by the respondents. Eighty three percent of the participants were chief executive officers of organisations. The lowest ranked person was two levels below the chief executive officer. Most respondents were male, with females accounting only for 10 percent of the sample. The average age of a study participant was between 41 and 45 years, while the average annual income was between A$120,000 and A$140,000. However, most had an income of more than A$160,000. The typical participant had a postgraduate qualification. Most of the above measures have a similar mode and a mean, demonstrating little variance. These characteristics indicate that the sample was homogeneous (see Table 4.1 for tabulation of demographic information).

Analysis of the responses also show that both the mean and the mode for the number of houses purchased is three houses, with the mean number of years since they bought a house 6.05 years with a standard deviation of 5.18 years. Although the recency varies appreciably, it is clear that subjects had relatively similar experience with buying houses.

Table 4.1: Characteristics of the sample and cohort descriptions (Sample Size = 39)

	Position	Gender	Age	Education	Income	No. Houses	Recency
Mode	CEO	M	41-45 Yrs	Bach. Deg.	Over	3	1
Mode Cohort	0		4	3	8		
Variance Ratio	0.27	0.10	0.77	0.62	0.47	0.64	0.82
Mean	0.41		4.77	3.18	6.21	3.21	6.05
St. Dev.	0.80		1.72	1.50	2.09	1.54	5.18

Position		Age		Education		Income	
0	CEO	1	25-30 Yrs	1	High School	1	Under $40K
1	CEO-1	2	31-35 Yrs	2	U/G Diploma	2	$41K - $60K
2	CEO-2	3	36-40 Yrs	3	Bach. Degree	3	$61K - $80K
3	CEO-3	4	41-45 Yrs	4	P/G Diploma	4	$81K - $100K
4	CEO-4	5	46-50 Yrs	5	Masters	5	$101K - $120K
5	CEO-5	6	51-55 Yrs	6	Doctorate	6	$121K - $140K
		7	56-60 Yrs	7	Other	7	$140K - $160K
		8	Over 60 Yrs			8	Over $160K

It was considered that typing individuals into the sixteen possible MBTI types was not feasible as there were only thirty-nine subjects involved in the study. The two modes of perception (*Sensing-Intuitive*) and judgement (*Thinking-Feeling*) were regarded as the most useful for understanding the decision-making preferences of an individual. This is because these two dimensions deal with how people collect data and come to conclusions about the data collected. A similar view of the MBTI dimensions has been taken by many previous research studies (Hirsh and Kunmerow, 1990; Huitt, 1992; Kerin and Slocum, 1981; Schweiger and Jago, 1982). Therefore it was decided to ignore the *Extroverted-Introverted* and the *Perceiving-Judging* dimensions in the analysis of the study data. This resulted in four possible two-letter types: ST, SF, NF and NT. The distribution of subjects among these types were 17, 2, 4 and 16 respectively as illustrated in Figure 4.3. Since it was considered that types SF and NF did not have sufficient subjects to identify discriminant qualities, the study will focus on types ST and NT. This distribution of MBTI types is similar to the distribution illustrated by Guthrie, 1993.

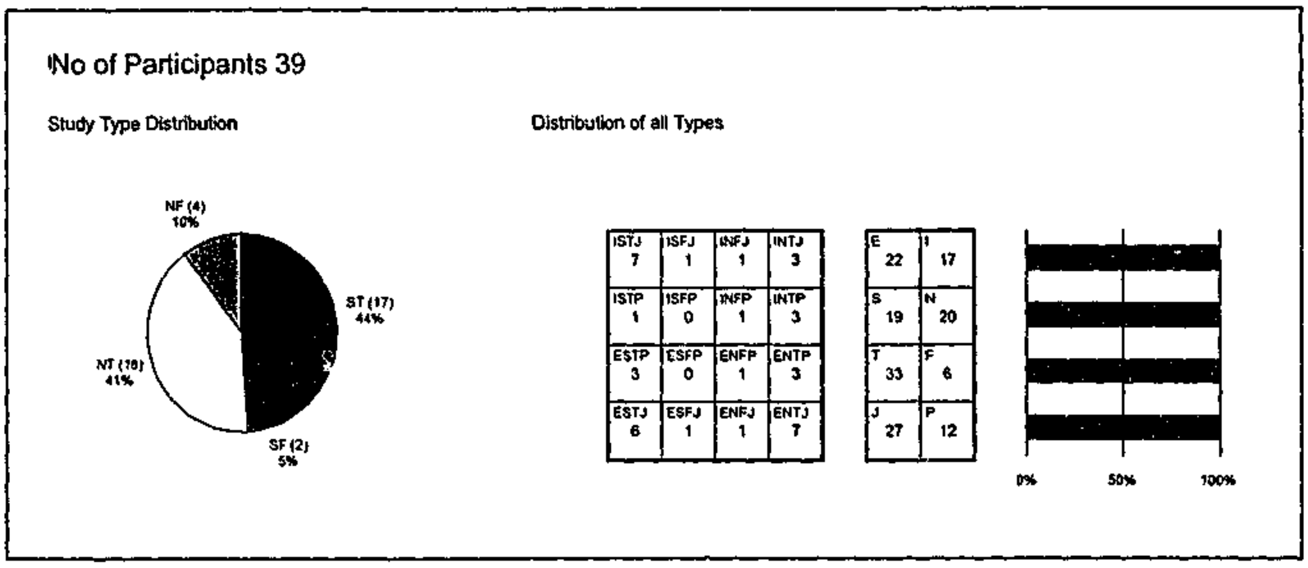


Figure 4.3: Distribution of MBTI types

The personality preference scores obtained through the MBTI (*E, I, S, N, T, F, J* and *P*) were also converted into continuous scores. This was done as according the MBTI theory, frequency distribution of continues scores should demonstrate a *bimodal* distribution. This is in contrast to a *normal* distribution that would be expected if there were no definite 'type' preferences in subjects. The MBTI preferences are converted to continuous scores by treating 100 as the mid-point in the scale. Preference score for E, S, T, and J is taken to be 100 minus the continuous score. The reciprocals of I, N, F and P have a preference score that is equal to continuous score minus 100. The frequency distributions are illustrated in Figure 4.4.

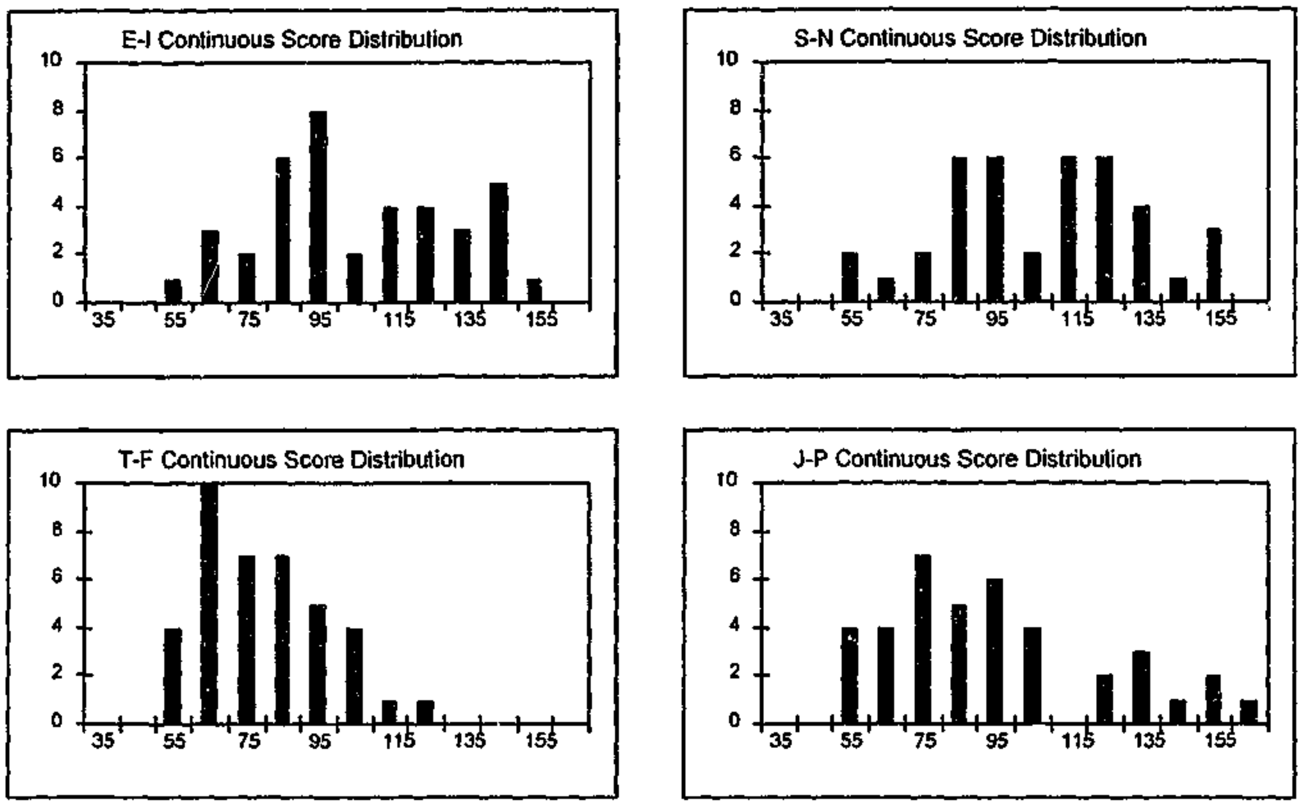


Figure 4.4: Continuous score distribution of study participants

It is evident from frequency distributions of E-I, S-N, T-F and J-P scales that they do not conform to a normal distribution. The T-F dimension is skewed to the T end as most subjects had a *thinking* preference. All four demonstrate a clear 'dip' near the mid-point of 100 and therefore a bimodal distribution. This indicates that there are definite 'types' among subjects as envisaged by Jung's (1923) theory and that the sample of senior managers is comparable to studies such as Rytting, Ware and Prince (1994).

4.3 Analysis of Data Using Discriminant Analysis

Much of the discussion on discriminant analysis in this section follows Hair *et al.* (1995) and Tabachnick and Fidell (1989).

4.3.1 Sample size

Thirty-nine individuals responded to the differential study. The analysis is regarded as a two-group discriminant analysis as only types ST and NT have sufficient cell sizes. This results in thirty-three possible cases with responses for F1 through to F15. Discriminant analysis is regarded as sensitive to the ratio between the number of predictor variables and the size of the sample. Since there are 15 predictor variables in this study, practically it is difficult to achieve the 20 observations for each predictor variable ratio espoused by some researchers. Given the nature of the subjects (very senior managers) in this study, this would be an impossible task. The result of lower subjects to independent variable ratio is the instability of results.

As a minimum practical requirement for MDA, the number of subjects in a smallest group should surpass the number of independent variables. This study satisfies this criterion by having 16 subjects in the smaller of the two groups, where there are fifteen independent variables. 20 subjects per group is used as an heuristic. 16 and 17 are relatively close to this target of 20 subjects. Another requirement is to have relatively similar group sizes to avoid higher correct classification ratios for groups with disproportionately large sample sizes. The spread of the personality types within the sample supports this criterion.

4.3.2 Division of the sample

One common procedure when using MDA is to test the generated discriminant function with a randomly selected sub-sample. The portion of the sample used for generating the function is known as the analysis sample where as the portion used for testing is known as a hold-out sample. This validation procedure is known as a *split-sample* approach.

The ratio between the analysis and hold-out samples is left to the analyst. Common ratios like 50-50, 60-40 or 75-25 are generally utilised. To apply this approach to testing, the initial sample should be fairly large. The sample size of this study would not allow such an approach. As this is a common problem in the application of MDA, researchers propose to use the same sample as both the analysis and hold-out samples. This leads to an upward bias in the accuracy of predictions in the hold-out sample. The analysis should then be careful in interpreting the results when this approach is taken.

With the current study, a hybrid of approaches is undertaken for testing the validity of the discriminant function. Not only will the results be tested using a hold-out sample that is the same as the analysis sample, but multiple hold-out sample testing will be undertaken. This will be achieved by randomly drawing-out a proportion of the sample to be a hold-out sample and then performing MDA repeatedly. Accuracy measures claimed will be calculated on the average of these multiple instances of MDA. This will prevent the occurrence of an upward bias.

4.3.3 Examination of data

4.3.3.1 Distribution

Before proceeding further with analysis, it is important that the nature of the collected data is examined. This examination comprises of both graphical techniques and descriptive statistics. This will lead to a greater understanding of the data. Figure 4.5 illustrates the ungrouped univariate frequency distribution of the independent (predictor) variables and the grouping variable NUM_TYPE. NUM_TYPE has values of 1 and 3 to represent personality types *ST* and *NT* respectively. The descriptive statistics for the ungrouped data are presented in Appendix C.

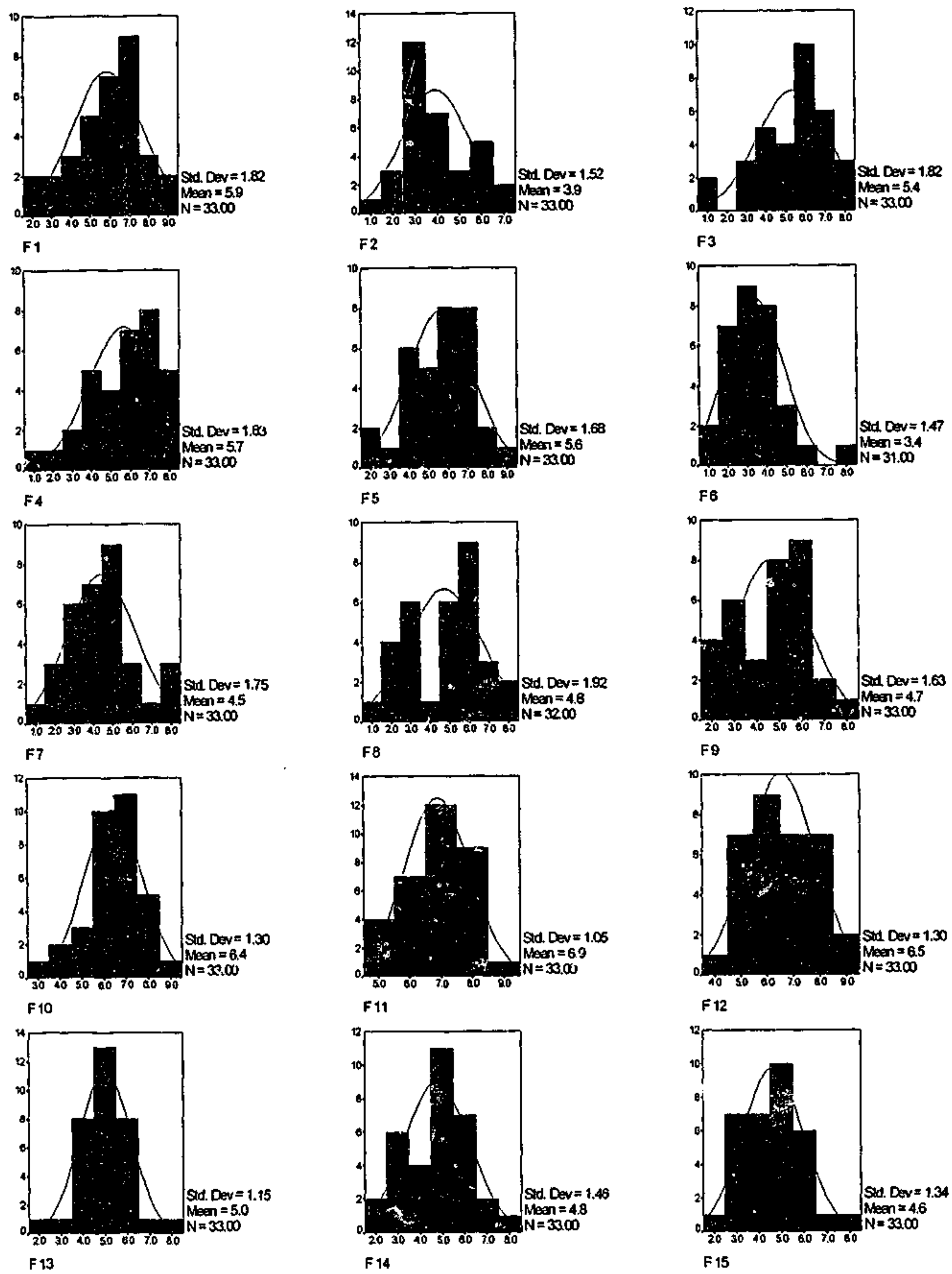


Figure 4.5: Univariate Frequency Distribution of Study Variables

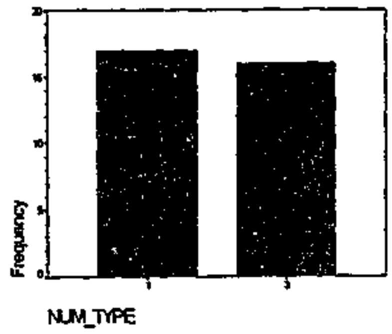
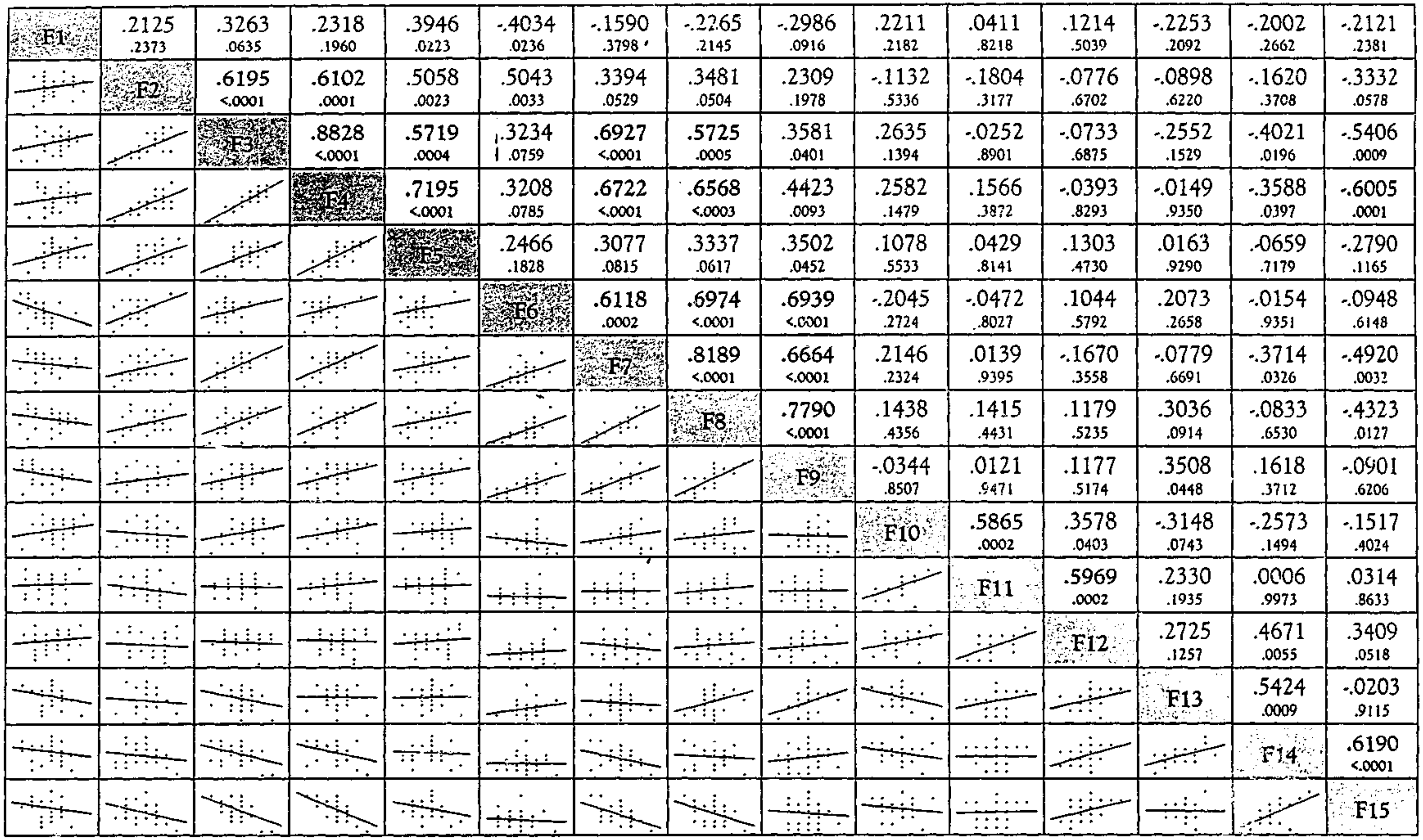


Figure 4.5: (cont.) Univariate Frequency Distribution of Study Variables

4.3.3.2 Relationships between variables

The most common method of investigating the bivariate relationships between variables is the scatterplot. When the values of two variables are plotted, organisation of the data points along a straight line indicates a linear correlational relationship. A random pattern in the points may indicate no relationship at all, while a curved organisation may represent a non-linear relationship. A complex organisation of bivariate scatterplots relating to all the variables in a multivariate analysis is termed a scatterplot matrix. Data pertaining to this study are illustrated in Figure 4.6 in a scatterplot matrix format. The figure tabulates the bivariate scatterplots for all the metric variables. The non-metric variable NUM_TYPE is not included as that would always have a linear relationship with the other variables (as there are only two possible values). The diagonal lists the variables. The cells below the diagonal contain the bivariate scatterplots, while the cells above the diagonal contain the respective correlation value and its statistical significance. The cells that are highlighted indicate bivariate correlations that are significant at the .001 level. Usually, a very conservative significance criterion is used for this purpose. How these may affect the analysis is discussed later.



	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	F1	.2125 .2373	.3263 .0635	.2318 .1960	.3946 .0223	-.4034 .0236	-.1590 .3798	-.2265 .2145	-.2986 .0916	.2211 .2182	.0411 .8218	.1214 .5039	-.2253 .2092	-.2002 .2662	-.2121 .2381
F2		F2	.6195 <.0001	.6102 .0001	.5058 .0023	.5043 .0033	.3394 .0529	.3481 .0504	.2309 .1978	-.1132 .5336	-.1804 .3177	-.0776 .6702	-.0898 .6220	-.1620 .3708	-.3332 .0578
F3			F3	.8828 <.0001	.5719 .0004	.3234 .0759	.6927 <.0001	.5725 .0005	.3581 .0401	.2635 .1394	-.0252 .8901	-.0733 .6875	-.2552 .1529	-.4021 .0196	-.5406 .0009
F4				F4	.7195 <.0001	.3208 .0785	.6722 <.0001	.6568 <.0003	.4423 .0093	.2582 .1479	.1566 .3872	-.0393 .8293	-.0149 .9350	-.3588 .0397	-.6005 .0001
F5					F5	.2466 .1828	.3077 .0815	.3337 .0617	.3502 .0452	.1078 .5533	.0429 .8141	.1303 .4730	.0163 .9290	-.0659 .7179	-.2790 .1165
F6						F6	.6118 .0002	.6974 <.0001	.6939 <.0001	-.2045 .2724	-.0472 .8027	.1044 .5792	.2073 .2658	-.0154 .9351	-.0948 .6148
F7							F7	.8189 <.0001	.6664 <.0001	.2146 .2324	.0139 .9395	-.1670 .3558	-.0779 .6691	-.3714 .0326	-.4920 .0032
F8								F8	.7790 <.0001	.1438 .4356	.1415 .4431	.1179 .5235	.3036 .0914	-.0833 .6530	-.4323 .0127
F9									F9	-.0344 .8507	.0121 .9471	.1177 .5174	.3508 .0448	.1618 .3712	-.0901 .6206
F10										F10	.5865 .0002	.3578 .0403	-.3148 .0743	-.2573 .1494	-.1517 .4024
F11											F11	.5969 .0002	.2330 .1935	.0006 .9973	.0314 .8633
F12												F12	.2725 .1257	.4671 .0055	.3409 .0518
F13													F13	.5424 .0009	-.0203 .9115
F14														F14	.6190 <.0001
F15															F15

Figure 4.6: Scatterplot Matrix with Bivariate Correlations

4.3.3.3 Examining group differences

When using methods such as the MDA procedure, it is important to see the differences that are obvious between the groups of interest. This would give confidence to the researcher on the need to perform further analysis. Since the objective of the investigation is to see group differences, grouped univariate descriptive statistics provide good initial indicators if such difference exist. Grouped univariate boxplots for metric variables F1 to F15 are presented in Figure 4.7. Examination of the boxplots shows that the means and the spread of observations differ markedly in a number of variables. The statistics pertaining to these observations are presented in Appendix C-2. Outliers which are between 1.0 and 1.5 quartiles away from the box are indicated with an 'O' on each diagram. How outliers are handled is discussed later.

4.3.3.4 Multivariate profiles

The examination of data has so far been limited to univariate or bivariate situations. Multivariate profiles are used to compliment the other approaches and to provide a graphical 'feel' of the holistic view of a subject when all variables are considered simultaneously. One such multivariate profiling technique is iconic representation. There are many forms of iconic representations, two of which are presented in Figure 4.8. These allow the identification of similarities and differences that may not be apparent when observing the original numeric data.

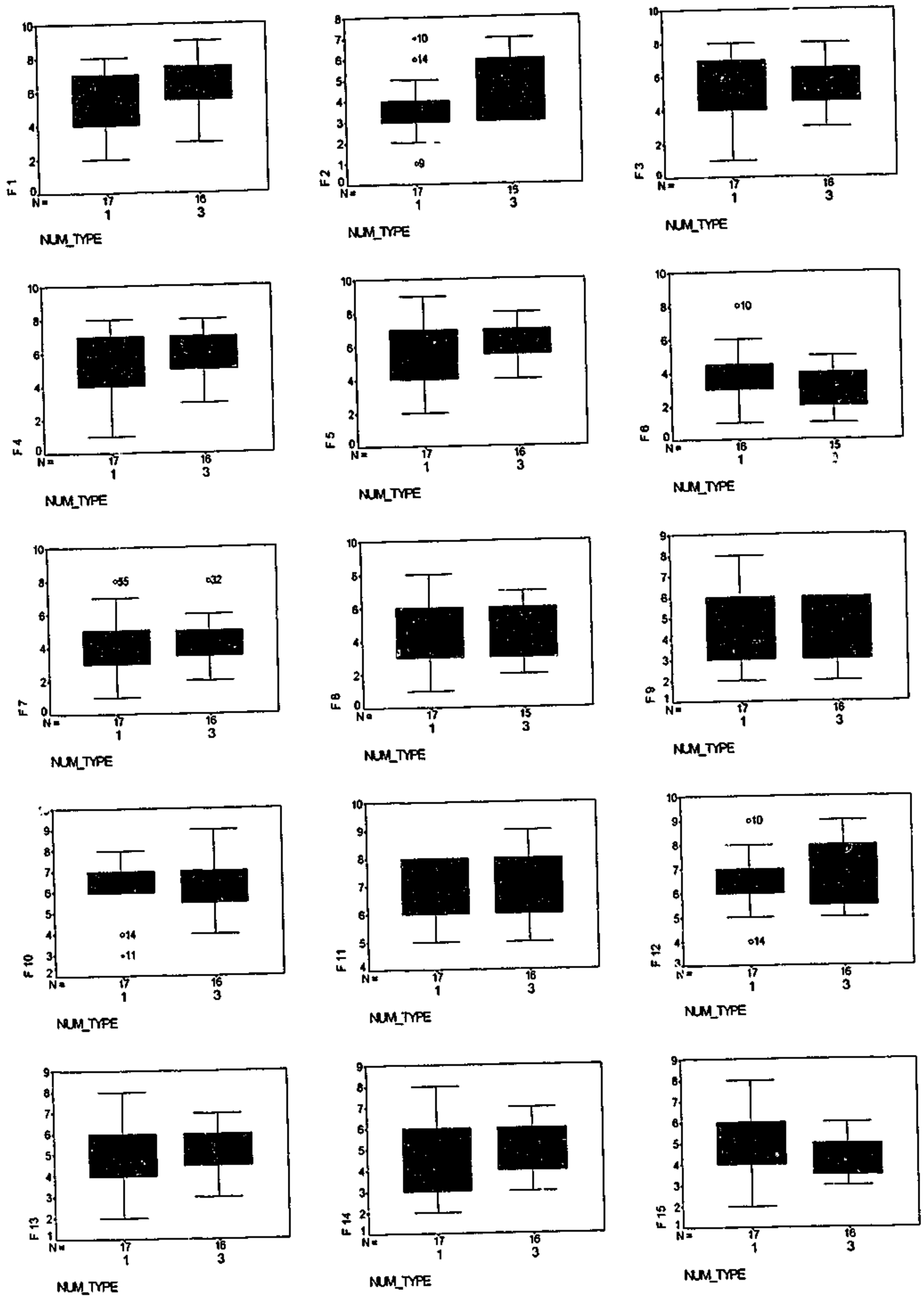


Figure 4.7: Grouped Boxplots for Metric Variables (Predictors)

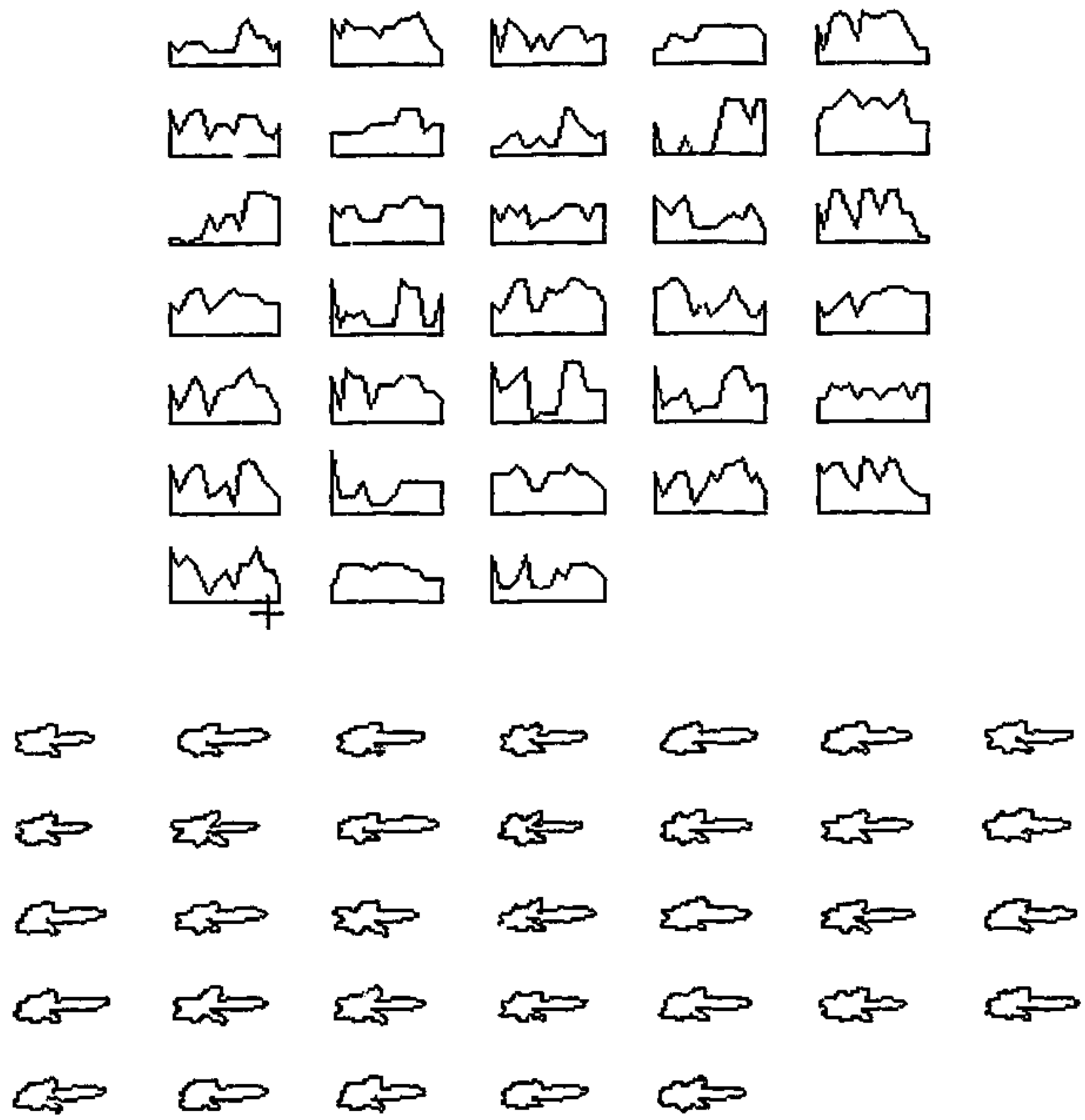


Figure 4.8: Multivariate Profiles of Cases in the Sample

4.3.4 Missing Data

Missing data is a common phenomenon of most studies. When the researcher has no control of the entire data collection process, missing data often results. When missing data is detected, the analyst needs to see if the missing data occurs as a result of some form of pattern or whether it is a random occurrence. Systematic missing data may occur as a result of study participants' action such as not responding to an intrusive question. Such systematic causes for missing data may result in the research findings being biased. Another problem with missing data is its influence in reducing the number of valid responses available for analysis. This can be a particularly damaging problem to a study such as our study where the initial sample size is relatively small.

Table 4.2 presents the descriptive statistics for all the variables in the analysis with the missing items highlighted. Since there are only a total of three missing items out of a possible 528, it is impossible to conduct any formal test available for investigating the significance or systematicness of the missing values. This would also indicate that the missing values are spread completely at random (MCAR -missing completely at random). MCAR values allow the use of any suitable technique to replace the missing values. The values missing in this study were replaced using the *series mean* technique. The new variables formed by replacing the values were labelled F_6_1 and F_8_1 respectively.

Table 4.2: Summary Descriptive Statistics with Missing Data

Descriptive Statistics

	Mean	Std. Dev.	Std. Error	Count	Minimum	Maximum	# Missing	Coef. Var.
F 1	5.879	1.816	0.316	33	2.000	9.000	0	0.309
F 2	3.939	1.519	0.265	33	1.000	7.000	0	0.386
F 3	5.364	1.817	0.316	33	1.000	8.000	0	0.339
F 4	5.667	1.831	0.319	33	1.000	8.000	0	0.323
F 5	5.606	1.676	0.292	33	2.000	9.000	0	0.299
F 6	3.355	1.473	0.265	31	1.000	8.000	2	0.439
F 7	4.455	1.752	0.305	33	1.000	8.000	0	0.393
F 8	4.750	1.918	0.339	32	1.000	8.000	1	0.404
F 9	4.667	1.633	0.284	33	2.000	8.000	0	0.350
F 10	6.424	1.300	0.226	33	3.000	9.000	0	0.202
F 11	6.879	1.053	0.183	33	5.000	9.000	0	0.153
F 12	6.545	1.301	0.227	33	4.000	9.000	0	0.199
F 13	5.000	1.146	0.199	33	2.000	8.000	0	0.229
F 14	4.758	1.458	0.254	33	2.000	8.000	0	0.307
F 15	4.606	1.345	0.234	33	2.000	8.000	0	0.292

Nominal Descriptive Statistics

	# Levels	Count	# Missing
Num Type	2	33	0

Missing Values

4.3.5 Assumptions of Discriminant Analysis

Similar to other multivariate techniques, conformity to underlying assumptions is a major part of undertaking MDA. Studies with relatively small sample sizes such as this study should especially adhere to the assumptions as the techniques of analysis are generally robust to failure of assumptions only when the sample size is large. Two key assumptions for MDA are multivariate normality and equal covariance of the independent variables for the groups formed by the dependent variable. However, other basic assumptions regarding outliers, linearity and multicolinearity are also addressed.

4.3.5.1 Detecting outliers

Outliers are a phenomenon that occurs due to some observations being distinctly different from others. Outliers can be both beneficial and detrimental to the study. They can be beneficial because they allow the identification of observations of interest about the population that would be lost when normal analysis is done through abstraction and aggregation. Outliers could be detrimental because of their ability to distort the final result through extreme values. Because of this nature of outliers, the analysis should take care to examine the presence and causes for outliers. If the outliers are caused by valid observations for the population, those outliers should be retained for valid inferences about the population. If the analyst feels that an outlier is caused by an unnatural value for the population, those outliers may have to be omitted from the analysis. Some outliers are detected when variables are taken in combination, although not evident as an outlier in a univariate analysis. Generally, these cases are omitted only when there is compelling reason to discount them.

The first step in detecting outliers is to convert data into standard scores, where the mean is zero and the standard deviation in one. The conversion of scores to standard values facilitates easy comparison between variables.

For small sample sizes, observations outside ±2.5 standard deviations are defined as outliers. For larger samples, this threshold value may be as high as 3 or 4.

Univariate scatterplots of the metric variables F1 to F15 are presented in Figure 4.9. Only cases 9, 10, 11 and 17 are outside the defined level of ±2.5 all variables and therefore assumed to be outliers (Appendix C-3). However, it is clear that these are only marginally outside the threshold. Grouped boxplots in Figure 4.7 also designate cases 9, 10, 11, 14, 15 and 32 as outliers at the ±3.0 level. Hence, cases 9, 10 and 11 appear as outliers in ungrouped and grouped situations. If these are also seen as outliers in multivariate outlier detection, serious consideration is needed on eliminating the case from the sample.

Multivariate detection of outliers involves the investigation of the position of a single observation in a multidimensional space defined by all observations in the sample. The statistic used to measure this distance is Mahalanobis D^2. This statistic requires the significance to be tested at a conservative value similar to .001 for outlier detection. Mahalanobis distances for the 10 worst case in our sample are listed in Appendix C-4. None of the distances listed are significant at the .001 level. Appendix C-5 provides a case-wise plot of standardised residuals where ±3.00 would indicate outliers. None of the cases are shown as outliers.

Although there are few marginal outliers indicated in univariate analysis, these are not enhanced through multivariate analysis. Hence, outliers are not considered as a problem in this study. In any event, analysts should take care not to define too many observations as outliers unless there is a compelling reason to do so.

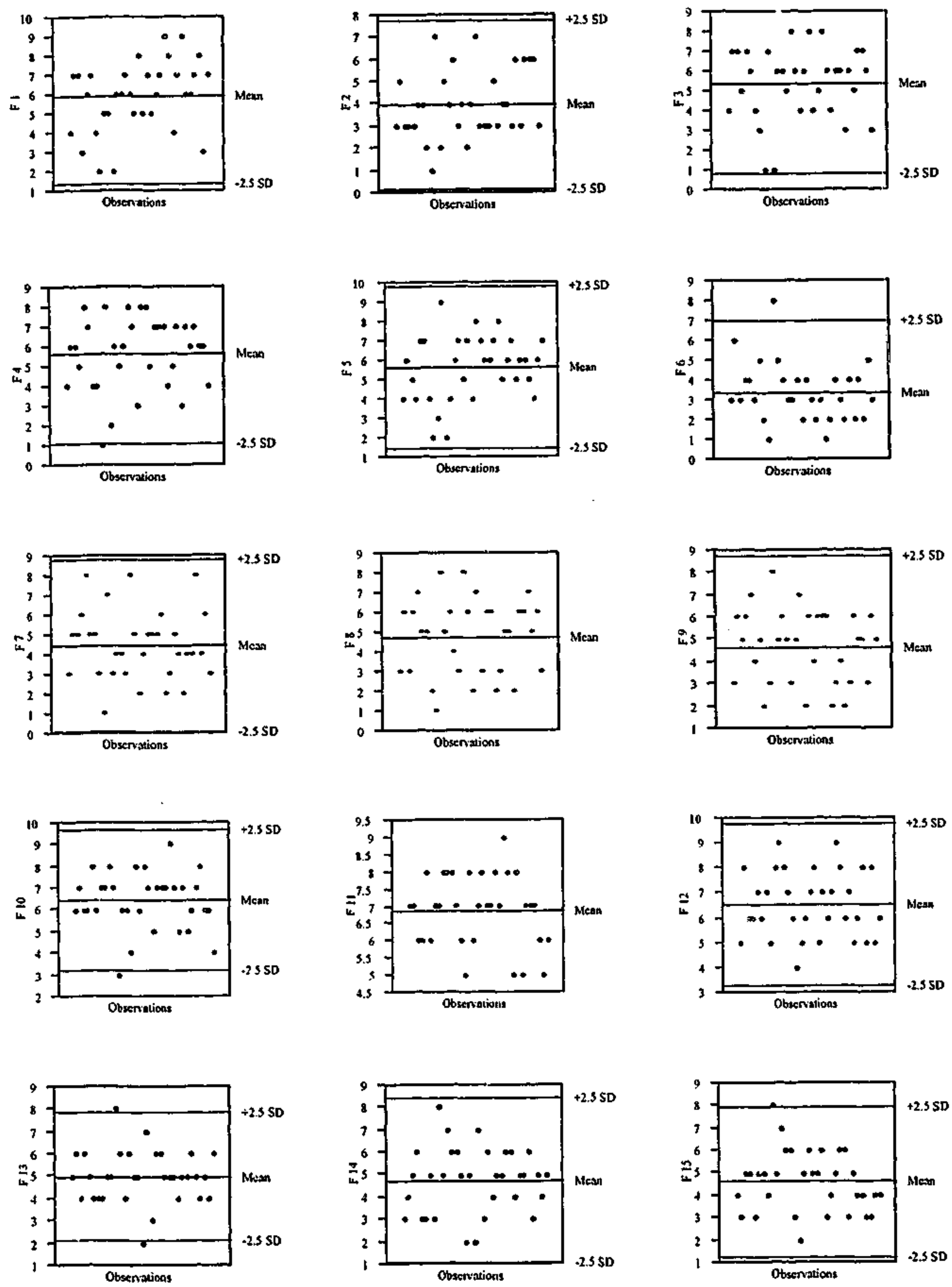


Figure 4.9: Univariate Scatterplots with Outliers at ±2.5 Standard Deviations

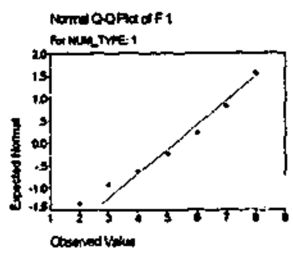
4.3.5.2 Normality

Similar to other multivariate analysis techniques, the most fundamental assumption underlying MDA is normality of data. Non-normal data is seen as a problem when calculating the discriminant function. To assess normality of a variable, its distribution is compared with the normal score curve. If there is a significant deviation from the normal curve, the statistics that are generated from that variable are invalid. For multivariate statistics, both the univariate and multivariate normality is assumed. If variables are univariate normal and their combinations are independent, then they are said to be multivariate normal.

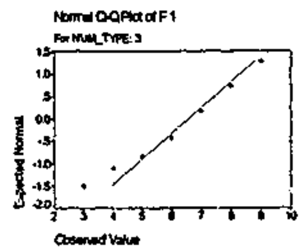
Although univariate normality can be tested easily, there is no known test for all linear combinations of sampling distributions of means of predictors. Thus, testing multivariate normality is difficult. If all variables are univariate normal there is a high chance that they would also be multivariate normal, although not certain. However, MDA is robust to failures of normality if violations are caused by skewness rather than outliers. Outliers have already been investigated in this study and no observation warrants being labelled an outlier. If variables can be shown to be univariate normal, then multivariate normality can be assumed.

Graphical analysis of univariate normality can be performed by comparing the normal curve to the observed sample distribution. A more reliable method has been employed in this study where normal probability plots of actual cumulative distributions are compared with the cumulative normal distribution (Figure 4.10). Since the study requires investigation of grouped data, all univariate plots have been performed group-wise. The diagonal represents the normal distribution while the data points portray actual values. Kolmogorov-Smirnov (Lilliefors) statistic has also been calculated for each grouped variable (Appendix C-6). The significance of this statistic is less useful when the sample size is small (less than 30).

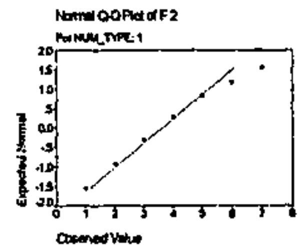
Hence both the graphical and statistical methods have to be used together. At the .05 significance level two grouped variables, F2 and F13 showed deviation from the normal curve.



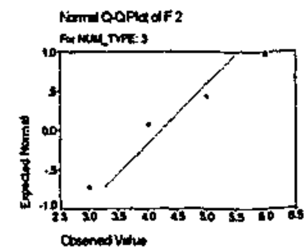
K-S (Lilliefors) Stat.. [illegible]
Significance >.2000



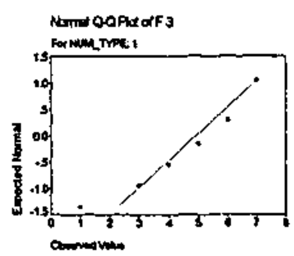
K-S (Lilliefors) Stat. .1171
Significance >.2000



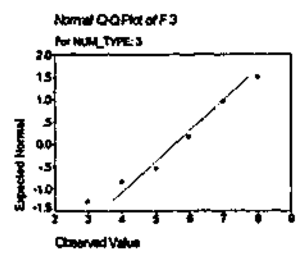
K-S (Lilliefors) Stat. .1566
Significance >.2000



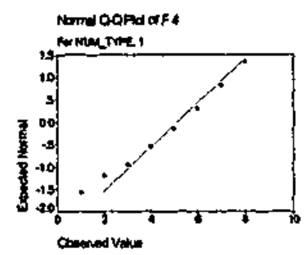
K-S (Lilliefors) Stat. .2513
Significance .0167



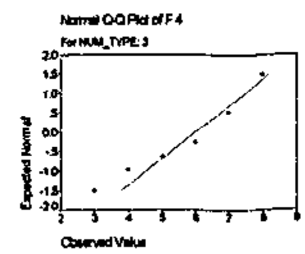
K-S (Lilliefors) Stat. .1491
Significance >.2000



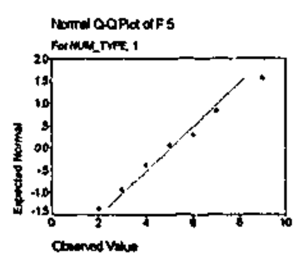
K-S (Lilliefors) Stat. .1697
Significance >.2000



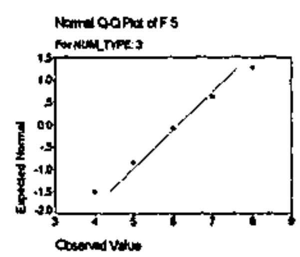
K-S (Lilliefors) Stat. .0854
Significance >.2000



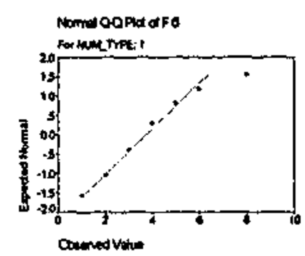
K-S (Lilliefors) Stat. .1764
Significance >.2000



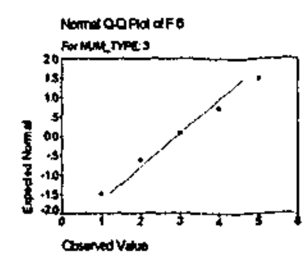
K-S (Lilliefors) Stat. .2010
Significance .0835



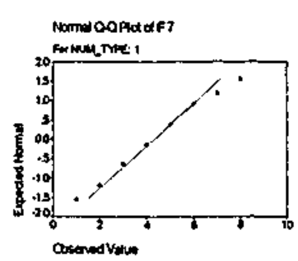
K-S (Lilliefors) Stat. .1916
Significance .1747



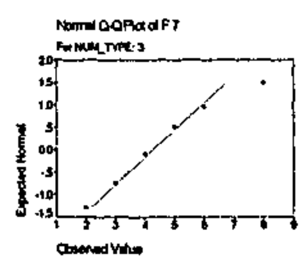
K-S (Lilliefors) Stat. .1913
Significance .1205



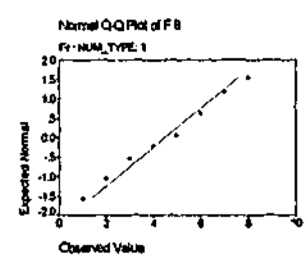
K-S (Lilliefors) Stat. .2207
Significance .0631



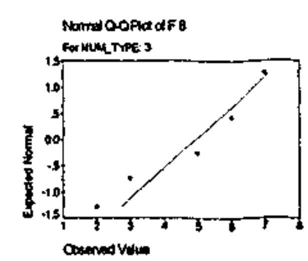
K-S (Lilliefors) Stat. .1650
Significance >.2000



K-S (Lilliefors) Stat. .2121
Significance .0878

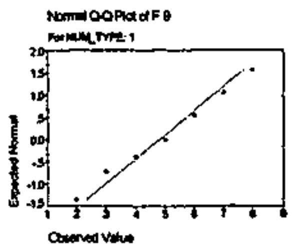


K-S (Lilliefors) Stat. .1484
Significance >.2000

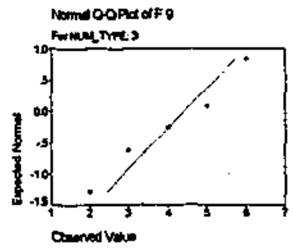


K-S (Lilliefors) Stat. .1532
Significance >.2000

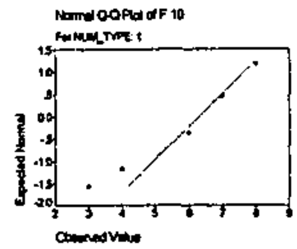
Figure 4.10: Univariate Normal Probability Plots of Variables (Group-wise)



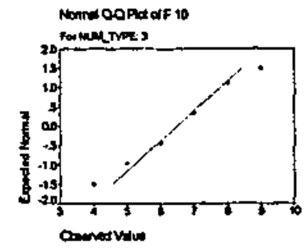
K-S (Lilliefors) Stat. .1510
Significance >.2000



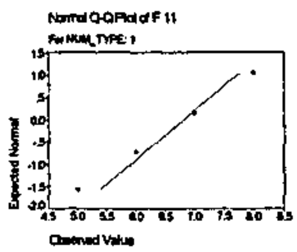
K-S (Lilliefors) Stat. .1780
Significance >.2000



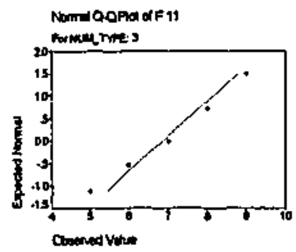
K-S (Lilliefors) Stat. .1539
Significance >.2000



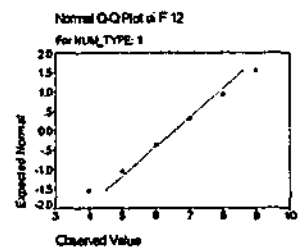
K-S (Lilliefors) Stat. .2059
Significance .1109



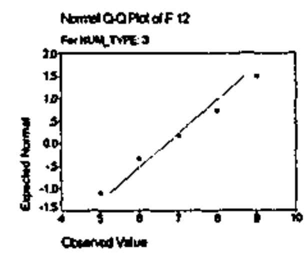
K-S (Lilliefors) Stat. .1889
Significance .1303



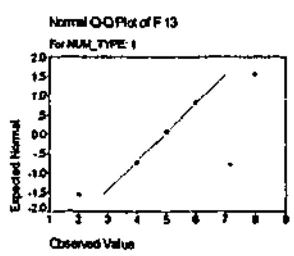
K-S (Lilliefors) Stat. .1389
Significance >.2000



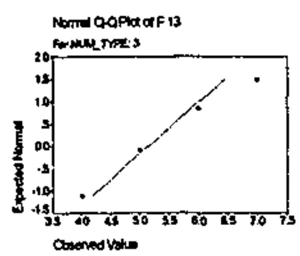
K-S (Lilliefors) Stat. .1656
Significance >.2000



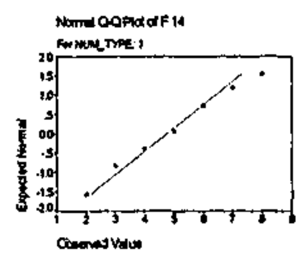
K-S (Lilliefors) Stat. .2049
Significance .1145



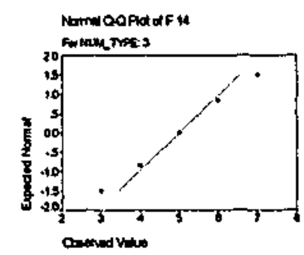
K-S (Lilliefors) Stat. .1689
Significance >.2000



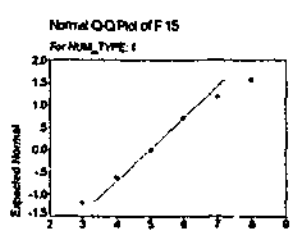
K-S (Lilliefors) Stat. .2799
Significance .0040



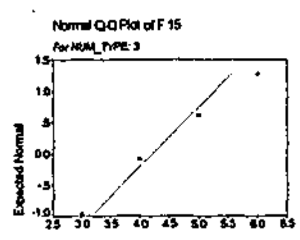
K-S (Lilliefors) Stat. .1676
Significance >.2000



K-S (Lilliefors) Stat. .2143
Significance .0808



K-S (Lilliefors) Stat. .1875
Significance .1359



K-S (Lilliefors) Stat. .2236
Significance .0560

Figure 4.10 (cont.): Univariate Normal Probability Plots of Variables (Group-wise)

Since normality is an important assumption in the analysis, it was decided to correct this anomaly through data transformation for the two offending variables. The transformation was performed using:

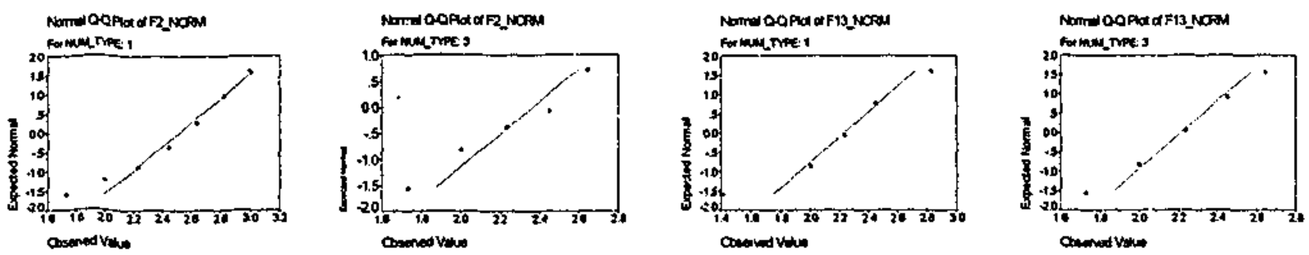
$$\sqrt{(K-X)}$$

Where,

K is a constant from which each score is subtracted so that the smallest score is 1; usually equal to the largest score + 1. For this study K = (9 + 1) = 10.

X is the variable to be transformed.

Probability plots and statistics were repeated after the transformation to test the efficacy (Figure 4.11/ Appendix C-7). Normal distributions were significantly achieved.



K-S (Lilliefors) Stat. .1051	K-S (Lilliefors) Stat. .1890	K-S (Lilliefors) Stat. .1759	K-S (Lilliefors) Stat. .2063
Significance >.2000	Significance .1298	Significance .1691	Significance .0672

Figure 4.11: Univariate Normal Probability Plots of Variables after Transformation

4.3.5.3 Linearity

As discussed previously, most inferential statistical procedures assume a linear relationship between dependent and independent variables. This is especially true for multivariate techniques such as MDA which uses a variate. Non-linear relationships would not be reflected in a discriminant function. Any non-linear variables should therefore be transformed to compensate for these effects.

Linearity for grouped data is predicted using grouped scatterplots, unlike ungrouped data where the residual plots are employed. The ungrouped scatter plots demonstrate ellipsical distributions for all combinations of variables (see scatterplot matrix in Figure 4.6). The are no univariate or multivariate outliers. All variables have normal distributions or have been transformed into normal distributions. Hence all variables can be taken to be linear.

4.3.5.4 Homoscedasticity (Equal Variance)

This assumption implies that the way the scores vary for one variable is approximately the same at all values of other variables. This assumption is related to the normality assumption. If both variables are normally distributed, they would also be homoscedastic. In MDA, the focus is placed on distribution of independent variables across the groups defined by the dependent variable.

A common test for homoscedasticity, the Levene test was utilised in this study to investigate the variance of predictor variables across groups formed by NUM_TYPE (Appendix C-8). Only two independent variables show heteroscedasticity across the groups of the dependent variable. F_14 displays significance marginally under .05 level while F_5 is still homoscedastic at the .01 level. These deviations are not acute enough to warrant remedial action. Therefore, overall the assumption of homoscedasticity is taken to be valid.

4.3.5.5 Multicolinearity

This assumption stipulates that there should not be variables that are highly correlated resulting in one variable being explained by other variables. Having such variables would not serve any useful purpose to the analysis. These are regarded as redundant predictors. Multicolinearity between independent variables can be a major problem in MDA, especially if a step-wise procedure is used.

The possibility ... ing multicolinearity is overcome by having a tolerance level defined in MDA. If a particular level of tolerance is not achieved by a variable, that variable is automatically excluded from the analysis. The statistical package used for this study, SPSS provides this facility as a built-in feature. Adherence to this assumption is therefore assured.

4.3.6 Estimation of the Discriminant Model

The discriminant function can be derived in two ways. The selection between the methods depends on the theoretical requirements of the study. The first approach is the simultaneous method. This involves the derivation of the discriminant function by considering all predictor variables without regard to their respective discriminant power. This method is useful when all the variables should be considered in combination as a single predictor and the individual contributions are not of a particular concern.

The other approach of discriminant function derivation is the step-wise method. This is useful when the analyst is particularly interested in investigating the relative discriminant power of a large number of variables. In the step-wise method, the analysis is started with the variable with the most discriminant power. Thereafter that variable is combined with others to see which combination provides the most discrimination. This procedure is repeated until it is decided that all the predictor variables are useful or that some of them do not add to the power of the function. The selected subset of variables is as good as or superior than the complete set of variables.

In this study, the individual pair-wise comparisons performed by the participants are not of a particular concern. The important issue is whether all comparisons pertaining to the given decision situation, in combination, are capable of discriminating between personality types. Hence the simultaneous method is used (see Appendix C-9). Since the grouping variable NUM_TYPE classifies subjects into two personality types, this is a two-group discriminant analysis. Two-group analysis results in one discriminant function. The characteristics of the derived function are as follows:

Fcn	Eigen value	Pct of Variance	Cum Pct	Canonical Corr	After Fcn	Wilks' Lambda	Chi-square	df	Sig
					0	.231701	27.053	15	.0283
1	3.3159	100.00	100.00	.8765					

Group centroids:

Group 1 (Personality type ST)	1.75472
Groun 3 (Personality type NT)	-1.75472

The overall mean is zero:

$$(1.75472 \times 14) + (-175472 \times 14) = 0$$

```
                          Canonical Discriminant Function 1
       4 +                                                            +
         |                                                            |
 F       |                                                            |
 r     3 +                     2                                      +
 e       |                     2                                      |
 q       |                     2                                      |
 u       |                     2                                      |
 e     2 +              2     22 2      1     11     1                +
 n       |              2     22 2      1     11     1                |
 c       |              2     22 2      1     11     1                |
 y       |              2     22 2      1     11     1                |
       1 +1       2    2 2 2  222 22 2 121   1111  11 111             1+
         |1       2    2 2 2  222 22 2 121   1111  11 111             1|
         |1       2    2 2 2  222 22 2 121   1111  11 111             1|
         |1       2    2 2 2  222 22 2 121   1111  11 111             1|
          X---------+---------+---------+---------+---------+---------X
        out       -4.0      -2.0        .0       2.0       4.0       out
 Class    2222222222222222222222222222222211111111111111111111111111111
 Centroids                    2                1
```

Figure 4.12: All groups Stacked Histogram (1: personality type ST, 2: personality type NT)

The discriminant function is significant at .0283, which is a conventionally acceptable level of significance. This significance is based on the value of the

Wilks' Lambda statistic. As the between group dispersion gets larger, the value of Wilks' Lambda gets smaller. Hence smaller values of Wilks' Lambda indicate greater significance. Although it is common to use conventional significance criteria like the .05 level, this has been subject to question by social scientists and business analysts. Although further action at less significant functions increase the risk, if the application justifies it may be plausible to use significance levels up to .3. The canonical correlation of .8765 indicates that 76.83 percent of variance in the personality type can be accounted through this discriminant model ($.8765^2$).

As the statistical tests for assessing significance of discriminant functions are not ideal indicators of how well the function is capable of classifying observations into groups, classification matrices are developed. When there is a sufficiently large sample the computed discriminant function could be statistically significant, but actual group predictions may only be marginally better than what may be expected by chance. The classification matrices facilitate more accurate estimation of the discriminatory power of a function.

Classification matrices for both the analysis and the hold-out samples were constructed for this study. Before investigating the classification matrices it is important that the cutting scores is calculated. The cutting score is the boundary value at which groups that the subjects belong to are determined. If the group sizes are different, the optimum cutting score will be different from the score for equal group sizes. If the analyst feels that the sample is representative of the population, the ratio of subjects belonging to each group in the sample is used for the analysis. If the population distributions are unknown, equal group sizes are assumed. In this study, the distribution ratio in the sample is approximately 50-50. As this distribution is similar to those obtained by other studies (Guthrie, 1993), it is assumed to be representative of the population. Thus, the cutting score is calculated using the following formula:

$$Z_{CE} = \frac{Z_A + Z_B}{2}$$

Where,

Z_{CE} = critical cutting score value for equal group sizes

Z_A = centroid for group A

Z_B = centroid for group B

The analysis sample selected also reflects the population distribution ratio (1:1):

$$Z_{CE} = \frac{1.75472 + (-1.75472)}{2}$$

Critical cutting score = 0

When classification matrices are constructed the discriminant score of each case is compared against the cutting score. The randomly drawn-out analysis sample consisted of 28 individuals belonging to both groups, divided equally (14:14). The results are tabulated in Table 4.3 below:

Table 4.3: Classification matrix for the analysis sample

Actual Group	No. of Cases	Predicted Group Membership	
		Group 1(ST)	Group 3 (NT)
Group 1 (ST)	14	13 92.9%	1 7.1%
Group 3 (NT)	14	1 7.1%	13 92.9%

Percent of 'grouped' cases correctly classified: 92.86%

The overall percentage of correct classifications is termed the hit ratio. The hit ratio for the analysis sample is 92.86 percent. This indicates that 92.86 percent of the time when pair-wise comparisons are given, the personality type of the person can be predicted accurately.

The next step is to determine whether this hit ratio is acceptable. This is achieved by comparing the obtained hit ratio with that expected by chance. The groups are of equal size in our sample. An equal chance of a subject belonging to either group results. Therefore the chance criterion is 50 percent. Although there are no strict guidelines for determining how superior the hit ratio should be above the chance criterion, researchers recommend a common heuristic. This stipulates that the observed hit ratio should be at least one-fourth greater than what is expected by chance. For this study,

Chance criterion - 50.00%

Hit-ratio (analysis sample) - 92.86%

The difference is much greater than one-fourth above the chance criterion. Therefore the hit ratio is taken to be significant.

A statistical measure for the validity of the classification matrix compared to the chance model is Press's Q. Press's Q is calculated using the following formula:

$$\text{Press's } Q = \frac{[N - (n \times K)]^2}{N(K-1)}$$

Where,

N = total sample size

n = number of observations correctly classified

K = number of groups

For this sample,

$$\text{Press's } Q = \frac{[28-(26 \times 2)]^2}{28(2-1)} = 20.57$$

The critical value at significance level .001 is 10.828. The obtained Press's Q is 20.57. Therefore it can be concluded that the classification is statistically significant. Press's Q is also sensitive to sample size and can indicate significance with a low hit ratio if the sample size is large.

4.3.7 Validation of Results

As mentioned earlier, claiming significance of results through the study of the analysis sample leads to an upward bias with exaggerated claims. There it is essential that a cross validation be performed using a hold-out sample.

This study conducted with 33 participants does not allow the sample to be completely split before analysis as that would result in an insufficient number of cases in both the analysis and hold-out samples. A strategy of repeated random allocation of cases to hold-out samples provides a means of overcoming the small sample size problem. Classification matrices and hit ratios were calculated for each hold-out sample. These results are presented in Appendix C-10. Table 4.4 summarises the sample distributions and hit ratios for each of these repeated runs and their aggregations.

The difference between the chance criterion and the average hit ratio of 74 percent is greater than one-fourth of the chance criterion. Therefore it is taken to be a good hit ratio.

Table 4.4: Summary of Classification Results for Repeated Hold-out Samples

Run	No of Subjects in Group 1 (ST)	No of Subjects in Group 3 (NT)	Percentage of Correct Classifications
1	5	3	75.00%
2	6	3	77.78%
3	6	3	77.78%
4	6	2	75.00%
5	3	3	66.67%
6	3	2	80.00%
7	6	1	71.43%
8	6	7	69.23%
Total	41	24	74.11%

Press's Q calculated for the aggregated hold-out samples is as follows:

$$\text{Press's } Q = \frac{[65-(48\times 2)]^2}{65(2-1)} = 14.78$$

This is greater than the critical value expected at the .001 level of statistical significance and therefore the predictions are appreciably better than that expected by chance.

Hit ratio comparisons and Press's Q calculations show that they are better than values expected by chance for both analysis and hold-out samples. It is safe to conclude that according to the statistical analysis, the differences of personality type can be predicted through the pair-wise comparisons of variables in the given decision task.

4.4 Analysis of Data Using Artificial Neural Networks

The pertinent data in testing the hypothesis collected from the differential study participants are tabulated in Figure 4.13. Rows represent decision and personality preferences of subjects. The decision preferences through pair-wise comparison of variables are tabled in section 1 (*F1* to *F15*). Section 2 lists the two-letter personality types of the subjects. This personality data has been represented in several formats, as the ANN can be sensitive to the representation. The first two columns in section 2 represent the personality type of a person in symbolic and decimal form respectively. The other four columns are used to represent the type as a binary number. The multiple formats allow the validation of results independent of the representation.

The ANN was exposed to these two sections and trained on them. It was then required to predict section 3. Hence, the first six columns of section 3 correspond to the six columns in section 2. The last column of section 3 indicates whether a subject in the study was used as a 'training item' or a 'testing item'. The researcher subscribed to the proposition that if the network could 'learn' a relationship between section 1 and section 2, using the 'training items', it should be able to predict the type of a 'test person', given that person's decision preferences. Ability to predict the type would conversely point to a real relationship between the personality type and the decision preferences. The closeness of the values in corresponding columns of sections 2 and 3 will indicate the ability of the ANN to predict the personality type of a person, and therefore the support available for the hypothesis.

4.4.1 Division of the Sample

As explained above, neural network analysis requires that the sample be split into two groups for training the neural network and prediction. This is similar to analysis and hold-out samples used in discriminant analysis. The strategy adopted in splitting the sample was to randomly allocate subjects between the two groups, with approximately equal group size. The neural network was trained on the randomly selected collection of cases. Predictions were made on the personality type of the remaining cases in the sample. This process was repeated a number of times using the random allocation facilities available in Neuralyst, the software package used for the analysis.

4.4.2 Results of Analysis Using Neural Networks

Section 4 shows the success of the ANN in predicting the personality type of subjects using the three different representations. A '1' in the first column indicates accurate prediction of the personality type using the symbolic representation format. A '0' indicates an inaccurate prediction. The second and third columns show the prediction accuracy using the decimal and binary representations respectively. Although there are predictions for all subjects, only the 'test' items have a meaningful interpretation when the ANN is in predicting mode.

As can be seen from the prediction results in section 4 of Figure 4.13, regardless of the representation format, the ANN was capable of accurately predicting the personality type of 83 percent of the test items.

The results indicate that subjects belong to definite 'types'. The ANN was able to extract a strong relationship between these personality types and the decision preferences of study participants. There were 17 participants with type ST and 16 with type NT. This number of training elements is usually adequate for an ANN to reliably 'learn' a relationship between inputs and outputs. The 83 percent prediction rate would indicate that there is in fact a relationship between the personality type and the decision preferences of people.

Experimental Data/Training Set

	VARIABLE COMPARISONS															PERSONALITY DATA						NEURAL NETWORK PREDICTION							PREDICTION ACCURACY		
Num	F 1	F 2	F 3	F 4	F 5	F 6	F 7	F 8	F 9	F 10	F 11	F 12	F 13	F 14	F 15	Study Types		ST	SF	NT	NF	Study Types		ST	SF	NT	NF	FLAG	ST	N	
49	7	5	7	6	6	6	5	6	6	7	7	8	8	4	3	ST	1	1	0	0	0	ST	1,07	1	0	0	0	TRAIN	1	1	1
60	7	3	7	8	5	3	5	3	5	6	6	6	4	5	5	ST	1	1	0	0	0	ST	1.27	1	0	0	0	TRAIN	1	1	1
81	3	3	5	5	4	4	6	6	6	8	6	6	6	6	5	ST	1	1	0	0	0	ST	1.10	1	0	0	0	TRAIN	1	1	1
100	6	4	6	5	6	3	4	4	5	6	6	6	4	6	6	ST	1	1	0	0	0	ST	1.20	1	0	0	0	TRAIN	1	1	1
129	7	6	5	6	7	3	3	3	3	4	5	4	6	5	3	ST	1	1	0	0	0	NT	1.98	1	0	0	0	TRAIN	0	1	1
135	6	3	7	8	7	4	8	7	7	8	8	7	5	3	3	ST	1	1	0	0	0	ST	1.13	1	0	0	0	TRAIN	1	1	1
144	6	3	8	8	5		8	8	5	8	8	5	5	2	2	ST	1	1	0	0	0	ST	1.01	1	0	0	0	TRAIN	1	1	1
241	5	4	6	7	7	4	5	6	7	6	6	6	5	5	5	ST	1	1	0	0	0	NT	2.48	0	0	1	0	TRAIN	0	0	0
269	2	2	3	4	2	2	3	2	2	7	7	5	4	3	4	ST	1	1	0	0	0	ST	0.96	1	0	-0	0	TRAIN	1	1	1
280	5	7	7	8	9	8	7	8	8	7	8	9	5	5	5	ST	1	1	0	0	0	ST	1.03	1	0	0	0	TRAIN	1	1	1
308	8	2	4	3	4	2	2	2	2	8	7	7	2	2	6	ST	1	1	0	0	0	ST	1.04	1	0	0	0	TRAIN	1	1	1
340	2	2	1	2	2	5	3	5	5	3	8	8	8	7	7	ST	1	1	0	0	0	ST	0.92	1	0	-0	0	TEST	1	1	1
26	4	3	4	4	4	3	3	3	3	6	7	5	5	3	4	ST	1	1	0	0	0	ST	1.80	1	0	0	0	TEST	1	1	1
190	7	4	6	7	7	3	5	5	4	6	6	6	4	3	5	ST	1	1	0	0	0	NT	2.51	0	0	1	0	TEST	0	0	0
243	4	4	4	4	4	5	5	5	5	7	7	7	4	5	5	ST	1	1	0	0	0	ST	0.92	1	0	-0	0	TEST	1	1	1
265	6	5	6	6	4	4	4	6	6	6	7	7	6	6	6	ST	1	1	0	0	0	ST	1.24	1	0	0	0	TEST	1	1	1
271	5	1	1	1	3	1	1	1	3	8	8	6	5	8	8	ST	1	1	0	0	0	ST	1.12	1	0	0	0	TEST	1	1	1
30	5	4	6	8	8	4	4	7	6	7	8	8	7	7	5	NT	3	0	0	1	0	NT	3,06	-0	0	1	0	TRAIN	1	1	1
62	7	7	8	8	7		5	3	4	5	7	5	3	3	5	NT	3	0	0	1	0	NT	2.69	0	0	1	0	TRAIN	1	1	1
66	5	3	4	5	6	3	5		6	7	7	7	6	6	6	NT	3	0	0	1	0	NT	2.98	0	0	1	0	TRAIN	1	1	1
110	6	3	5	7	6	2	5	6	6	7	8	8	6	4	3	NT	3	0	0	1	0	NT	3.09	-0	0	1	0	TRAIN	1	1	1
124	7	3	8	7	7	3	6	6	6	7	7	7	5	5	4	NT	3	0	0	1	0	NT	2.66	0	0	1	0	TRAIN	1	1	1
217	3	5	6	6	6	5	6	6	6	6	5	5	4	4	4	NT	3	0	0	1	0	NT	2.60	0	0	1	0	TRAIN	1	1	1
292	9	3	3	3	5	2	2	2	3	5	5	5	5	5	5	NT	3	0	0	1	0	NT	2.93	0	0	1	0	TRAIN	1	1	1
294	6	6	6	7	6	4	4	6	6	6	7	6	6	5	4	NT	3	0	0	1	0	NT	2.67	0	0	1	0	TRAIN	1	1	1
326	6	3	5	6	8	2	4	6	5	7	7	8	5	6	4	NT	3	0	0	1	0	NT	3.09	-0	0	1	0	TRAIN	1	1	1
33	7	6	7	7	5	4	6	7	5	6	7	5	4	3	3	NT	3	0	0	1	0	NT	2.67	0	0	1	0	TRAIN	1	1	1
90	8	6	7	6	4	2	4	5	3	6	6	6	5	5	3	NT	3	0	0	1	0	NT	2.61	0	0	1	0	TEST	1	1	1
163	9	5	6	7	8	1	2	2	2	9	9	9	5	5	5	NT	3	0	0	1	0	NT	3.09	-0	0	1	0	TEST	1	1	1
178	8	3	4	4	5	2	3	3	3	7	8	8	5	6	6	NT	3	0	0	1	0	NT	2.74	0	0	1	0	TEST	1	1	1
231	4	4	6	5	6	4	5	5	4	5	5	6	4	6	6	NT	3	0	0	1	0	ST	1.08	1	0	0	0	TEST	0	0	0
273	7	4	6	7	7	3	4	5	2	7	8	7	5	4	3	NT	3	0	0	1	0	NT	3.02	-0	0	1	0	TEST	1	1	1
333	7	3	3	4	7	3	3	3	5	4	6	6	8	5	4	NT	3	0	0	1	0	NT	3.00	0	0	1	0	TEST	1	1	1
																ST,NT												SYMBOL			
	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	NT	3	1	0	1	0							MAX			
	1	1	1	1	1		1		1	1	1	1	1	1	1	ST	1	0	0	0	0							MIN			

Accuracy 83% 83% 83%

83.3%

Neuralyst (TM) Version 1.4
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Network Run Statistics
0.256166 RMS Error
72 Number of Data Items
61 Number Right
11 Number Wrong
85% Percent Right
15% Percent Wrong
594 Training Epochs

Network Parameters
1 Learning rate
0.9 Momentum
0.1 Input Noise
0.3 Training Tolerance
0.3 Testing Tolerance
1 Epochs per Update
0 Epoch Limit
0 Time Limit (Hrs)
0 Error Limit (Increase)

Genetic Training Statistics
0 Generation Count
0 Structure Count
0 Least RMS Error
0 Least Epochs

Network Architecture
3 Layers
15 Neurons per Layer
9
6

Section 1 Section 2 Section 3 Section 4

Figure 4.13: Tabulation of experimental and prediction data

4.5 Discussion and Conclusions for Stage 1

The objective of this stage of the research program was to investigate the hypothesis that individuals with different personalties will attach different importance to decision attributes in a given decision situation.

The differential study conducted to test this proposition included 39 senior managers and was conducted using the Myers-Briggs Type Indicator and a purpose-built decision making exercise. The analysis of the characteristics shows that the sample was well selected and homogenous. This is important to both the internal and external validity of the study. The obtained sample distribution was congruent with other similar studies and is representative of the population. However, due to practical constraints imposed when conducting research with very senior managers, the sample size was relatively small. This resulted in limiting the study to the detailed investigation of only two personality types created by focusing on the *Sensing-Intuitive* and *Thinking-Feeling* dimensions of the MBTI.

Multivariate discriminant analysis was selected as the most suitable statistical instrument for the investigation of the hypothesis. Statistical methods such as MDA often produce unreliable results when working with small samples. Hence, it was considered essential to strictly adhere to all the assumptions associated with using such methods. As a method of cross-validating the results, Artificial Neural Networks were employed. ANNs are good at extracting relationships in data even when the data sets are small. If there were any instabilities in the conclusions obtained through the use of MDA, they would have been made apparent by the ANN analysis.

The statistical analysis shows that the discriminant function developed is statistically significant at the .05 level of confidence. As the statistical significance may have some deficiencies in evaluating the efficacy of the function to distinguish between personality types, further testing was conducted to investigate the predictive accuracy. The analysis using multiple holdout (testing) samples show that ability of the discriminant function to predict the personality type of a person, given the decision preferences, is significantly greater than that expected by chance.

Validation of the results using an ANN show that the predictive model developed by the ANN produces very similar results to those obtained through the application of MDA. Thus, it is plausible to conclude that the hypothesis that *individuals with different personalties will attach different importance to decision attributes in a given decision situation* is supported through the data collected and analysed.

Chapter 5

An Architecture for Adaptive DSS

The major concept pertaining to this research project, the relationship between the personality and decision preferences of individuals, was articulated through the procedures described in the previous chapter. Since it was shown that there are differences in decision preferences between personality types, the next step in the project is to investigate how it may be put to practical use in supporting senior decision-makers. This next step is addressed in the dissertation as two distinct tasks. The first task is to investigate the conceptual framework required to utilise the concept. The activities performed within this task constitute the second stage of the system development research process, *developing a system architecture*, as proposed by Nunamaker *et al.* (1990). If a conceptual framework can be successfully produced, it may be possible to develop an artefact based on that framework. Developing such an artefact is the second task.

This chapter reports on developing the conceptual framework and the resulting system architecture. The research question pertaining to this task is:

Q2. **How can the distinct decision preferences of individuals belonging to different personality types be used as the basis of building decision support systems that adapt to individuals?**

Before describing a potential framework, it is useful to define a set of requirements for such a framework. In doing so, the knowledge gained from the survey of relevant past research is used. The requirements defined here focus on provision of adaptive support based on decision preferences. However, it is also essential that general requirements for a framework are discussed as those general requirements should be adequately achieved for any decision support system to be successful. The following section starts with more generic requirements for decision support and progresses to discuss specific requirements for answering the research question, Q2.

5.1 The requirements

Many decision support architectures emphasise the importance of supporting all phases of decision-making: intelligence, design, choice and implementation (Sprague and Carlson, 1982). While supporting all three phases is desirable, intelligence, or the recognition of a situation that warrants a decision, needs constant monitoring of the environment. To achieve true 'intelligence support', a steady stream of data may have to be compared with internal knowledge by some recognition mechanism.

The implementation phase of a decision process involves putting the selected course of action into operation. Decision support systems rarely assist in this phase. However, it is advantageous for a system to record how a particular course of action was implemented. Decision support systems such as case-based systems strive to achieve this objective. As with intelligence, though this is a desirable feature, achieving it is beyond the capacity of this research. Thus, the focus of this work is to support the other two phases of design and choice.

In a well-defined decision, there are clear objectives, defined outcome alternatives and known probabilities. The decision-maker selects between the known alternatives. Such problems have traditionally been the subject of information processing approaches to decision making. The representation of the problem and the decision-maker's perception of the problem are important attributes in the outcome and the process of such decisions (Covaliu and Oliver, 1995; Dixon and Moore, 1997; Hackathorn, 1981; Paivio, 1986; Shepard, 1966; Simon 1976; Simon and Hayes, 1976). Hence, an architecture that purports to support decision-making should give high consideration to these two factors. This requirement is reinforced by the importance attached to representation by all the decision support frameworks described earlier (Chapter 2).

Mintzberg, Raisinghani and Theoret (1976) also point out that two important decision routines, authorisation and screening, are rarely rational. Authorisation is done in a climate of uncertainty, where the authority lacks in-depth decision knowledge, is subject to time limitations and other inhibiting factors. The screening routine has been labelled as superficial as there is no systematic filtering of decision alternatives. Similarly, evaluation-choice is not systematic as the name implies. Convenience and not rationality is the major concern. One objective of supporting decision-making is to achieve a higher degree of rationality by avoiding emotions, politics, personality biases and cognitive limitations. The support framework should then facilitate the quest for rationality by enhancing human decision-making abilities.

The structure of a decision is the level to which the problem has been encountered in the same manner before and the availability of a predefined way of solving the problem (Simon, 1960; Gorry and Scott Morton, 1971 etc.). In most managerial decisions, there is minimal amount of structure (Mintzberg, Raisinghani and Theoret, 1976; Weick, 1983). Decision support methods attempt to gradually improve the structure of unstructured problems. Proceduralisation of decision-making is only possible if the problem is well structured and defined. Traditionally, structuring has received less emphasis than problem solving (Pracht, 1990). The framework should therefore support this 'structuralisation' process.

A process of structuring has to begin with the decision-maker making a statement of the problem to the support system. This involves defining the variables and elements that are present in the problem situation and how they interact (Pracht, 1990). This is not an easy task, as the decision-makers may not have sufficient decision knowledge at this stage. Therefore, any system that aims to support decision-making should have facilities to assist in describing the decision situation. The description of the decision leads to an internal model within the support system. To achieve greater confidence in this model, it should remain within the comprehension capabilities of the decision-maker. The objective should be to keep the model as simple as possible, while at the same time providing a viable framework for solving the problem. This argument is supported by research that shows that only marginal improvement of decision quality is achieved by using complex models as against simple models (Bazerman, 1990). The model used by the support system will still remain one of the most important components, as it will form the basis for solving the decision problem.

Mills, Meltzer and Clark (1977) point out that decision-makers reduce information search as the number of possible decision alternatives increase. A similar effect is observed if the number of attributes is increased (Svenson, 1979). Limiting the number of attributes or alternatives will cause lower decision quality, as important characteristics may be lost. Effectively managing and presenting attributes and alternatives without loss of quality should be a desired goal of a support framework. This could be achieved by augmenting the decision-maker's perception abilities through support tools. Such effective management of attributes may reduce the tendency of decision-makers to 'filter-off" information due to overload.

Managerial decision-makers make decisions under significant time constraints. Researchers have shown that under these conditions, decision-makers attempt to select safer alternatives (Hurwitz, 1996; Wright, 1974; Hansson, Keating and Terry, 1974). Unfavourable alternatives are eliminated using disproportionate weights. By allowing the decision-maker to exercise better control of the decision process, and reducing cognitive demand, it may be possible to reduce cognitive pressure due to time limitations.

Ease of conceptualising the problem would also help towards this end. Information presentation formats have been shown to have an impact on the way decisions are made (Johnson and Russo, 1978; Slovic, 1972; Tversky, 1969). Familiar patterns of representation have a positive impact towards the efficiency of decision-making (Bettman and Zins, 1979). All these point to the importance of presentation of information and selection of representations in support of decision-making. A good representation method may help in supporting the cognitive capabilities of decision-makers.

The model is also used in describing and understanding the decision. Therefore, it should provide familiar constructs that the decision-maker can use to describe the particular decision situation at hand. In the model construction process, the variables that affect the decision should be defined along with the relationships between them. Humans are better at identifying the relevant variables than they are at defining the relationships and integrating data (Dawes, 1979). The models provided by a support system should therefore provide assistance in defining the relationships. This would contribute towards structuring the decision.

A decision model should enable the decision-maker to evaluate various possible outcome alternatives. When evaluating alternatives and making choices, the decision-maker should try to maximise the objectives while at the same time avoiding emotions, biases and striving for rationality. This is a process that also requires high cognitive effort. A support system can minimise this cognitive load by performing tasks that enhance the decision quality. Enforcing certain constraints and generating ideas for problem solving are two appropriate options. Jelassi, Williams and Fidler (1987), Kremar and Asthana (1987), and Raghavan (1984) postulate this 'active' role for decision support systems.

Interactions with other people, bargaining and persuasion are all inherent characteristics of making decisions (Mintzberg, Raisinghani and Theoret, 1976). Sometimes there is also a need for justifying the process and the outcome. All these characteristics highlight the need to communicate the process to others. A decision support tool should facilitate this communication process.

Mintzberg, Raisinghani and Theoret (1976) also point to the existence of dynamic factors in decision processes. They propose that interrupts, scheduling delays, speedups, feedback delays, comprehension cycles and failure cycles prevent the smooth progress of the decision-making process. Just as humans are able to cope with such dynamic environments, systems that augment human decision-making should support decision making under the same conditions. Improved tolerance of these dynamic factors, through the use of decision tools, is a desirable objective.

As Raghavan and Chand (1988) assert, even with all these facilities, a support system can only be good as the control that the decision-maker can exercise over the tool. The framework should cater for the need for the decision-maker to understand the available facilities. The decision-maker should have reasonable control over the decision making process. Ease of use should be a major goal, and therefore should be embodied in the framework.

The discussion so far has focused on the requirements for specific decision support systems. If the intention is to model the decision-maker in terms of personality in addition to modelling the decision situation, the effort required is bound to be more than what is expected in ad-hoc decision support systems. This would be true on the part of the builder as well as the decision-maker. The decision-maker has to participate in a personality assessment exercise in addition to the role in actually participating in making the decision. The assessment process will be a time-consuming exercise if it is to be a comprehensive assessment of the individual's personality. However, it has been shown that some components of an individual's personality remain relatively static even though there are dynamic and evolving facets (Costa and McCrae, 1988). Considering the effort required to acquire personality profiles, it can argued that it would be economical to preserve some acquired personality characteristics between decision instances or between different decisions.

To reap the benefits of such a scheme, the system should be capable of retaining some form of profile of the decision-maker. If the system is designed to support only a single decision, after the novelty of the system runs out, not much use can be made of the profile. However, if the system is capable of supporting many independent decisions, such profiles may be retained across decision boundaries. This would reduce the effort required in acquiring the decision-makers personality characteristics for the subsequent decisions. Research has also shown that it is more economical to build such generic user modelling shells and tools (McTear, 1993). Thus, the framework for adaptive system is envisaged as a DSS generator rather than a specific DSS.

Sprague and Carlson (1982) define important criteria for a DSS generator. They propose that capabilities of a generator should be organised around the data, dialogue and model (DDM) paradigm, providing balanced capability in all three areas. A generator should have the overall objectives of:

1. facilitating quick and easy development of a wide variety of specific DSS, and
2. must be flexible and adaptive enough to facilitate the iterative design process by which specific DSS can respond quickly to changes-in the organisational or physical environment, in the style of the user, or the nature of the task

(Sprague and Carlson, 1982).

They also define an approach for identifying the requirements for providing DDM capability. This approach is based on four user-oriented entities: representations, operations, memory-aids and control mechanisms (ROMC). The requirements for specific DSS, discussed previously in this section, can be classified into these four categories. A DSS generator should provide a set of generic ROMC capabilities. A sub-set of these capabilities is embodied in specific decision support systems (SDSS). How DSS capabilities should be organised under the DDM paradigm is illustrated in Figure5.1.

While there are many aspects of the DDM paradigm that are useful for the current project, it should be noted that some aspects are based on the technology available at the time. Another distinction is the scale of the generator; the Sprague and Carlson definition of a generator encompasses large-scale organisational systems, while the current emphasis is on supporting senior decision-makers with relatively small systems. Adaptiveness envisaged by Sprague and Carlson is based on the iterative development cycles that are common to DSS development projects. The involvement of the DSS builder in adaptation and augmentation is emphasised in their approach. However, adaptation envisaged in this project is without intervention from the builder. Hence, the framework for the generator should have constructs to support such adaptation.

Since the attempt is to provide adaptation based on the decision preferences of individuals belonging to different personality types, a system based on this framework should have the capability of knowing the personality type of an individual. This may be achieved either by supporting a personality assessment exercise or simply accepting an input of the personality type. If the personality type is expected as an input, the actual assessment may have to be performed using a standard manual instrument.

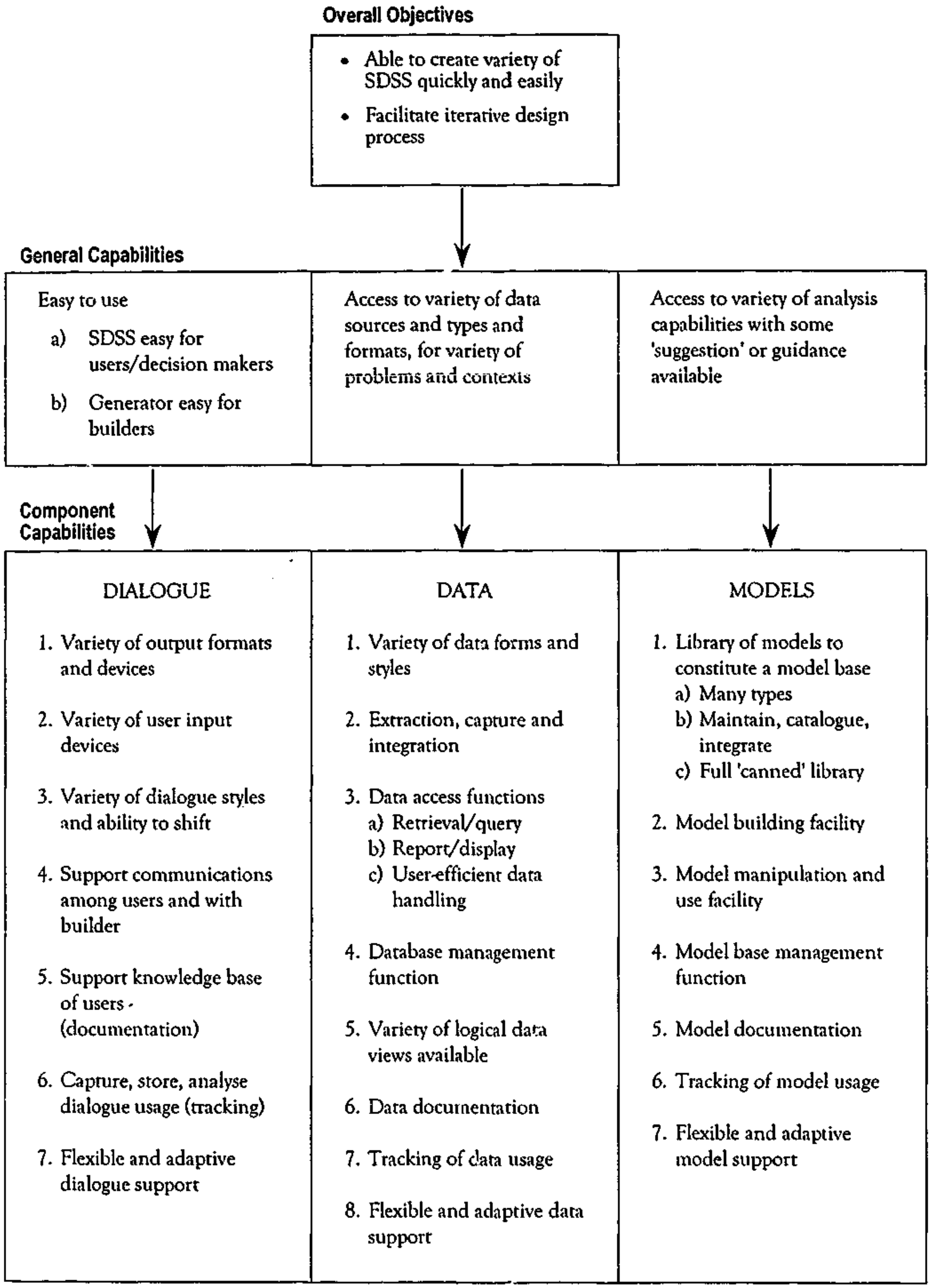

Figure 5.1: Summary of DSS generator capabilities (after Sprague and Carlson, 1982)

As a DSS generator, a system should be able to assist in many different decision situations. Similarly, supporting many different users is also a desirable objective. If the system is to adapt to personality types, having many users is essential. A system would be capable of adapting to a particular personality type only if many individuals of that type have used the system. However, it should be noted that most decision support systems are used by one individual. This is particularly true for systems that assist senior managers. Hence, while adapting to personality types is the primary objective, the architecture should facilitate adaptation to individuals.

As embodied in the research question, adaptation should be based on decision preferences. Decision preferences are defined as comparisons between the variables relevant to a decision situation. The objective of adaptation is to predict the comparison values for variables in a given situation, for the current user. If the predictions are close to the final preference values given by the decision-maker, a system can be regarded as adaptive. By adapting to personality types, the system can always be expected to provide reasonable predictions, even when an individual is using the system for the first time. This is because the system is expected to build a profile for each personality type. The only constraint to providing this facility is that at least one person from each personality type should have used the system before. The DSS framework should include components that are capable of retaining profiles of personality types and individuals. These profiles should not be static collections of preference information. They should be dynamically augmented as individuals of various personality types use the system.

Predictions generated by the system may not sometimes be acceptable to a decision-maker. The decision-maker should have the discretion of changing any suggestion provided by the system. Those changes should be monitored, so that they can be used to improve the predictions for the subsequent occasions. Improvements should also be dynamically reflected in the profiles. Hence, the profiles can be expected to be better models of the entities that they represent with increased use.

Retaining information on decisions that have been previously supported using the system is also important. Not only should the decision-maker that defined a decision be able to recall it; it should be modifiable to suit a new scenario. The decision preferences used in the previous instance should also be accessible. If the same decision is repeatedly made, a profile of decision preferences for that decision can also be useful. Such a profile is useful in the absence of a profile for a new decision-maker or a personality type. Indeed, such a decision profile may be more appropriate as the source of prediction, as it is widely accepted that situational factors have large bearing on decision preferences. Hence, in addition to profiles of personality types and decision-makers, profiles of decisions should be supported.

The profiles can only be useful if they can be used as the basis for adaptation. As discussed previously, adaptation is the ability to predict the decision preferences most relevant to a given situation in support of an individual. The framework proposed here should have a mechanism that determines the most appropriate source of information for generating predictions. If there are more than one suitable source, priority for the multiplicity of the sources should be established. Once the sourced has been determined, predictions based on those sources should be generated.

Although the major focus of this doctoral research project is to develop systems that adapt based on personality, it cannot be regarded as the final conclusion of this stream of research. Adaptation cannot be an end by itself, as the aim of building decision support systems is to enhance the decision making process. As discussed in chapter 2, active decision support is a desirable goal to which this project contributes. As an illustration of the possibilities for active support based on the contribution of this project, the framework should include a basic set of active support components. The active support components could be seen as reducing the cognitive effort required from the decision-maker by complementing reflective processes (Angehrn, 1993).

Before describing details of the framework, it is useful summarise the requirements for an adaptive decision support system generator architecture based on personality. Such a framework should:

- support Intelligence, Design, Choice and Implementation phases of decision-making (however, for the purposes of this research, it is limited to Design and Choice);
- provide facilities to adequately represent decision situations;
- help conceptualise the decision situation and internal constructs of the support system;
- aid in structuring the decision scenario;
- provide constructs for decision model building;
- have facilities for manipulation of the model to evaluate decision outcomes;
- reduce cognitive load of the decision-maker;
- help the decision-maker communicate the decision to others;
- be tolerant of dynamic factors of decision-making;
- use simple constructs and keep within comprehension of decision-makers;
- give the decision maker the ability to exercise control over the decision-making process;
- be able to generate and manage several specific systems;
- have the capability of supporting many individuals (one at a time);
- have the capability of capturing personality information about decision-makers;
- be able to build and maintain profiles of decision preferences for all individuals who use the system;
- be able to build and maintain profiles of decision preferences for all the personality types;
- be able to build and maintain profiles of decision preferences for all the decisions that have been supported using the system;
- have facilities to determine the most appropriate sources of preference information for the support of an individual in a given situation;
- have facilities to determine the priority for assembling the preference predictions for a given situation;

- be able to incorporate decision preferences into the model;
- be able to adapt to personality types, individuals and decision situations thorough generation and dynamic improvement of predictions for decision preferences; and
- have components that illustrate the ability of adaptive systems to provide active decision support.

It is now pertinent to illustrate how components of an adaptive decision support system generator may be organised.

5.2 Overview of the architecture

The Adaptive DSS Generator Architecture (Figure 5.2) is organised with the decision model as the central component. The other components support the role of the decision model. Decision model is a representation of the decision situation. It should help in conceptualisation of the problem. The type of model is determined by the nature of the problem. The Model Base (MB) is a collection of generic decision models. The most appropriate model for a given situation can be selected from the MB by the decision-maker. Major interactions in a decision support session occur between the decision-maker and the decision model.

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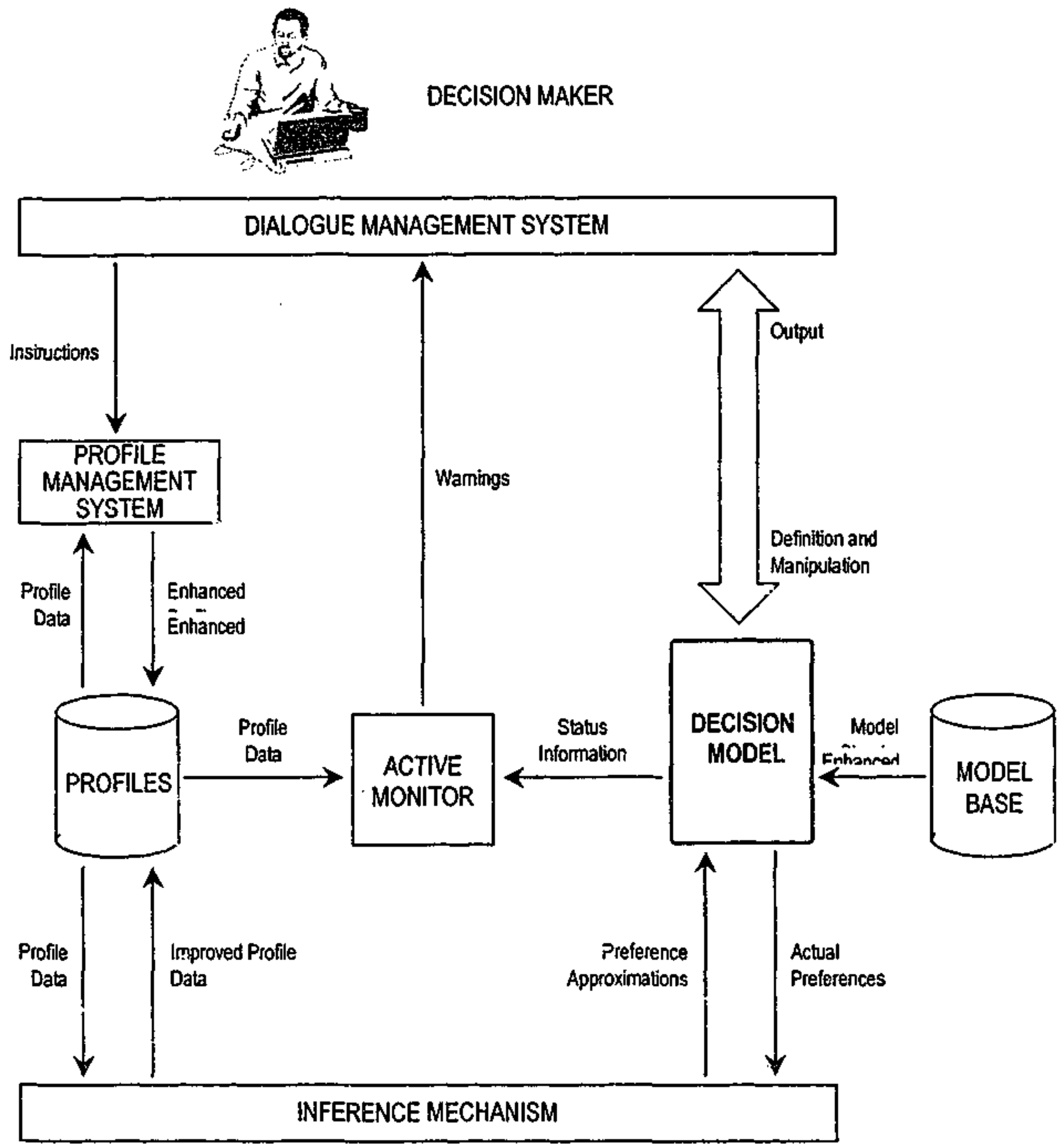

Figure 5.2: The Adaptive DSS Generator Architecture

For a new decision, the decision-maker has to make the definition in accordance with the selected model. The model should have associated operations that allow the decision-maker to manipulate various aspects of it. Alternative solutions to the problem can be evaluated through these manipulations. When a particular model organisation is accepted by the decision-maker as a satisfactory outcome for the problem, the Inference Mechanism (IM) has the task of building new profiles or enhancing existing profiles of preference information. At this stage, several abstractions and generalisations may have to be performed.

The Inference Mechanism determines the most appropriate profiles to build or improve. The results of abstraction and generalisation are then stored as profile information. When the system is used next, the Inference Mechanism determines the context of that use and assembles relevant decision preference information from the profiles. If there are multiple sources, the IM should ascertain the priority for the preference information. The preferences are included in the model for the new decision. These preferences act as an approximation that the decision-maker can either accept or change as desired. If the preferences are changed, the new values are fed back through to the profiles.

While a decision model is manipulated, the Active Monitor (AM) has the task of observing the state of the model. If certain predefined rules are contravened, the Active Monitor alerts the decision-maker. The decision-maker may or may not act on these warnings. The Active monitor makes use of information in the profiles to generate warnings. AM is the active decision support component in the architecture.

All interaction between the users of the system and internal components is facilitated by a Dialogue Management System (DMS). The DMS has to provide an interface that makes the system easy to use and promotes comprehension of the constructs. It should make decision definition and manipulation easy.

A Profile Management System (PMS) is also important, as the profiles have to be periodically maintained to improve relevancy. This component is not analogous to a database management system, as it is not intended to provide simple data access operations. It will not be part of the normal decision making cycles, but be used periodically to improve the quality of the profiles.

Although models and data (profiles) require model-base management and database management respectively, those components are not explicitly shown in the adaptive DSS generator framework. This is because they will perform minor implicit roles that do not contribute to the uniqueness of this framework.

In the following sections of this chapter, major components of the architecture are described in detail. The primary goal in describing an architecture for a system is to illustrate the conceptual framework. However, in the following discussion, some implementation aspects are also described. This is because the *development* stage of this research project is focussed towards illustrating the viability of the *concept* through the development of a prototype system.

5.3 The decision model

The central component of the architecture is the Decision Model. The model is essentially a mathematical representation of the decision situation, as perceived by the decision-maker. It is a set of symbolic statements, which declare some beliefs or truths about an aspect of reality (Young, 1989). However, in a DSS, the model should not be limited to a static representation; it should also provide the basis for analysis and understanding of the problem. According to Sprague and Carlson (1982), the modelling component in a DSS should support projection, deduction, analysis, creation of alternatives, comparison alternatives, optimisation and simulation.

Model building and manipulation is a common form of decision-making, both manual and automated. The use of mechanical models has been shown to be useful in improving consistency in making decisions (Peterson and Pitz, 1986). Decision-makers use conceptualisation methods to understand and evaluate decisions (Carlson, 1983; Greeno, 1973). They use familiar methods like charts and pictures. The decision model proposed in this framework is such a conceptualisation method that also has associated functionality. Thus, the decision-maker is not limited to a static model. While a good representation may reduce the cognitive effort required, the decision-maker's comprehension of the decision will depend on this model.

The decision-maker's interaction with the support system will be through the model. As Carlson (1983) articulates, decision support systems should provide representations with associated operations, instead of operations that result in representations. This framework is based on the same view. The Model is considered the central component. Other components of the architecture exist to support the functions needed for using the model effectively.

The large arrow (Figure 5.2) between the Decision Model and the decision-maker, through the DMA, represents a broadband communication channel between the two. Model definition, manipulation and modification are all performed through this communication channel. The decision-maker is usually only interested in solving the problem at hand through the use of the model. Therefore, other system functions should facilitate uninhibited interaction between the Model and the decision-maker. These other components will also interact with the Model by supplying required data and management functions. A model management component should control the working of the Model and its interaction with other components.

The full benefits of any representation can only be gained if the same representation can be used in both the design and choice phases of a decision process. This will save the decision-maker from having to switch between different conceptualisations, thereby reducing cognitive load.

The usefulness of graphics in improving task performance and decision quality has been articulated by many researchers (Angehrn and Luthi, 1990; DeSanctis, 1982; Kaufmann, 1980; Pracht and Courtney, 1988). A graphical modelling technique would also include an underlying mathematical model. This model can be any appropriate structural model, such as those described in Chapter 2. However, one major objective in selecting a structural model should be its simplicity.

Most modelling languages presently available are textual (Pracht, 1990). Researchers such as Richardson (1983) and Weber (1986) contend that familiar graphical representation methods are more successful in eliciting and activating knowledge posited in human long-term memory. Most decision models described earlier (Chapter 2) are limited to quantitative data. However, many decision situations include some form of qualitative data. The ability to incorporate qualitative data is a desirable feature. Graphical methods also have the potential to achieve this objective.

A good decision model would also facilitate communication of the decision scenario. Just as the decision-maker needs to use a familiar representation, such familiarity will ensure ease of communication to others involved in the process. Graphical methods may also be preferred in this sphere. Hence, the Decision Model should have a graphical interface, while providing the underlying mathematical constructs.

The main objective of this framework is to facilitate building adaptive decision support system generators. The adaptation should be based on distinct decision preferences of individuals belonging to different personality types. Hence, the model used in a decision situation should accept decision preferences as one of its constituents.

As discussed in Chapter 2, linear models naturally lend themselves to the inclusion of decision preferences. It is proposed that linear multi-criteria models should be utilised with the adaptive DSS framework. For illustration of the concepts, deterministic models that do not explicitly deal with uncertainty or risk are suitable. It is assumed that uncertainty can be handled by repeatedly evaluating several possible scenarios. This assumption is needed to ensure ease of comprehension of the constructs in the system. Further, there is little to be gained from the inclusion of more complex models, especially for supporting senior managers (Bazerman, 1990).

There are four important elements to consider in a multi-criteria decision situation: the set of alternatives, the set of criteria, the outcome of evaluation of each alternative against each criterion and the preference structure of the decision-maker (Yu, 1985). Since the models to be used in the framework are limited to deterministic models, the consequence of each choice is not an important issue. The *preference structure* refers to preference to the possible outcomes. In addition, *preference structure* can also refer to the preference to criteria on which alternatives are evaluated, as used in Saaty's (1980) Analytical Hierarchy

Process. In this context, a multi-criteria situation is evaluated by determining *weights* and *criteria* scores for the alternatives. Weights are an expression of preference to criteria. A weighed-sum approach can be adopted to arrive at final values for alternatives. This approach results in compensatory evaluations.

The Decision Model in the framework should then be able to accept definitions of alternatives, criteria and their respective scores for each alternative, and weights for the criteria. Decision preferences, as articulated by the decision-maker, or as a result of inferring, should be included in the model as weights of decision criteria. The Profiles should be stored in the form of preferences to criteria, which then can be inferenced as appropriate to the current situation. How this process is implemented will be discussed in detail in the next chapter.

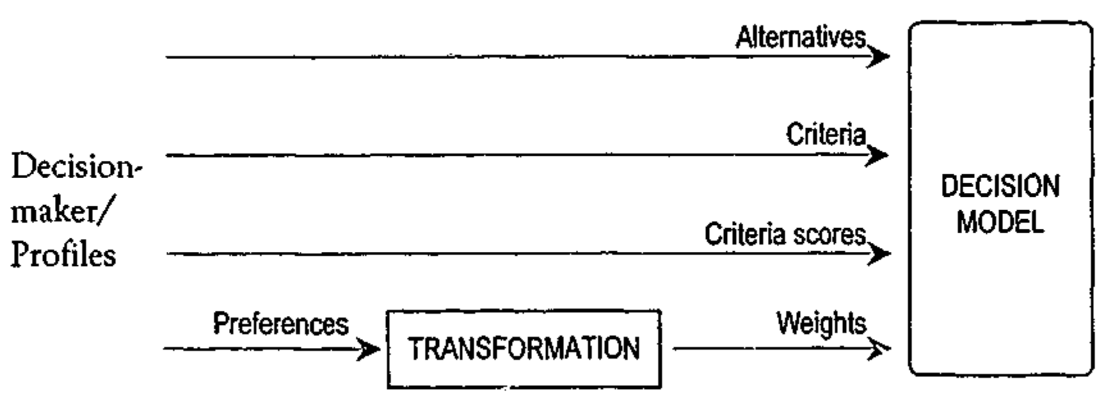

Figure 5.3: Functional view of Decision Model inputs

A functional view of the inputs to the Decision Model can be illustrated as in Figure 5.3. The elements in the model can also be formally expressed in the following manner:

The set of Alternatives is denoted as A $\quad a_i \in A,\ i = \overline{1,k}$

The set of Criteria is denoted as C $\quad c_j \in C,\ j = \overline{1,l}$

The evaluation of each alternative is given by $c_j(a_i) = (c_1(a_i),\ldots c_l(a_i))$

The outcome of the decision, $\quad Z = \{c(a_i) | a_i \in A\},\ i = \overline{1,k}$

$c(a_i)$ is assumed to be deterministic

The value of a criterion $c_j(a_i) = f(W_j S_j(a_i))$

where, W is the weight and
S_j is the score for a_i

The weights for the criteria in the decision situation are determined by the collective set of preferences to those criteria.

The weight of a criterion $W_j = f(P(c_1, c_1), \ldots, P(c_l, c_l))$

where, P is the preference between c_x, c_y

Preference between two criteria, P, is determined by one of:

$$P(c_x, c_y) \in \{\succ\approx\}, c_x \succ\approx c_y$$
$$P(c_x, c_y) \in \{\prec\approx\}, c_x \prec\approx c_y$$
$$P(c_x, c_y) \in \{\sim\}, c_x \sim c_y$$

where, $c_x, c_y \in C$

For logical consistency, $(c_x, c_y) \in \{\succ\}$ *iff* $(c_y, c_x) \in \{\prec\}$

The collective set of preferences is termed as the *criteria preference model*. The term *preference model* is used in this research to refer to the criteria preference model. The preference model for a given situation can also be expressed by $\{P(c_1, c_1), \ldots, P(c_l, c_l)\}$. As the differential study showed that individuals with different personalities have distinct preference models, inclusion of individual differences in the model will be through the weights. Therefore, in this study, weights are a function of personality.

The preference between two criteria can be denoted by the symbols $\succ$, $\prec$, and ~ to refer to greater than, less than and indifferent/equivalent respectively. However, this essentially binary comparison provides little granularity. Hence, it is proposed that a scheme with greater granularity, Saaty's (1980) nine-point pair-wise comparison scheme should be used. It is also possible to use other suitable scales. Selection of Saaty's scheme allows the possibility of using comparison scales in their semantic form. This could be more appealing to senior manag ʻ.

The Model Base should consist of several forms of the basic model presented here, so that the most suited representation for a given situation can be selected by the decision-maker.

5.4 The profiles

How preferences could be incorporated into a decision model was shown in the preceding discussion on the Decision Model. The objective of the Profiles in the Adaptive DSS Generator Architecture is to retain such preference information, so that they can be used as appropriate to support decision-makers. As discussed in the requirements for this architecture, retaining information about decision-makers, personality types and decisions is essential to deliver adaptive decision support system generators. This section presents the structure and organisation of Profiles.

The multi-criteria linear decision model described in the previous section expect a set of alternatives, a set of relevant criteria, scores on how the criteria are satisfied in each alternative and the weights for the criteria as input. The weights are a function of the decision-maker's preferences to criteria, as expressed by the decision-maker or as inferred by the system. The structure of Profiles is determined by the requirement to supply the decision model with preference information. Synthesis of information held in the profiles and transforming them into weights is performed by the Inference Mechanism.

The preference model for a given situation is derived by declaring the preference between all the criteria, two-at-a-time. Such comparison results in a pair-wise comparison matrix. A complete pair-wise comparison matrix takes the form of:

$$\begin{pmatrix} P(c_1,c_1) & P(c_1,c_2) & \cdots & P(c_1,c_q) \\ P(c_2,c_1) & P(c_2,c_2) & \cdots & P(c_2,c_q) \\ \cdots & \cdots & \cdots & \\ P(c_q,c_1) & P(c_q,c_2) & \cdots & P(c_q,c_q) \end{pmatrix}$$

However, if logical consistency is assumed, only one-half of this matrix has to be completed. Logical consistency can be stated by:

$$(c_x, c_y) \in \{\succ\} \; iff \; (c_y, c_x) \in \{\prec\}$$

The concept of logical consistency may also be applied to the nine-element comparison scale proposed by Saaty (1980).

With the assumption of logical consistency, the total number of comparisons to be performed is reduced to $((l^2 - l)/2)$.

If two or more preference models are intersected, a composite preference model can be constructed. Such a composite model will include the criteria that are in all the decisions. Some criteria may be common to many preference models. The composite preference model for a single decision-maker, across many decision instances, is that decision-maker's Profile. This scheme can be shown with a Venn diagram. The situation where the same decision-maker makes three decisions with some common criteria can be shown as in Figure 5.4. The profile based on this Venn diagram will be similar to Figure 5.5.

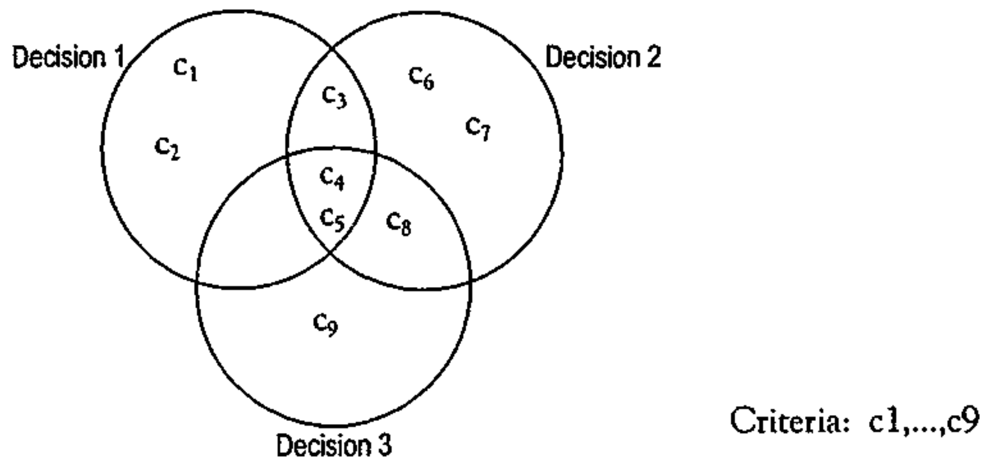

Figure 5.4: Venn diagram depicting criteria for composit preference model

As can be seen in Figure 5.5, building a composite preference model results in situations where some criteria can have many sources of comparisons. However, decisions do not occur simultaneously. The multiple comparisons for the same pair of criteria can be viewed as a time-series of consecutive events. The task of managing multiple values for the same pair of criteria is the task of the Inference Mechanism and will be explained in the following section. Another characteristic to note is that the preference model is only partially completed.

If this manner of preference model is built for every decision-maker who uses the system over time, a collection of decision-maker profiles accumulate within the system. Similar cumulative preference models can be built for individuals of the same personality type. This results in the system having a collection of preference information for each personality type. The personality-based profiles are termed *stereotype profiles*, as they result in a description of a stereotypical person who belongs to a personality type. The same concept can also be extended for decisions, where many people, or the same person over a number of times, has used the system to support the same decision. Hence, a number of decision profiles will result. Each profile will be more extensive than a single decision instance or a single person's preferences. The collection of *decision-maker-*, *stereotype-* and *decision-based profiles* provide a pool of criteria comparisons that can be utilised for providing customised decision support.

Source	Decision 1	Y	Y	Y	Y	Y				
	Decision 2			Y	Y	Y	Y	Y	Y	
	Decision 3				Y	Y			Y	Y
Preference Model		C1	C2	C3	C4	C5	C6	C7	C8	C9
	C1	1	Pc_1c_2	Pc_1c_3	Pc_1c_4	Pc_1c_5				
	C2		1	Pc_2c_3	Pc_2c_4	Pc_2c_5				
	C3			1	Pc_3c_4	Pc_3c_5	Pc_3c_6	Pc_3c_7	Pc_3c_8	
	C4				1	Pc_4c_5	Pc_4c_6	Pc_4c_7	Pc_4c_8	Pc_4c_9
	C5					1	Pc_5c_6	Pc_5c_7	Pc_5c_8	Pc_5c_9
	C6						1	Pc_6c_7	Pc_6c_8	
	C7							1	Pc_7c_8	
	C8								1	Pc_8c_9
	C9									1

Figure 5.5: Composite criteria preference model based on Venn diagram

One cautionary aspect to be remembered here is that the comparisons provided by the decision-makers can have contextual influences. Preferences to some criteria may only be valid in the situation in which it was originally expressed. The differential study showed that there are stabilities that cross the situational boundaries. The differential study was conducted in a controlled situation where the task remained constant. The observance of personality-based differences indicates that some preferences may transcend situations. However, it is not prudent to ignore the influence of the context. Hence the concept of *domains* is introduced to the structure of the profiles.

Domains can be defined in this context as the general subject area to which a decision belongs. It is proposed that *decision-maker* and *stereotype profiles* should be aligned with domains. The same cannot be applied to *decision profiles*, as a decision is a more restrictive concept than a domain. Thus, while a decision-maker will have a general profile, there will also be profiles for that decision-maker that are aligned with domains. *Stereotype profiles* will have the same structure, where there is a general profile for each personality type and multiple profiles that are aligned with domains.

If a given decision is made repeatedly by the same decision-maker, a profile may also be built on the preferences defined for that decision, by that decision-maker. Hence, in addition to the general profile for a decision, decision-maker specific profiles should also be maintained. The *decision* is loosely defined as the *same general description of the decision*, and is not restricted by the selection of criteria or the scores for the criteria.

If a system is to maintain such a vast collection of profiles, each one should be of some use. Examination of the profiles introduced above shows that there are of different levels of abstraction. The profiles can therefore be organised in a hierarchical pattern based on the level of abstraction (Figure 5.6). The least abstracted profile is at the top of the hierarchy. It should also be noted that some profiles might be of such a level of abstraction that it would not be of any use. When implementing systems based on this architecture, the profiles to be implemented should be carefully selected. The strategy in using the profiles would be to use the least abstract, relevant profile as the basis for providing preference approximations. The method of using the profiles is the subject of the next section.

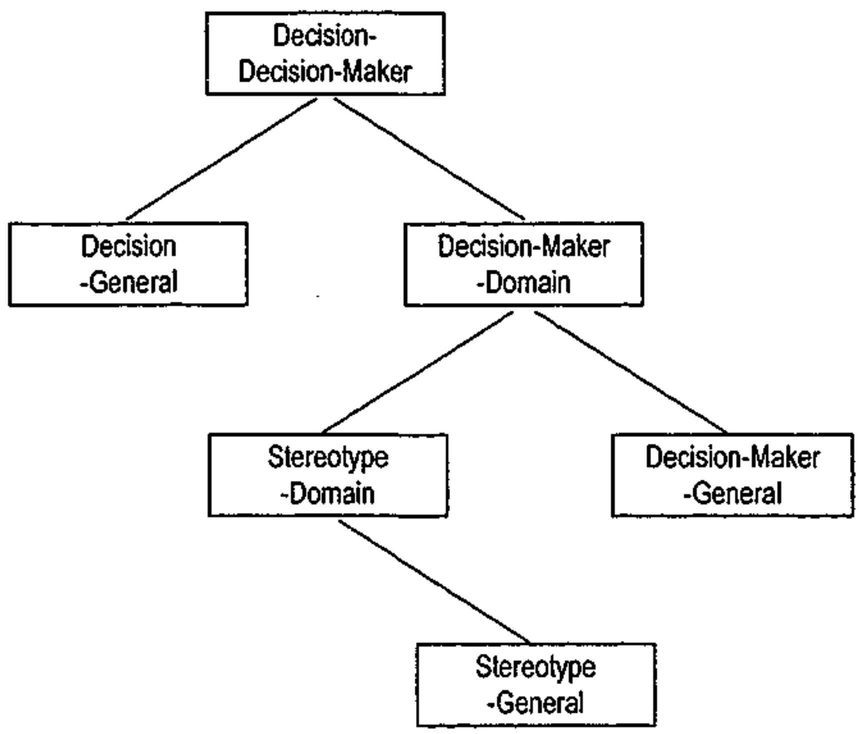

Figure 5.6: The profile hierarchy

The profiles introduced in this section are based on stereotypical behaviours. This is a common form of modelling users of systems (Encarnação, 1997; Rich, 1979; Strachan, Anderson, Sneesby, and Evans, 1997). The uniqueness of this arrangement lie in the use of criteria preference models as the basis for profiles. The use of stereotypical behaviour reduces the problems associated with modelling each unique decision-maker, especially when there is incomplete information (McLoughlin, 1987). Therefore this approach facilitates adapting to contingencies.

The Profiles component illustrated in the architecture is the repository of certain other information, in addition to the criteria preference models. Other information includes textual names and descriptions of decisions, names and descriptions of criteria, information on decision-makers such as personality type and customised interface characteristics. These aspects are considered conceptually trivial compared to the major task of the Profiles.

5.5 The inference mechanism

The preceding two sections articulated the structure of the Decision Model and the Profiles that hold the preference information. The major functions of the Inference Mechanism are ascertaining which preference information is relevant to a given situation and determining how to improve the profiles as a result of the interaction. These functions are at the core of the adaptive ability of a system based on the architecture. Adaptation is achieved by predicting the comparison values for variables in a given situation, for the current user. If the predictions progressively get close to preference values given by the decision-maker, a system can be regarded as adaptive.

Two major functional components can be identified in the Inference Mechanism: the *Inference Manager* and the *Prediction Module*. These two components interact with the Decision Model and Profiles in operating the Inference Mechanism (Figure 5.7). When a decision-maker uses the system, the Inference Manager determines the context for that use. The context is defined by the status of the decision-maker, the decision, and the domains to which the decision belongs. The status of the decision-maker includes the personality type of the individual, whether that person has used the system before and whether other people of the same personality type have used the system before. The status of the decision includes whether this decision has been supported using the system, while the status of the domain is determined on whether a decision of this domain has been supported previously.

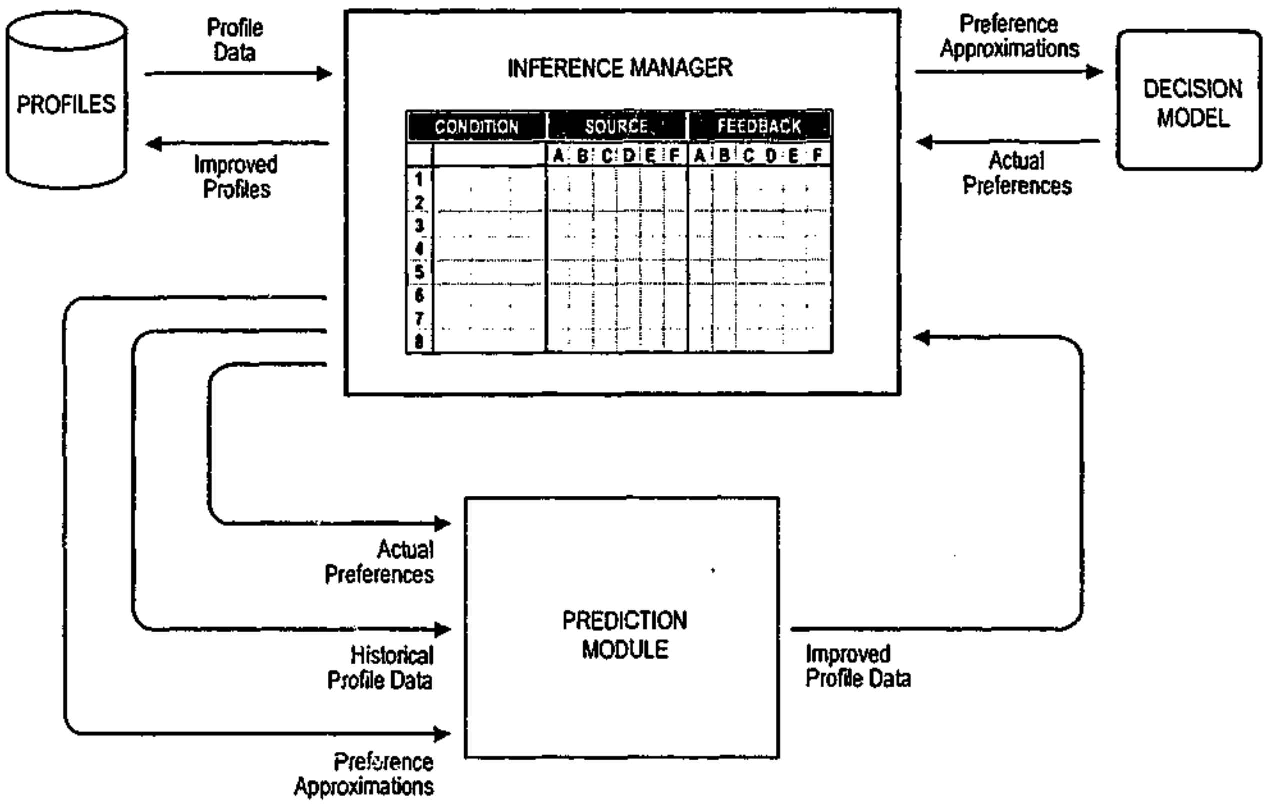

Figure 5.7: Functional view of the inference mechanism

Depending on the context, the Inference Manager directs the assembling of preference approximations to be presented to the decision-maker. The relevant criteria are also listed. A *Context Selection Table* that is built-in to the Inference Manager determines the approach that the Inference Manager takes. This table, elaborated in Figure 5.8, stipulates the contextual conditions and the sources for assembling the preference information based on the conditions. It also stipulates the scheme for creating or improving the profiles after the decision-maker has used the system.

CONDITION				SOURCE						FEEDBACK					
No.	New Decision-maker	New Decision Domain	New Decision	Decision-maker Profile		Stereotype Profile		Decision Profile		Decision-maker Profile		Stereotype Profile		Decision Profile	
				GEN A	DOM B	GEN C	DOM D	GEN E	DM F	GEN A	DOM B	GEN C	DOM D	GEN E	DM F
1	YES	YES	YES							C	C	C	C	C	C
2	YES	YES	NO												
3	YES	NO	YES			2	1			C	C	E	E	C	C
4	YES	NO	NO				2	1		C	C	E	E	E	C
5	NO	YES	YES	1		2				EI	C	E	C	E	C
6	NO	YES	NO					1							
7	NO	NO	YES		1		2			E	E	E	E	C	C
8	NO	NO	NO	4	2			3	1	E	E	E	E	E	E

Legend:

GEN	General profile	1...4	Priority for assembling preferences
DOM	Domain specific profile	C	Create profile
DM	Decision-maker specific profile	E	Improve existing profile

Figure 5.8: The context selection table

The priorities for assembling the preferences are indicated in Figure 5.8 as numbers in the *source* area. Priorities are decided based on where the most relevant information for a given situation exists. Most relevant is defined by the ability to generate approximations with the least amount of abstraction. If more than one profile is relevant to a given situation, combinations of profiles are used with priority given to the most relevant.

After determining the context, the decision-maker should be provided with a list of relevant available criteria. If the decision-maker decides to select criteria from the list, the respective preferences are automatically included in the model definition. It should be recalled that, as shown in the composite preference model (Figure 5.5), although some criteria are defined, their comparisons with other criteria may not be present in the profile. In such circumstance, the decision-maker should be prompted to provide the comparison for the current decision situation. Similarly, some criteria that the decision-maker wishes to include in the current model may not be in the list generated by the Inference Mechanism. The decision-maker should be allowed to add criteria to the model. When adding new criteria, pair-wise comparisons with other criteria already in the model should be performed.

Once the criteria have been selected, the decision-maker can complete the definition of the decision model, including alternatives and criteria scores for those alternatives. In this process, the criteria comparisons generated by the system may also be changed by the decision-maker to reflect new circumstance. If the decision was previously defined, such detailed definitions may also be accessed from the profiles. The decision-maker can use the operations provided in the decision model to manipulate and evaluate various aspects. When the user is satisfied with the model organisation, the Inference Mechanism has the task of enhancing the existing profiles to reflect the preferences selected for the current decision. New profiles may also be created.

The profiles to be improved or created are ascertained with reference to the *feedback* section of the *Context Selection Table*. Once the recipients of feedback are decided, the *Prediction Module* has the task of combining previous profile values with new preference values. The result of this process can be used to provide approximations for subsequent decision support instances. The raw values supplied by the decision-maker should only be included in newly created profiles.

Combining existing profiles with new ones is similar to time-series analysis. Simple mathematical operations such as the *arithmetic mean* provide a very basic mechanism to combine profile information. The complex trend in how the preference to a single pair of variables changes over decision instances cannot be predicted easily as the shape cannot be pre-defined. Since the differential study showed that some characteristics remain relatively stable across decision-makers, the *mode* of the comparisons should have a considerable influence in prediction. Therefore the *Prediction Module* should consist of a sophisticated analysis and prediction mechanism.

The inputs to the prediction exercise include the existing comparison value in the profile, the new preference given by the decision-maker (if the current prediction was changed) and historical information on the changes in the comparison value for this pair of variables. By having access to this information, it is also possible to determine errors involved in prediction. Error figures can also be an input to the prediction exercise. Similar predictions should be performed on every pair of criteria, in every profile that is relevant to the current decision. The results of this process should be reflected in the Profiles.

As the number of feedback loops increase (with the use of the system), the approximations can be expected to become closer to the decision-maker's actual preferences. This is the primary goal of building systems that reflect this architecture.

5.6 The active monitor

The major focus of this architecture is to facilitate building adaptive decision support system generators. However, adaptation by itself does not increase the level of support provided by the system. The end goal of adaptive systems is to provide support that goes beyond the passive toolbox approach. This approach entails understanding human decision making and providing more interventionist support where the opportunity exists; support systems are seen as modifiers of the decision making process, with the decision-maker still maintaining control over the exercise. Terms such as intellectual support (Keen, 1987) and active support (Jelassi, Williams and Fidler, 1987; Manheim, 1988) are used to describe this manner of decision support.

The Active Monitor is introduced into the architecture to illustrate the possibilities of active support within the personality-based adaptive system paradigm. The Active Monitor is intended to augment cognitive capabilities of decision-makers. Researchers such as Angehrn (1993), Davis and Olson (1984), Kremar and Asthana (1987), Manheim (1988), and Young (1982) have proposed some form of idea stimulation functionality in decision support systems. When making decisions, the objective is to achieve rationality within defined bounds. Cognitive limitations of humans inhibit achieving true rationality. This can occur as a result of information over-load, emotions, politics and personality biases. Avoidance of such factors is therefore an objective of using automated support tools. The Active Monitor has this objective. It can act as a 'watch-dog' that keeps track of bounds to be observed in making a decision and testing scenarios, it can have the capability of generating warnings when these bounds are exceeded, suggest problem solving strategies and generate outcome alternatives. By taking over some decision-making functionality, the Active Monitor can help reduce cognitive pressure on the decision-maker.

The Active monitor consists of a set of predefined conditions in which the decision-maker should be alerted. These conditions can relate to decision biases or maintaining consistency of decision-making. The latter is important in the adaptive systems context as, if the system is capable of adapting to individuals or personality types, it is relatively easy to identify departures from 'usual' behaviour. The ability of a system to provide warnings when inconsistencies are observed may be of utility to senior managers, the target population of this research work.

This functionality can be provided by constantly monitoring the activity of the Decision Model. If the Monitor detects any unusual preferences that are beyond the predefined thresholds, the decision-maker may be alerted. Similarly, certain biases in the model definition may also be observed by monitoring the contributions by criteria to the outcome of the decision.

The thresholds should be under the control of the decision-maker. The actual values observed are compared with the values held in the Profiles to determine departures from the norm. Hence the Active Monitor should have access to the Profiles. It is also important to provide natural language or graphical warnings that are easy to understand without much effort.

5.7 The dialogue management system

A support system will only be effective if the decision-maker understands and can make use of the functionality available in the system. The Dialogue Management System facilitates this process. The Dialogue Manager will play an important role by providing an interface between system functionality and the decision-maker. Model description, manipulation, personality information elicitation, alternative evaluation and active support alerts will all require the services of the Dialogue Manager. Mintzberg, Raisinghani and Theoret (1976) point to the existence of dynamic factors in decision processes. They propose that interrupts, scheduling delays, speedups, feedback delays, comprehension cycles and failure cycles prevent the smooth progress of the decision making process. The dialogue management component should be tolerant to this inherent dynamism of decision-making. The success of the support attempt will depend to a large extent on the effectiveness of the Dialogue Manager.

The dialogue management component does not contribute to the uniqueness of this research project. It is function that is essential in the operation of a successful decision support system and has been described in many influential decision support frameworks (Bonczek, Holspapple and Whinston, 1981; Raghavan, 1984; Sprague and Carlson 1982).

It should however be noted that all components that communicate with the decision-maker should be able to interact with the Dialogue Management System to successfully achieve their objectives. How the Dialogue Management System is implemented can vary with each implementation of the architecture. It is indeed possible to incorporate Dialogue Management functionality in other components of the architecture, without the need for an explicit component.

5.8 The profile management system

The Profile Management System is a component in the architecture that is not essential in the normal operation of a system. As described in the preceding sections, the Profiles are generator and maintained within a system without the intervention of the decision-maker or a DSS builder. This automation is essential, as the primary objective is the adaptiveness of the system.

Over-time, with increased use of the system, the Profiles have the potential to get congested. One reason for this possibility is multiple definition of the same criterion. A criterion may be assigned various labels even when they mean the same objective measure. This is especially possible, but not restricted to, in situations with multiple users of a system. This situation inhibits proper operation of the system as it prevents adaptation, even when the preference information is available. It can also lead to unnecessary growth in profiles. Even without the problem of multiple definitions, the Profiles have the potential of uncontrolled growth.

Such problems can be corrected by periodically maintaining the Profiles in a system. Although this process may be performed manually, it can get tedious in a large system. Therefore there is a need for a component in the architecture that is capable of identifying problems in Profiles and corrects them. How this capability is implemented can vary. One such implementation may use 'Intelligent agents'.

In addition, the Profile Management Component has the task of performing simple database operations such as erasing profiles on request and managing records of decision makers.

This chapter was devoted to describing the first of the two step process in developing an adaptive decision support system generator. This step entailed investigating the conceptual framework required to utilise the concept of adapting based on personality. A system architecture that achieves this objective was articulated and the components were described. The next step is to implement a prototype system that is based on the architecture. Developing such an artefact is the subject of the next chapter.

Chapter 6

ADAPTOR, an Implementation of the Architecture

This chapter describes the implementation of a system that is based on the architecture illustrated in the previous chapter. The prototype built was named as ADAPTOR. The intention of developing a prototype system is to demonstrate the feasibility of the architecture. Such a prototype also facilitates the evaluation of the *concept* that was the subject of the research project. Thus, the research question pertaining to this stage of the projects is:

Q3. **How can a prototype computer-based system be built to implement the Adaptive Decision Support System Generator Architecture?**

How components of the system reflect the architecture is the aspect of interest in this stage of the research project. Hence, in describing the implementation of the architecture, a specific system development life-cycle approach is not followed; rather, the modular nature of the architecture is used to describe the development of the system.

The description in this chapter is limited to essential implementation aspects. Detailed instructions on how to use ADAPTOR are provided in the user manual. The user manual of the system and the program code listings are provided as appendices to the thesis.

6.1 The technology

Traditionally, decision support system developers have adopted the view that whatever appropriate hardware technology should be used without limiting to specific technologies. Most DSS architectures reflect the technological limitations of the era in which they were developed. However, there has been reluctance to adopt some software technologies that have been viewed as philosophically different from the passive approach of DSS. Researchers have seen this traditional approach as a limiting influence on decision support and in the advancement of the discipline (Alter, 1992).

This research project is not limited to a *passive* approach to decision support; indeed the Adaptive DSSG Architecture makes a conscious attempt at providing *active* decision support. Hence, software technologies are not restricted. Any appropriate software and hardware technology, regardless of their philosophical underpinning are considered as candidates for the implementation of the architecture. The primary objective in selecting technology is to achieve the objectives of the architecture.

Since the support of senior managers is the aim of this research project, technology that is accessible to such a constituency is also important. Hence, a personal computer hardware platform was selected. The software selection process was limited to software that can be implemented on personal computers. Since this is an attempt to build a DSS generator, currently available DSS shells were not suitable. Therefore, the software selection process focused on the selection of a suitable programming language. Most programming languages provide the constructs to build the basic functionality required of an implementation of the architecture.. However, one important criterion is the ability to provide a graphical interface. Hence, the search was limited to software that works on the Microsoft® Windows™ graphical user interface (GUI) platform. This platform is also widely used by the target constituency of the project. The GUIs allow the use of input devices that require little keyboard input. This is beneficial in supporting senior managers. Graphical methods may also be helpful in effectively communicating the results of analysis to decision-makers.

Microsoft® Visual Basic™ version 3.0 was selected as the implementation language for ADAPTOR. Visual Basic facilitates the exploitation of the graphical user interface capabilities of Windows, while providing a versatile programming environment. It is a 'pseudo' object-oriented, event-driven language. Visual Basic is also capable of communicating with other software products, and is well supported by major off-the-shelf software developers.

The compatibility with other products is considered important as there may be a need to interact with other pre-packaged utilities to provide the profile building/learning capabilities envisaged in the Adaptive DSS Generator Architecture. Use of pre-packaged utilities can reduce the programming effort required in building ADAPTOR. The database schema and program code used in ADAPTOR are provided in Appendix D.

6.2 Implementing the decision model

As described in the previous chapter, the Decision Model is the central component of the architecture. Similarly, an implementation of the architecture should also place emphasis on the Model. Other components should support the definition and manipulation of a decision model by the decision-maker. As prescribed in the architecture, the Model Base should consist of different forms of linear multi-criteria models that can be selected depending on the current decision situation. A common requirement for the models in the Model Base is the ability to accept alternatives, criteria, criteria scores and weights as inputs. In addition, the models should facilitate a consistent graphical interface and allow relevant operations to be performed on them.

ADAPTOR implements two representations of linear multi-criteria model; multiple alternative and binary. In a multiple alternative situation, the decision-maker has to select between many pre-defined outcomes. Binary decisions are a special instance of selecting between alternatives. Binary decisions have only two possible outcomes. This can be either selecting between two distinct outcomes, or deciding whether to implement a particular strategy. As discussed in Chapter 2, for the purposes of this research, binary decisions are defined in terms of situations where a particular alternative is pursued or discarded. Hence they take the form of 'yes' or 'no' decisions.

A linear weighted sum approach is used to evaluate decision alternatives in both binary and multiple-alternative decisions. The formal expression of the general model is as follows:

The set of Alternatives is denoted as A $a_i \in A$, $i = \overline{1,k}$

The set of Criteria (variables) is denoted as C $c_j \in C$, $j = \overline{1,l}$

The evaluation of each alternative is given by $a_i = \sum_{j=1}^{l} (s_j w_j)$

Where, *s* is the score, and

w is the weight

The outcome of the decision, $Z = \{a_i | a_i \in A\}$, $i = \overline{1,k}$

a_k is the highest a_i.

a_i is assumed to be deterministic.

The weights for the criteria in the decision situation are determined by the collective set of preferences to those criteria.

The weight of a criterion $W_j = f(P(c_1, c_1), \ldots, P(c_l, c_l))$

where,

P is the preference between c_x, c_y

Hence, changing the criteria preferences or the score given for a criterion can vary the evaluation of an alternative. The organisation of the model can be graphically illustrated as in Figure 6.1.

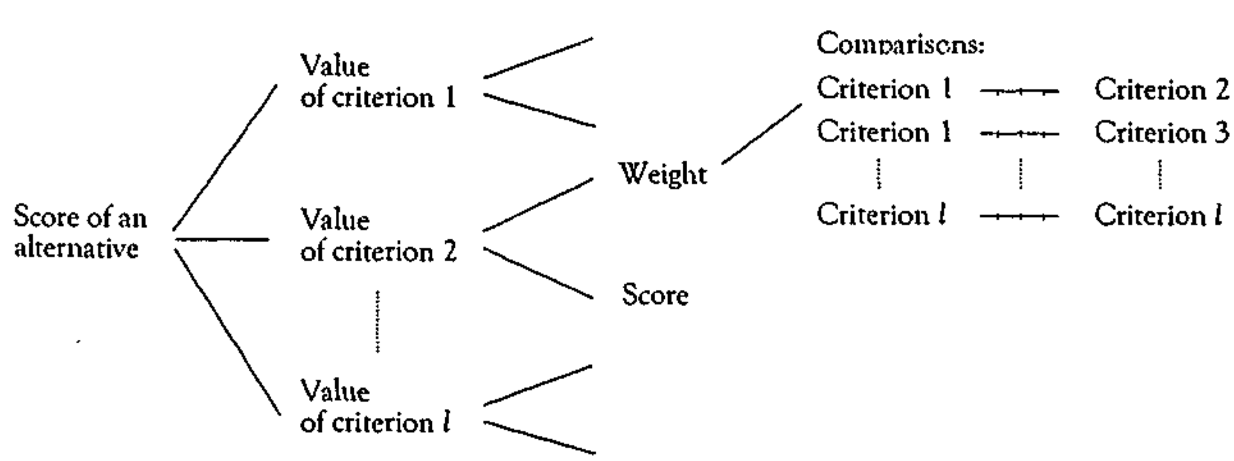

Figure 6.1: Evaluation of an alternative

6.2.1 Multiple-alternative decision representation

This model is implemented in its generic form in the multiple-alternative decision representation in ADAPTOR. The organisation of the model interface is analogous to a spreadsheet layout. However, graphical controls and feedback is provided to enhance the basic spreadsheet layout as shown in Figure 6.2. The alternatives are displayed as column headings across the top of the screen, while criteria that are used to evaluate the alternatives are listed as a column on the left-hand side of the screen. At the intersection between a criterion and an alternative is the *value* of that criterion for the respective alternative. The criterion score for an alternative can be varied by clicking on the spin buttons at the intersection between the two. The score given is graphically shown as a percentage fill as well as a number between 0 and 9. The weight used for the calculation of the value is listed beside each criterion. The transformation of criteria preferences to weights is discussed later in this section. The total score of an alternative is simply the weighted sum of the values of all the criteria for that alternative. The order of the scores obtained by alternatives is indicated at the top beside each alternative. The best alternative is further highlighted with a coloured bar.

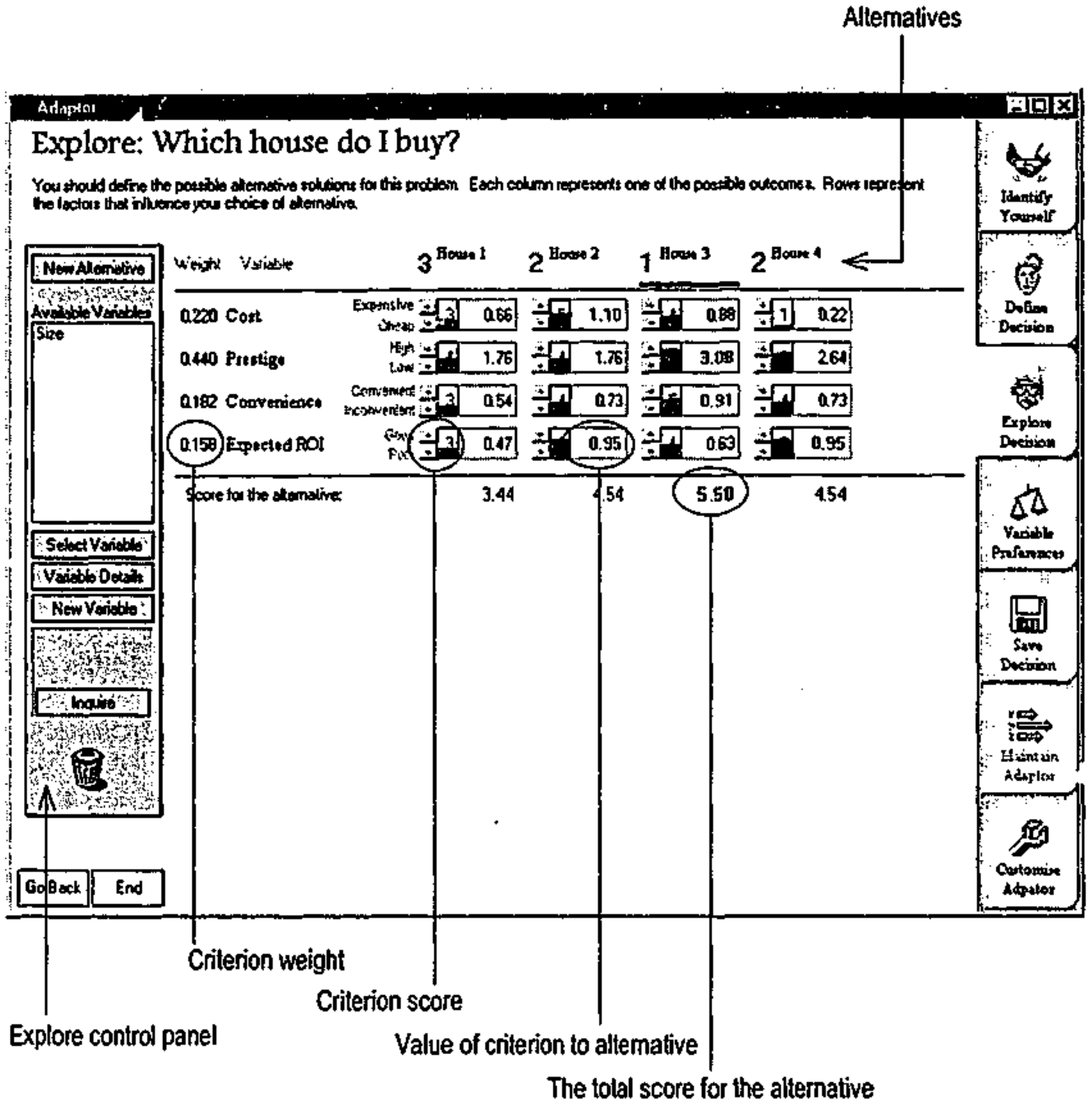

Figure 6.2: Multiple-alternative decision evaluation screen

When a decision-maker uses ADAPTOR to support a decision instance, the criteria (variables) relevant to the current situation are determined by the *inference mechanism*. This is achieved by referring to the *context selection table* that specifies the source profiles. The decision-maker can select variables that are listed in the *explore control panel* or define new variables. If existing variables are selected, the preferences for those variables are also retrieved from the relevant profile. This preference information is then used to calculate the criteria weights for the current decision situation.

New variables are defined on a window similar to Figure 6.3 In addition to the name, description and the domain of the variable, labels are also required to indicate the high and low extremes of the possible scale for criterion scores. These labels are displayed on the evaluation screen previously shown. The domain of a variable is used to determine the relevance of a stored profile.

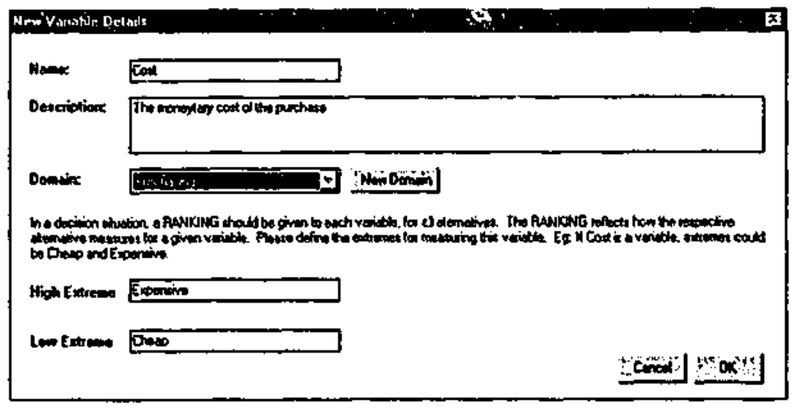

Figure 6.3: Variable definition window

If there are other variables already defined in the model when a new variable is added, the window is extended as in Figure 6.4 to obtain preference comparisons between the new variable and the existing variables. The comparisons are presented to the decision-maker one at a time, until all variables have been compared to each other.

Variable comparisons are done using an adapted version of Saaty's (1980) semantic comparison scale. Saaty's basic nine-point scale is a one-way scale which ranges from *equally preferred* to *extremely preferred*. The scale used in ADAPTOR is a two-way scale that is independent from the direction in which the two variables have been presented. However, internally this is transformed into a ratio scale value between 9 to 1 to 1/9. Hence it is similar to Saaty's original scale. How the comparisons are converted into criterion weights is explained later in this section.

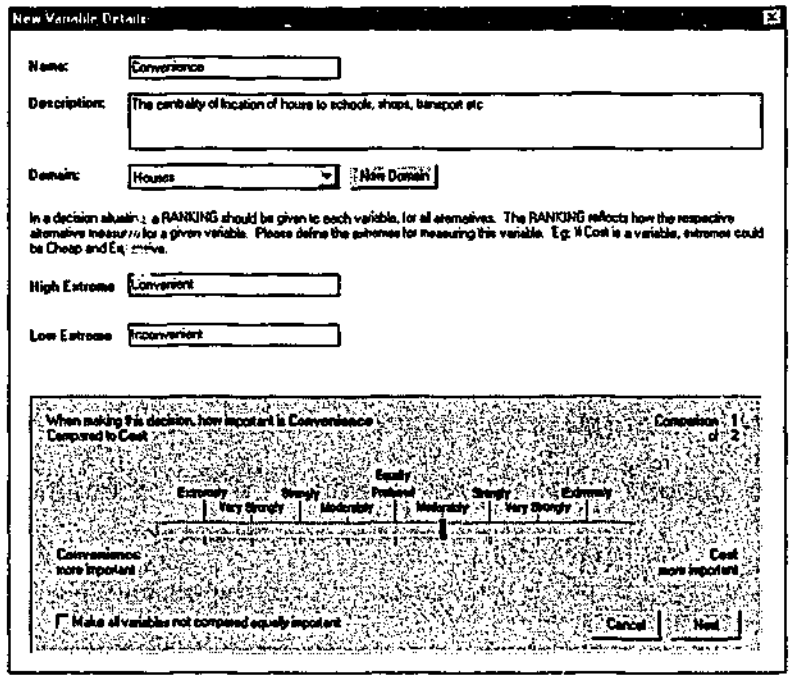

Figure 6.4: Extended variable definition window

If the source profile is partially completed without all possible comparisons, new comparisons are sought from the decision-maker for those variables that do not have values in the profile. In the decision evaluation process the decision-maker can also change the comparisons given to any variable. The new comparisons are included in the relevant profiles at the end of the session, where the decision-maker indicates that the organisation of the model components is satisfactory.

6.2.2 Binary decision representation

Binary decision representation uses the same underlying principles employed in the multiple-alternative representation. However, there are differences in the interface and the decision model implementation. The representation is adopted from Lewin's (1952) field theory, as discussed in Chapter 2. This representation is based on the existence of a *quasi-stationary equilibrium*, held in position by two sets of opposing forces. Hence, there is a need to classify the decision criteria into driving and restraining groups. This is analogous to positive and negative utility.

The equilibrium (the decision) in the in the middle of the opposing forces can be shifted by changing the relative total values (forces) of driving and restraining criteria. A total driving force that is stronger than the total restraining force shifts the decision towards the perceived positive outcome, while a stronger restraining force shifts the decision towards the perceived negative outcome. Hence the possible outcome of the decision process lies on a continuum from the positive to the negative outcome. Instead of having many possible alternatives, this is representative of either accepting or rejecting an alternative (*yes* or *no*). The preferences to criteria expressed through weights are not affected by this representation as the importance of a factor is independent from the direction of its influence. This arrangement of the model can be expressed mathematically as follows:

The set of Criteria (variables) is denoted as C $\quad c_j \in C,\ j = \overline{1,l}$

The set of driving criteria is denoted by D $\quad d_x \in D, D \subseteq C, x = \overline{1,m}$

The set of restraining criteria is denoted by R $\quad r_y \in R, R \subseteq C, r = \overline{1,n}$

The total driving force is given by $\quad F_d = \sum_{x=1}^{m} (s_x w_x)$

The total restraining force is given by $\quad F_r = \sum_{y=1}^{n} (s_y w_y)$

Where, *s* is the score, and

w is the weight

The total force in the force-field, $\quad F = F_d + F_r$

If $F_d > F_r$ then the perceived positive outcome is the decision recommendation.

If $F_r > F_d$ then the perceived negative outcome is the decision recommendation.

As can be seen from the mathematical expression, this is an adaptation of the basic linear weighted-sum approach, with prominence given to the force-field analogy. The decision exploration screen for binary decisions is similar to Figure 6.5. The explore control panel on this screen is identical to the multiple-alternative screen, with the exception of not having a facility to add alternatives. Criteria are listed on either side of the screen based on the driving and restraining classifications. The decision-maker may change the direction of the influence of a criterion at any time by simply dragging it to the opposite side of the screen. ADAPTOR has the capability of automatically interchanging the labels given to the high and low extremes of the range of scores for a criterion. The decision-maker may also override this automatic interchange facility. Clicking on the spin buttons next to the criterion name can change the score given to a criterion. The score is graphically shown as a percentage-fill. The weights are also listed beside the criteria.

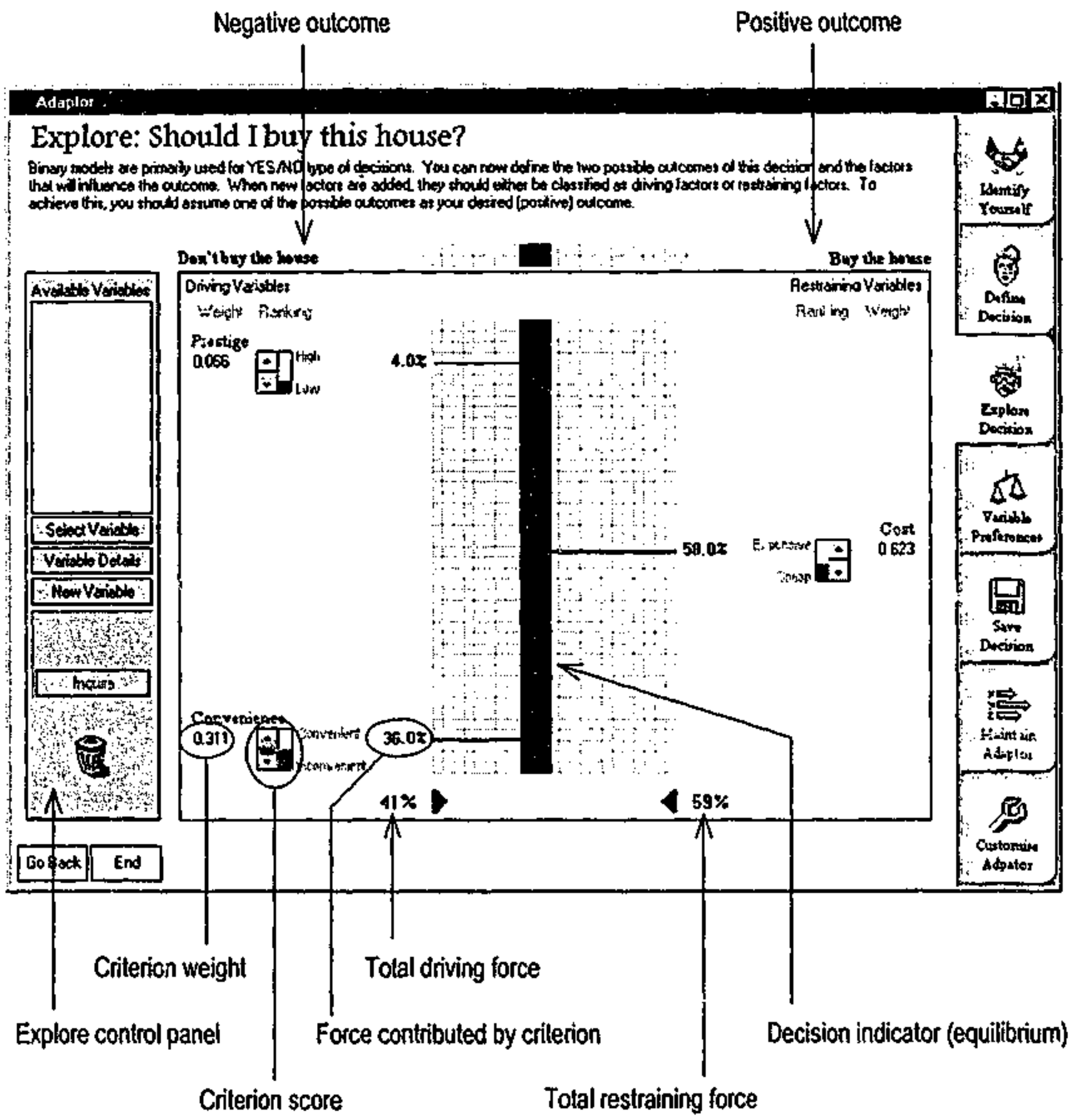

Figure 6.5: Binary decision evaluation screen

Different decision scenarios can be evaluated by changing the scores given to criteria or by changing the preferences. In addition to the movement of the decision indicator and the numerical figure, the strength of a force contributed by a criterion is graphically illustrated by varying the thickness of the connecting line. Criteria (variables) are defined identically to the multiple-alternative representation. Criteria already available in profiles may also be selected from the list available on the *explore control panel.*

In both multiple-alternative and binary decision representations, criteria can be deleted by dragging to the trashcan. These deleted criteria are added to a pool from which they can be recalled. These criteria can be recalled by double clicking on the criterion name in the explore control panel. The preference comparisons are retained even if criteria are deleted from the working model.

6.2.3 Transforming criteria preferences into weights

As discussed in the previous chapter, the profiles are held in the form of criteria preference models. However, the decision model expects criteria weights as the expression of importance of criteria. Even when new criteria are added, importance is expressed as pair-wise comparisons. Therefore, regardless of whether preference information is obtained directly from the decision-maker or from profiles maintained in the system, some transformation has to be performed.

Pair-wise comparisons are performed on a nine-point scale similar to Saaty's (1980) semantic scale. Hence the preference between two criteria ranges from 1 to 9 or their reciprocals. Comparisons between the criteria relevant to a particular decision result in a matrix. However, the profiles maintained in the system only contain one-half of the comparison matrix. The other half is completed by calculating the reciprocals of the relevant comparisons. This is possible because logical consistency is assumed. The vector priorities for criteria measured on a ratio scale are then established, as shown below:

$$\begin{pmatrix} c_1/c_1 & c_1/c_2 & \cdots & c_1/c_l \\ c_2/c_1 & c_2/c_2 & \cdots & c_2/c_l \\ \vdots & \vdots & & \vdots \\ c_l/c_1 & c_l/c_2 & \cdots & c_l/c_l \end{pmatrix} = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_l \end{pmatrix}$$

Where, criterion $c_j \in C$, $j = \overline{1,l}$ and w_j is the priority

The vector values add up to unity. In establishing vector priorities, Saaty recommends '...raising the matrix to a sufficiently large power, then summing over the rows and normalising to obtain the priority vector. The process is stopped when the difference between components in the priority vector obtained at the kth power and at the $(k + 1)$st power is less than some predetermined small value'.

ADAPTOR implementation solves the matrix by normalising the elements and then averaging over rows. In most cases the results obtained in this method are identical to solving the eigenvector. However, this strategy can lead to preference reversals in large matrices. This possibility is compromised as the current implementation only supports up to 12 criteria for a single decision situation. Furthermore, the preference matrices are only used as approximators of the decision-makers preferences and not as strict basis for problem solving.

The priorities in the vector are regarded as the weights of the respective criteria that are input to the decision model. As added assistance to decision-makers, the consistency of their comparisons are indicated, even though ADAPTOR does not impose consistency. This is achieved by calculating a *consistency ratio*. A higher consistency ratio indicates a low consistency while a low number indicates good consistency. ADAPTOR shows the level of consistency to its users with a colour-coded sliding indicator.

The first step in determining consistency is to construct a *weighted sum vector* by multiplying the comparison elements by the respective vector priorities (weights) as shown below:

$$\begin{pmatrix} c_1/c_1(w_1) & + & c_1/c_2(w_2) & + & \cdots & c_1/c_l(w_l) \\ c_2/c_2(w_1) & + & c_2/c_2(w_2) & + & \cdots & c_2/c_l(w_l) \\ \vdots & & \vdots & & \cdots & \vdots \\ c_l/c_1(w_1) & + & c_l/c_2(w_2) & + & \cdots & c_l/c_l(w_l) \end{pmatrix} = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_l \end{pmatrix}$$

Where, S is the weighted sum vector $s_j \in S$, $j = \overline{1,l}$ and w_j is the priority (weight).

A consistency vector is then constructed by dividing the weighted sum vector by the weights:

$$\text{Consistency vector} = \begin{pmatrix} s_1/w_1 \\ s_2/w_2 \\ \vdots \\ s_l/w_l \end{pmatrix} = \begin{pmatrix} k_1 \\ k_2 \\ \vdots \\ k_l \end{pmatrix}$$

Where, K is the consistency vector $k_j \in K$, $j = \overline{1,l}$

$$\text{Consistency index, CI} = \frac{\lambda - n}{n - 1}$$

Where, λ is the average value of the consistency vector.

n is the number of criteria.

The final step is to calculate the consistency ratio, $\mathrm{CR} = \dfrac{\mathrm{CI}}{\mathrm{RI}}$

Where, RI is a random consistency index that is looked up in a table generated from a large sample of randomly generated comparison matrices. The algorithm implemented in ADAPTOR is taken from Saaty (1995). The pair-wise comparison matrix and the consistency of comparisons are accessible in ADAPTOR in a screen similar to Figure 6.6. The decision-maker is given the facility to amend the comparisons by double clicking on variable names. Changing preferences on this screen is advantageous because of the immediate feedback on consistency.

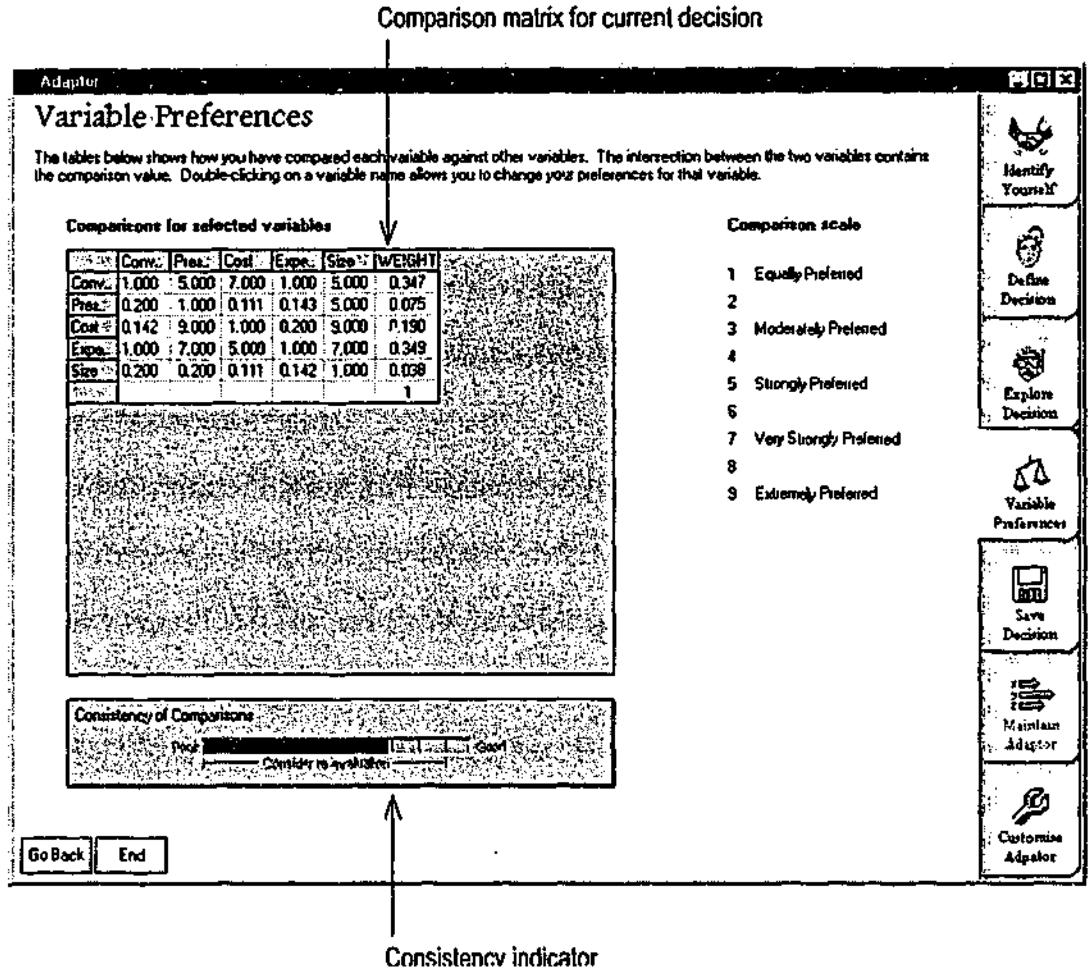

Figure 6.6: Criteria preference screen in ADAPTOR

6.3 Implementing the Profiles

Profiles are the structural components in the architecture that retain information between decision instances. Retention of information is needed for several reasons. Since the architecture supports DSS generators, storing and recalling defined decisions is essential. In addition, this architecture is specifically designed to build adaptive support systems that are based on criteria preferences. Criteria preferences evolve between decision instances. Hence, criteria information has to be retained so that the system is able to adapt to new circumstances.

The Profiles consist of several different types of information to support the different functions it facilitates. The Profiles in ADAPTOR maintain the following information:

- Criteria preference information for decision-makers, decisions and stereotypes.

- Criteria definitions: names, descriptions, measurement scales and domain assignments.
- Decision definitions: names, descriptions, domain assignments, criteria lists, and alternative lists.
- Decision alternative definitions: names and descriptions.
- Decision evaluation results.
- Domain definitions: names and descriptions.
- Decision makers' identification details, interface and warning threshold preferences.
- Personality types (MBTI) and their descriptions.

The majority of this information is held in a normalised relational database. The approximate database schema is shown in Figure 6.7. Some relationships and the cardinality of relationships in the database are not shown in this figure to reduce complexity. The dashed-lines are not actual relationships, but links that show proximity in the implementation method; they link tables that contain closely related information.

ADAPTOR includes a password system that restricts access to personal information such as the personality type of users. To safeguard the privacy of such information, the decision-maker details are held in a flat-file that is independent from the database. This mechanism also restricts access to the raw criteria preferences of individuals.

As discussed in the previous chapter, criteria preference information can be organised in a hierarchy that represents the level of abstraction from the raw values supplied by the decision-makers (shown in Figure 5.6). The least abstract or raw criteria preferences are held in the *Decision-Decision*-maker profile. ADAPTOR does not implement *the Stereotype-General profile* because of the level of abstraction in this profile would be extremely high. Provision for inclusion of such a profile has however been included in ADAPTOR, if the basic profiles indicate validity in the concept. The criteria preference models implemented are: *Decision-maker-General* (1), *Decision-maker-Domain* (2), *Stereotype-Domain* (3), *Decision-General* (4) and *Decision-Decision-maker* (5). Each of these profiles consists of a collection of database table as shown in Figure 6.7.

The criteria preference models are conceptually matrices of comparison values. However, the dynamic nature of the criteria preference models prevent them being implemented as fixed sized matrices. The implementation scheme should allow dynamic growth of the matrices. Hence, ADAPTOR maintains lists of criteria that have been used by each decision-maker and stereotype and for each decision. These are also segregated into domains. The comparisons between the criteria in each list are maintained in a database table independent to the relevant table that keeps the list of criteria. This scheme can be illustrated with the *Stereotype-Domain profile* (3) in Figure 6.7. The criteria (variables) used by each personality type are stored in the *Stereotype_Domain* table while the comparisons for those criteria are stored in the *ST_Domain_Comparisons* table. The Inference Mechanism is capable of building the *Stereotype-Domain* comparison matrix for a given personality type and a domain, based on a search of these two database tables. Embedded Structured Query Language (SQL) routines are utilised for database queries in ADAPTOR.

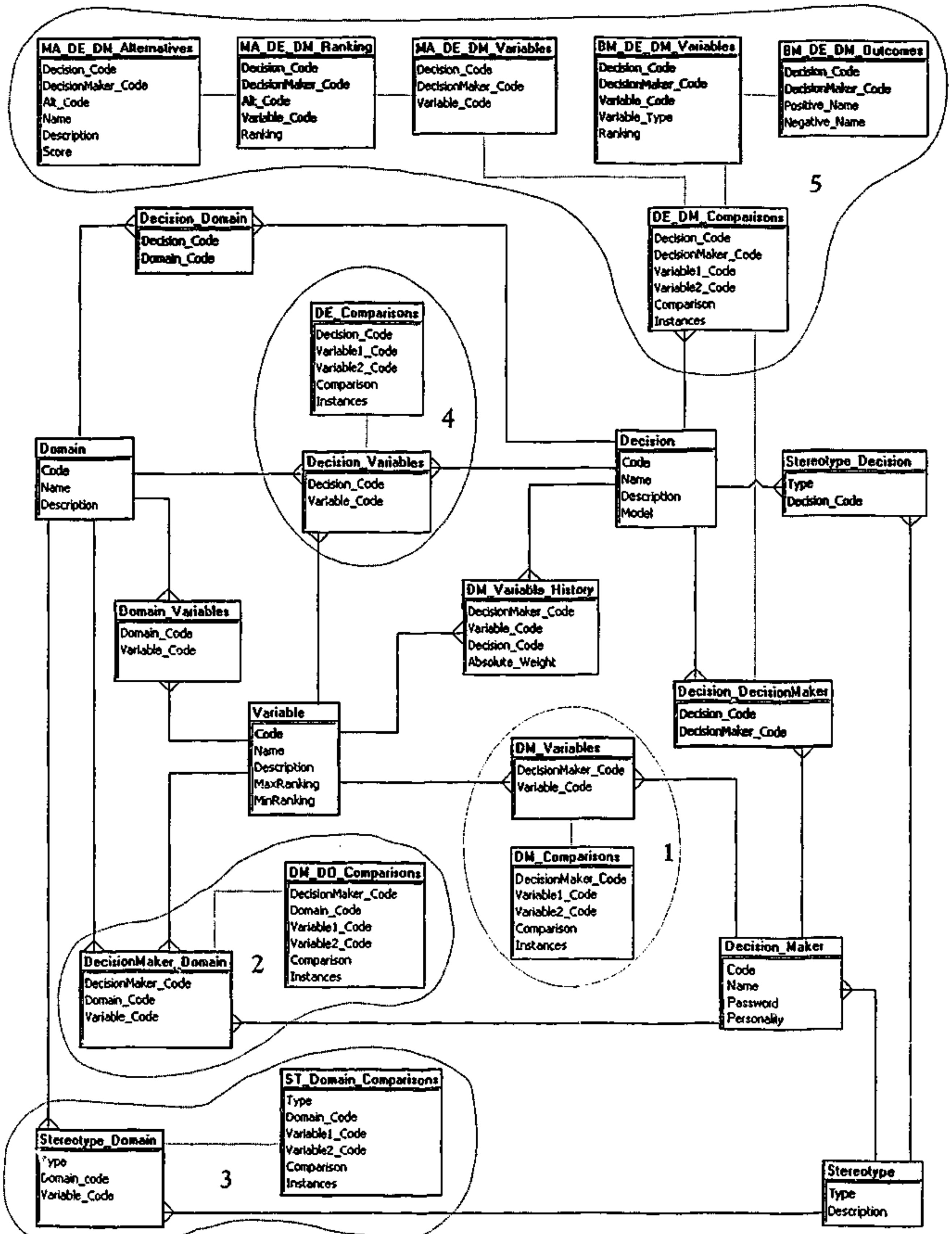

Figure 6.7: Database schema for Profiles in ADAPTOR

It should be noted that the *Decision-Decision-maker* profile is more extensive than other types of profiles. This profile consist of raw criteria comparisons given by a decision-maker for a given decision instance. In addition, this profile also contains all the information needed to recall the decision instance as it was stored by the decision-maker.

This information includes the alternatives and criteria relevant to the situation, the criteria scores for alternatives, and in the case of binary decisions, the direction of the influence of criteria (*driving* or *restraining*). Access to the *Decision-Decision-maker* profile is restricted to the owner of a decision instance.

Creation and manipulation of profile information is handled by the Inference Mechanism discussed in the next section.

6.4 Implementing the Inference Mechanism

The major activities performed by the Inference Mechanism are determining relevant criteria preferences to a given situation, and improving the profiles already in the system as a result of a decision-maker using the system. Therefore, the adaptive capabilities of a system are controlled by the Inference Mechanism. As described in the previous chapter, the Inference Mechanism consists of two major components: the *Inference Manager* and the *Prediction Module*. These components can also be distinguished in the ADAPTOR implementation.

The Inference Manager coordinates the activities of the Inference Mechanism by determining relevant sources of criteria preferences for a situation. It also dictates which profiles are improved as a result of an interaction with a decision-maker. Hence, it acts as a filter on the passage of preference information between the working Decision Model and the stored Profiles. At the core of the Inference Manager is the *Context Selection Table* (illustrated in the previous chapter - Figure 5.8) that is implemented as a series of IF...THEN rules in ADAPTOR.

When a decision-maker defines a decision to be supported using ADAPTOR, the system determines three conditions:

- whether the current decision-maker has used the system previously,
- whether the current decision has been supported previously, and

- whether the domain to which the decision belongs has been previously used with the current decision or another decision.

The conditions are evaluated by searching the Profiles stored in the database. Depending on the outcome of evaluating these possibilities, ADAPTOR varies the source for assembling a list of relevant criteria for the current decision, as specified in the Context Selection Table. Multiple sources of criteria can also be employed. If multiple sources are available, the priority between those sources is stipulated in the Context Selection Table. In addition to the list of criteria, a composite criteria preference model of those criteria is built. This composite preference model is hidden from the users.

As the criteria may be assembled from many sources, common comparisons may occur. The priority stipulation in the table is used to determine the precedence. The decision-maker is then presented with the list of available criteria on the Explore Control Panel in the decision exploration screen as in Figure 6.8.

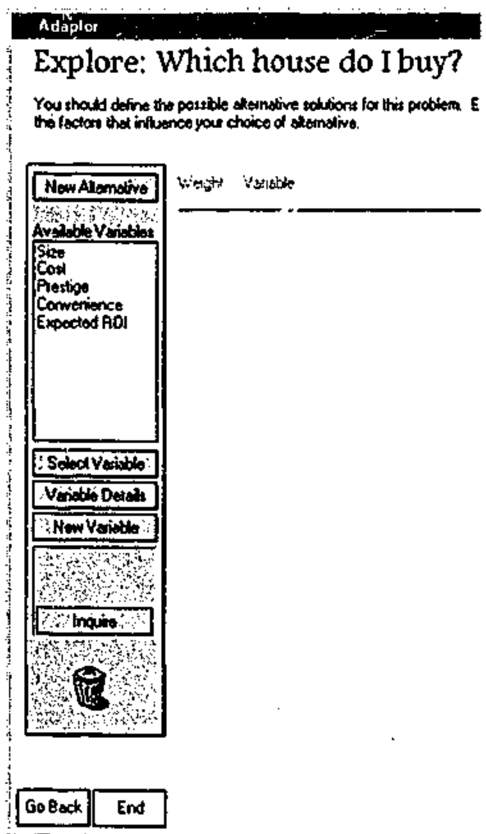

Figure 6.8: Explore Control Panel with criteria relevant to current decision

The decision-maker can make use of all or some of the criteria that are listed by double-clicking on the criteria (variable) name or define completely new criteria. When a criterion is selected, its preferences compared to other variables that have already been selected for the decision are added to the *working criteria preference model*. The working criteria preference model is available to the decision-maker to see how the weights have been calculated based on the preferences (Figure 6.6). It should be noted that the working criteria preference model is limited to the criteria that are being used by the decision-maker and does not contain all the available criteria. If some criteria have not been previously compared to each other, the decision-maker is prompted for these comparisons as shown in Figure 6.9.

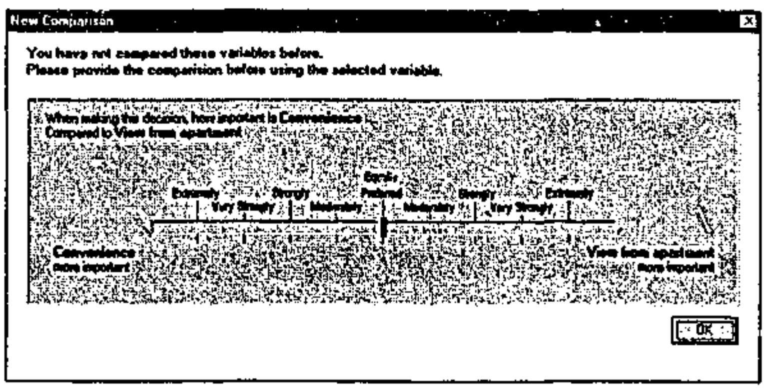

Figure 6.9: New comparison prompt

The approximation of the preference between a given pair of criteria (as retrieved from the profile) is $P(c_x, c_y)$, also expressed as $P_{x,y}$ where criterion $c_j \in C$, $j = \overline{1, l}$.

The decision-maker may change $P_{x,y}$ to a new value $\overline{P_{x,y}}$, forming a new working criteria preference model. $\overline{P_{x,y}}$ is the value used in the current decision situation. Note that if the decision-maker is satisfied with the approximation provided by the system, $P_{x,y}$ = $\overline{P_{x,y}}$.

As seen in Figure 5.7 in the previous chapter, the *Prediction Module* of the Inference Mechanism requires three inputs - actual preference between a given pair of criteria

($\overline{P_{x,y}}$), historical preference to those criteria ($\overline{P_{x,y}}_{-1}, \overline{P_{x,y}}_{-2}$, etc.), and the approximation provided by the system ($P_{x,y}$).

The ADAPTOR Prediction Module consists of an artificial neural network. The above values are passed onto a neural network with a five-layer structure. This is achieved by establishing a *dynamic data exchange* link between the Visual Basic™ program and an Excel™ spreadsheet. The neural network software, Neuralyst™ is implemented on the Excel spreadsheet platform as a collection of macro commands.

The structure of the neural network used for preference prediction is as follows:

Inputs: the error term between $P_{x,y}$ and $\overline{P_{x,y}}$

historical values $\overline{P_{x,y}}_{-1}, \overline{P_{x,y}}_{-2}, \ldots, \overline{P_{x,y}}_{-20}$

Target: actual comparison $\overline{P_{x,y}}$

Layers: five

Neurones in each layer: 21, 16, 11, 5, and 1

The output $\overline{P_{x,y}}_{+1}$ is passed back to the Inference Manager to be stored in profiles as specified in the Context Selection Table. The neural network is trained using only the past 20 actual comparisons given by the decision-makers. Each time a new prediction is made, the oldest value is dropped from the series (first in - first out). However, the neural network is not initialised between prediction instances. Hence, the learning from the 'dropped' values is retained throughout the life of the system. The structure of the network was decided to optimise the prediction accuracy, by performing repeated experiments on arbitrary series of numbers.

Before being passed into the neural network, the comparison values are converted into symbols ranging from 1 to 17 representing 1 to 9 and their respective reciprocal values of 1/2 to 1/9. This conversion is performed so that the neural network can identify sufficient intervals between adjacent values. This is an important issue when dealing with reciprocals that have fractional values. The symbols are converted back into their respective ratio scale values upon the completion of the prediction routine. Since this is a symbolic manipulation, the meaning of values is not affected in anyway.

ADAPTOR maintains four separate neural networks representing the *decision-maker-general*, *decision-maker-domain*, *stereotype-domain* and *decision-domain* profiles. Within the first three of these networks, it is also important that prediction values are not combined for different decision-makers and different personality types. Hence, the criterion sets for individuals and personality types are grouped. Only the relevant individual or stereotype values are used in a single prediction cycle. The *decision-decision-maker* profile does not need any prediction as it holds the raw values in a state that the owners could recall them.

Although the above explanation encompasses the general functionality of the Prediction Module, ADAPTOR does not utilise the neural network prediction mechanism to predict criteria comparisons for pairs of criteria that have less than ten instances. This is because less than ten training items may not be sufficient to obtain a reliable prediction from a neural network. In the absence of at least ten instances, the *mean* of the available series is used as the prediction. Mean is taken in preference to regression analysis, as it is a superior predictor in the absence of a clear relationship between values in the series (Grimm and Wozniak, 1990). It is not prudent to expect a clear relationship in a series with very few items.

6.5 Implementing the Active Monitor

The implementation of the Active Monitor in ADAPTOR is aimed at illustrating the active support potential of an adaptive decision support generator. Hence, it is limited to provision of basic active decision support. The Active Monitor has the function of constantly analysing elements of the model to identify predefined conditions. The conditions that ADAPTOR scans for are deviance from 'usual' preferences to criteria and in the case of binary decisions, uneven distribution of forces.

When a decision-maker selects a criterion to be used in the current decision situation, the Active Monitor determines the *mean* and the *standard deviation* of the absolute weights given to that criterion by that decision-maker in previous decision instances. Recall that the absolute weight (priority) for a criterion is obtained by solving the criteria preference matrix. The ADAPTOR database maintains a table that records the absolute weight of criteria at the time the decision-maker indicates satisfaction with the decision model organisation. The mean and the standard deviation are calculated using these values held in the table. If the weight calculated for the current decision scenario through solving the current criteria preference model is significantly different from the mean of the historical values, a flashing icon is displayed on the *explore control panel*. The decision-maker is able to get an explanation of the warning by selecting the *Inquire* button or double-clicking on the flashing icon. The warning explanations are provided as natural language statements as shown in Figure 6.10.

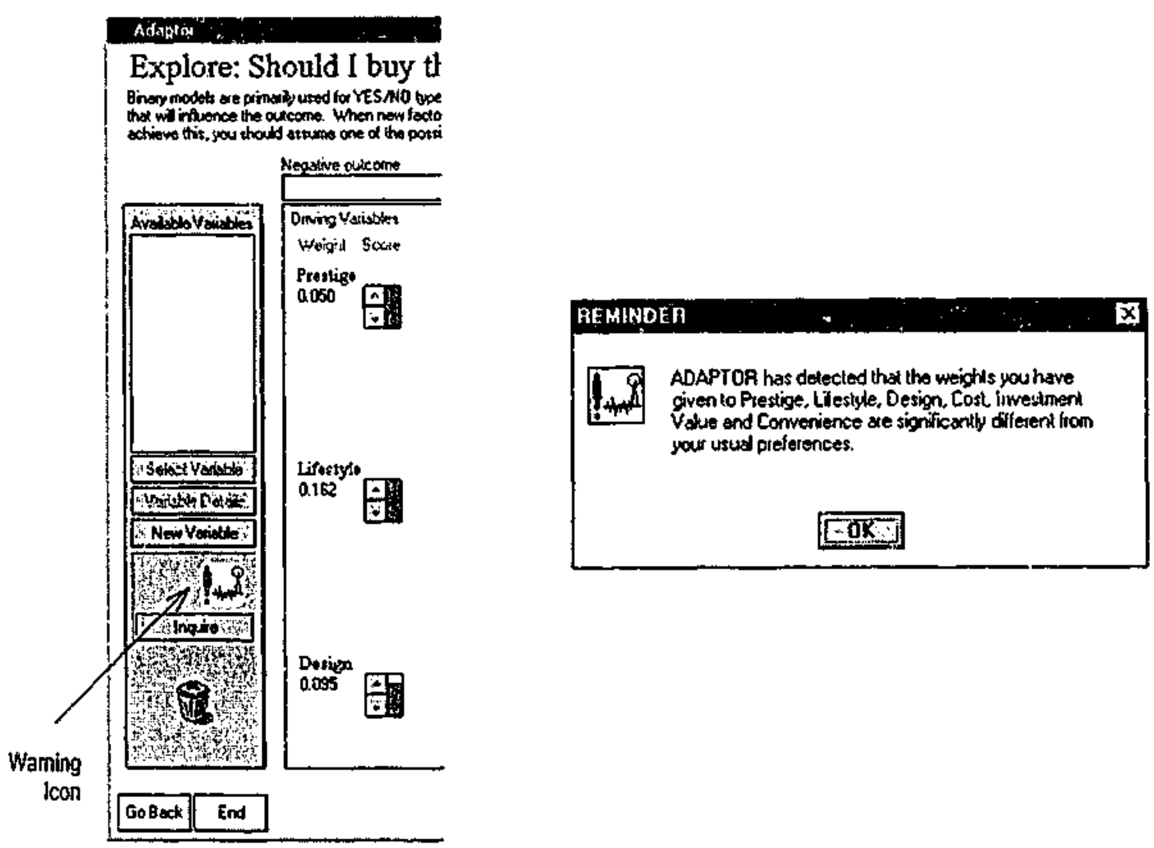

Figure 6.10: Warning Icon and Explanation

The decision-maker can see the trend in the weights given to a particular criterion over a number of decision instances by double clicking on the respective criterion name. In addition to showing the trend, the mean priority and standard deviations are displayed on the graph that is displayed (Figure 6.11). The user may limit the graph to only instances where the criterion has been used for the current decision or get a general graph of all uses of the criterion. These graphs allow the decision-makers to understand changes in their preference structure over time, both for a particular decision and in general decision- making behaviour terms. This can be a useful cognitive feedback mechanism.

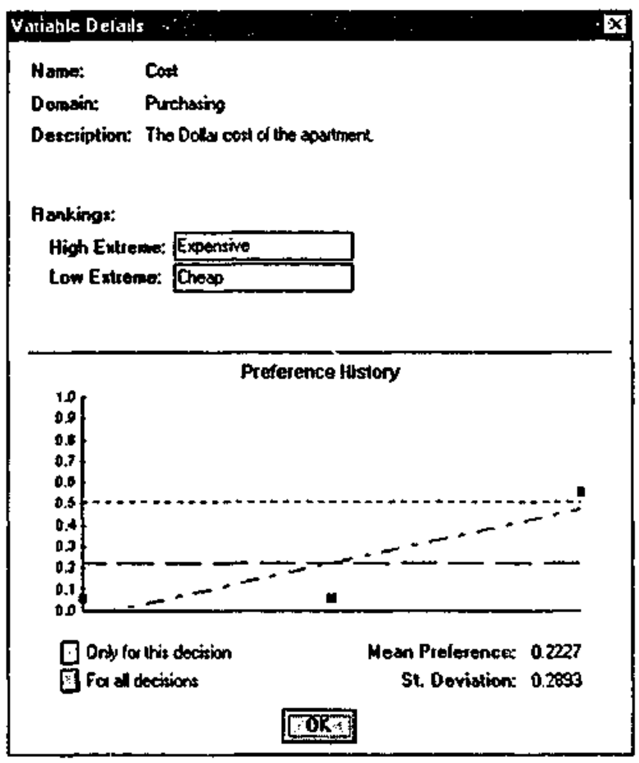

Figure 6.11: Criterion Details including Weight Trend Graph

When evaluating scenarios with binary decisions, ADAPTOR provides active support that is specific to the force-field analogy, in addition to monitoring inconsistencies in criteria preferences. This special condition is encountered when the forces contributed by elements in the force-field are uneven. The Active Monitor looks for situations where there is a large difference in percentage contributions of the criteria.

This is achieved by ordering the criteria according to the contribution they make to the force-field. If there is a large gap in the contributions, a warning is generated. However, the gap should be observed between a top minority group and a bottom majority group; there should a smaller number of criteria in the group of criteria whose contribution is significantly larger than the other criteria. This is because a larger group whose contributions are equally large will indicate a relatively even distribution.

When this conditions is observed, ADAPTOR displays a flashing icon on the explore control panel. The details of the warning can be obtained by double-clicking on the icon or selecting the *Inquire* button. The warnings provided in this instance are similar to Figure 6.12.

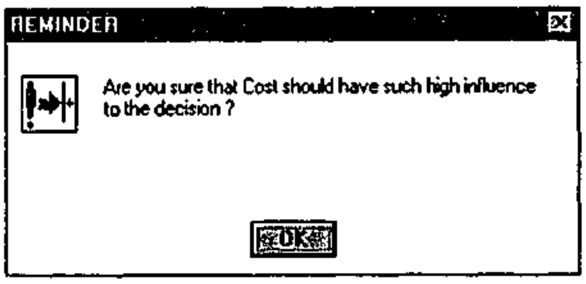

Figure 6.12: Uneven Forces Warning

The thresholds for both types of warnings are controllable by the decision-maker. The *Customise ADAPTOR* option allows the decision-maker to select the thresholds as well as completely disable the warning functions. The significance level for the inconsistent criteria preferences is expressed as standard deviations from the mean, while the uneven forces warning threshold is expressed as a percentage of the forces in the force-field. The default values for these are set at one standard deviation and 20 percent respectively. The customising screen is similar to Figure 6.13.

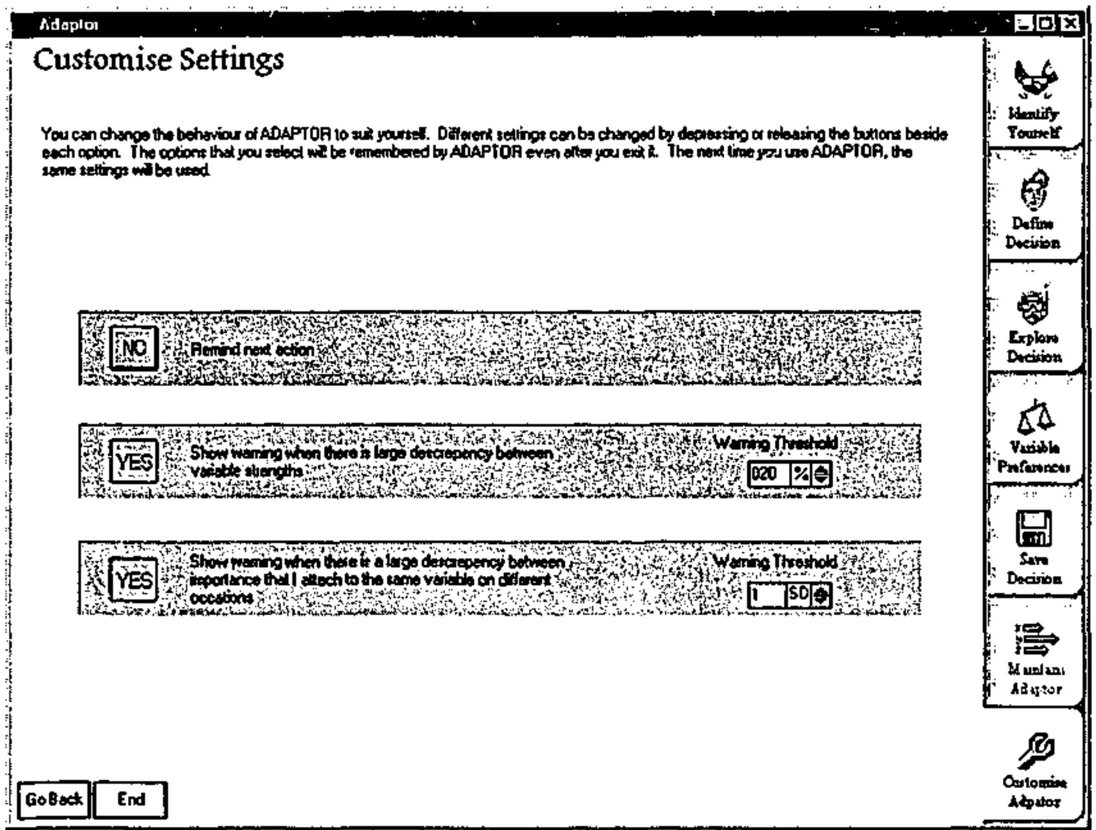

Figure 6.13: ADAPTOR customise screen

6.6 Implementing the Dialogue Management System

Identifying an independent Dialogue Management System is not possible in ADAPTOR. The functionality required from this component has been distributed among the other components of the architecture. However, the focus of the dialogue component has been to provide a consistent graphical interface across all functions. Supporting the dynamic nature of decision-making has also been a high priority. ADAPTOR implements a one level menu structure that prevents the decision-maker from having to traverse several levels of interfaces before accessing the relevant information. As can be seen in Figure 6.14, a tab-based menu is displayed on the right-hand end of the ADAPTOR screen. This menu remains active at all times, regardless of where the decision-maker is in the decision process.

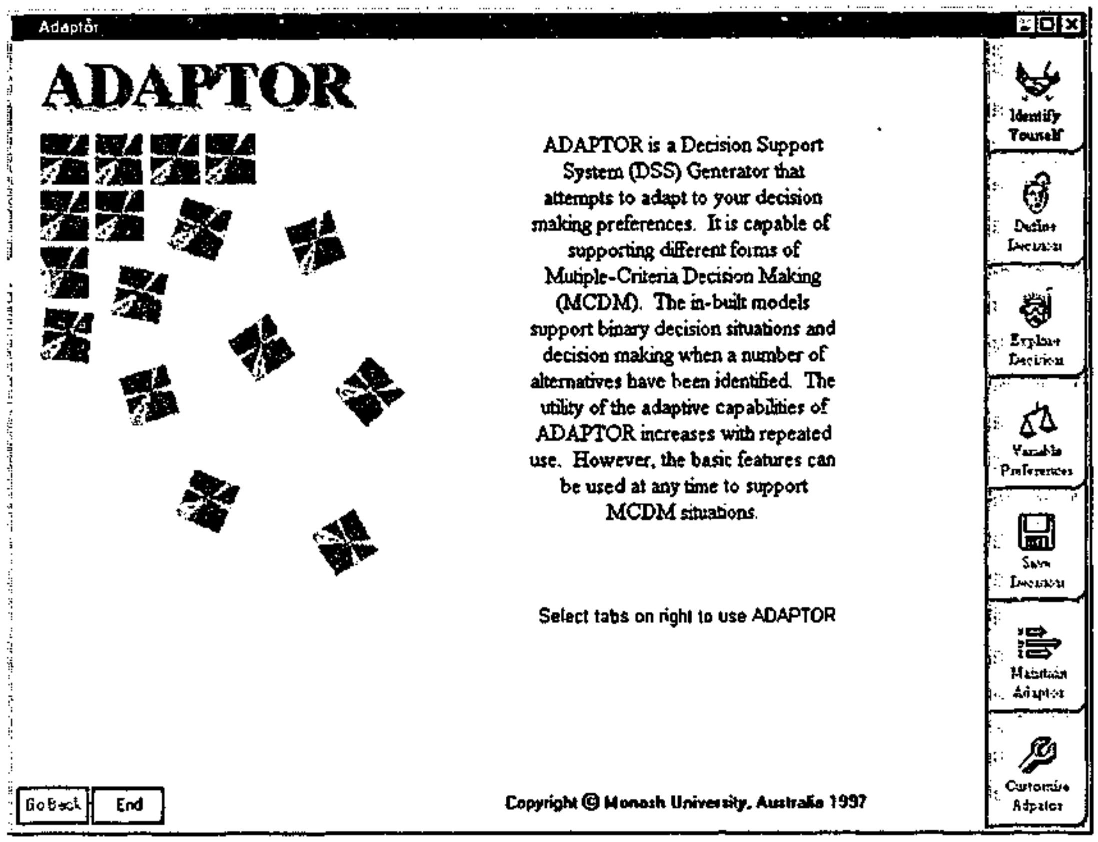

Figure 6.14: ADAPTOR Introduction screen with the Tab-Menu on the right

ADAPTOR can guide the user through the steps in defining a decision and evaluating alternatives by pointing to actions that have to be performed. The user can select to make use of this facility or disable it. Both binary and multiple-alternative decision routines share a common form of interface. This prevents the decision-maker from having to switch between different interface characteristics in addition to differences in the decisions.

The Dialogue Management Systems attempts to facilitate the definition and evaluation of decision situations without adding an overhead on the effort required from the decision-maker.

The user manual for ADAPTOR is attached to this dissertation as Appendix E.

Chapter 7

The Impact of an Adaptive System

This chapter reports on the procedures carried out to measure the success of implementing a system that adapts to individuals, based on their decision making preferences. The major research question pertaining to this stage is:

Q4. **Is the implemented decision support system generator (ADAPTOR) capable of incrementally adapting to individuals' decision making preferences based on their personality?**

This research question is a surrogate to evaluating the impact of the concept of adapting decision support systems to their users, based on their personality characteristics. It is considered as a surrogate, as the same concept could have been implemented in a manner different to how it is implemented in ADAPTOR. As developing many different adaptive systems is not feasible, ADAPTOR is used as the vehicle to investigate the viability of the concept.

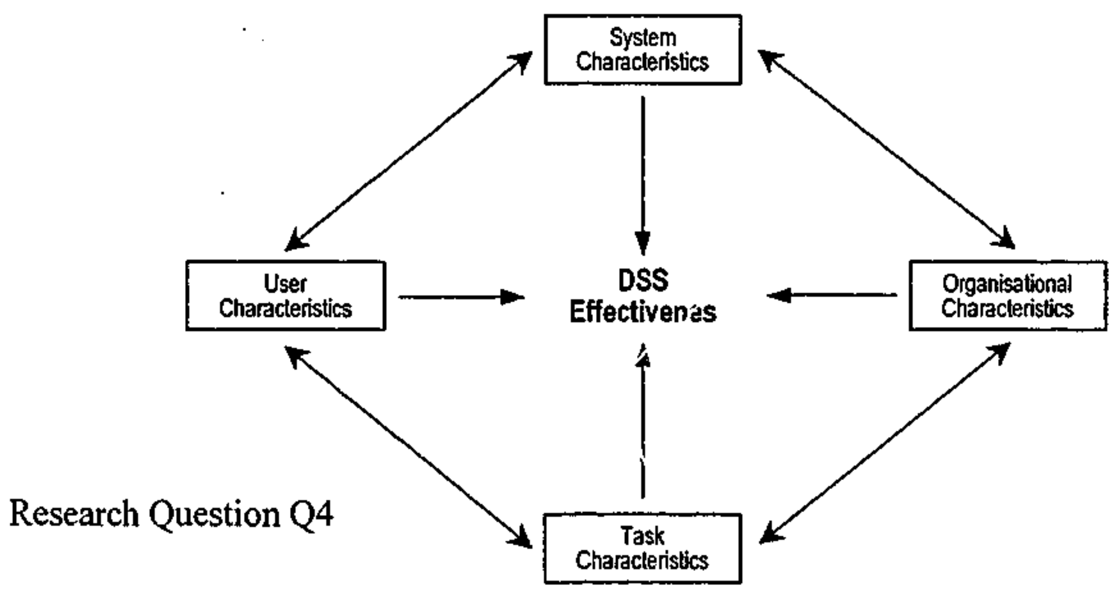

Figure 7.1: DSS Effectiveness Model with Areas of Interest for Research Question (after Ramamurthy *et al.*, 1992)

The research question can be put into the context of the Ramamurthy *et al.*'s (1992) DSS effectiveness model (Figure 7.1). This model stipulates that DSS effectiveness is influenced by four major factors: *system, user, task and organisational characteristics*. Each of these characteristics, in addition to influencing the overall DSS effectiveness, may also influence each other. Thus, the interactions between them can determine the effectiveness of a decision support system.

7.1 Hypothesis

Question Q4 is designed to investigate how the interaction between user characteristics and system characteristics is assisted by ADAPTOR to facilitate decision support in varying task conditions. The ultimate objective is to investigate whether ADAPTOR incrementally adapts to its users. Consequently, the research question translates to the following hypothesis:

H4: ADAPTOR provides better approximations of the decision-makers' preferences to criteria with increased use of the system.

When using ADAPTOR, if a decision-maker re-uses decision variables that have been used previously, approximations are provided for the preferences between those variables. The decision-maker has the option of using the approximations provided by the system or changing those preferences as appropriate to the new situation. If the decision-maker changes the preferences, the difference between the approximation and the actual value is recorded by the system. This value is the *error term*. Operationally expressed the hypothesis can be explained as, the error term associated with a given pair of criteria will show a declining trend (toward zero) against the number of times ADAPTOR has been used for decision support. This trend should be observed across all pairs of criteria that have been re-used.

As explained in the research methods chapter (Chapter 3), it should be noted that this stage of the research project falls in to the theory refinement category. It is not an exercise to establish a causal relationship. The hypothesis is tested as a means of understanding what impact the implemented concept has on the target audience. Observations should lead to refining the concept, although it may not be performed within this research project. Case study research technique was selected as the most appropriate for this stage of the project, while acknowledging the relevance of single-subject experiments.

Case studies were considered most appropriate because of the desire to secure a realistic decision environment. This was considered extremely important as genuine individual characteristics may only be obtained in situations with real consequences. It was also necessary to conduct a longitudinal study with the same subjects to observe adaptation. In such field situations, there is little opportunity to control possible confounding factors. Therefore, testing causal relationships is not possible. The aim in case studies in this project is analytic generalisation; whether the case study observations conform to the hypothesis. If all case studies conform to H4, replication may also be claimed. In addition to measuring the error terms, case studies permit the articulation of a rich picture of the impact of the implementation of the concept of adapting decision support systems to their users based on their personality.

The within-subject design of the case studies, however, reduces the ability to compare between different personality types. This is considered as a practical constraint that should be balanced with the aptness of the case studies to observe adaptability to individuals. Adaptability to individuals is considered more important because of the nature of decision support systems as individual support tools.

7.2 Method

7.2.1 Subject selection

The senior executives who participated in the initial differential study were asked whether they would like continu participation in the research project. It was explained to them that a prototype system was likely to be developed, and that they could volunteer to use this system. It was made clear that their use of the system would be part of the case study investigation into the efficacy of the implementation of the concepts. Fifteen participants in the first stage indicated their interest in continued involvement. There was also keen interest shown by a pilot study participant who was holding managerial responsibility.

After the system was developed and initial testing had been completed, detailed explanatory letters were sent to these individuals. Three agreed to participate in the case studies, while three others requested further information. Further explanations on the required commitment on their part, and user manuals of the system were sent to those who requested further information. There has not been any communication from these individuals since then. It was decided that conducting case studies with one of the three who agreed to participate was not feasible because of his remote location from the investigator Thus, there was potential to conduct case studies with the two remaining volunteers. One of these individuals held the position of Chief Executive Officer of his organisation, while the other held a Director position. The two individuals will be referred to as X and Y in the research report.

The perceived amount of commitment required from participants was considered a major problem in obtaining a higher number of cases. The target population of senior executives poses an added challenge because of the busy nature of their work schedules.

Unlike in experimental situations, case studies rarely provide an opportunity to select random samples. Case studies are carried out in field settings that are of some interest to the investigator. With this project, the objective is decision support for senior executives. Even if there were volunteers from other populations, it was essential to conduct case studies with senior executives, in order to maintain external validity of the findings. Although statistical generalisation is not possible through case studies, it would have been advantageous to conduct multiple case studies with individuals of different personality types. This was not possible because of the unknown distribution of personality types in the accessible population of senior managers and the reliance on voluntary participation. Both groups of personality considered in the differential study (ST and NT) were represented in the subjects selected for the case studies.

7.2.2 Study design

The main decisions to be made in a case study investigation is whether single or multiple case studies will be conducted, and what is to be considered as the unit of analysis (Yin, 1989).

As consent was given by two individuals to be case study subjects, the decision for this project was whether there was an advantage of studying two separate cases over the study of a single case. Single studies are useful if the selected case is a critical, an extreme or a revelatory case (Yin, 1989). The hypothesis for this stage of the project does not require specific investigation of such unique cases. The goal is to investigate the efficacy of the concept. In evaluating efficacy, replication is an important issue. If two cases show similar confirmation of the hypothesis, the results may be considered more reliable. This manner of replication is termed *literal replication*. If the case study participants belonged to different personality types, differences could be observed between the types. Observing contrary results that have predictable reasoning is termed *theoretical replication*.

Although not a major aim, theoretical replication may be possible in this study as the consented individuals belong to different personality types. The conformity to the hypothesis was measured through the declining overall error term across all pairs of variables that have been re-used by the decision-maker. Replication does not mean that this overall error term should be identical across cases. A comparable declining trend would be sufficient. It should be noted that even if subjects were of different personality types, the expected trend in the error term should be a similar declining trend. The differences would be in the actual preferences to variables, not in the trend.

The number of cases to be studied was dictated by the practical constraint of finding consenting subjects. The sample size is not an important consideration in attempting literal or theoretical replication, as a sampling logic is not followed. An increased number of replications can only strengthen the belief in the observed phenomena (Strauss and Corbin, 1990).

Another major decision was on the unit of analysis for each case study. A case study may have more than one unit of analysis that is of interest to the investigator. If there are such multiple units, it is termed an *embedded design*, while if the unit of interest is the complete case, it is termed a *holistic design*. In testing hypothesis H4, the unit of analysis is a single measure of the trend at the end of the agreed study period. Holistic case study design can therefore have relevancy to this study. However, the final trend figure is derived using the actions that the decision-maker (study subject) and the system perform over a number of decision instances. The extent to which each decision instance is supported by the system may be of special interest to the decision-maker. Study participants were asked to note such special decision instances so that they can be reported as self-contained units of analysis within the case studies. In addition, the use of the active support facilities provided by the system was also monitored. At the end of the case study, participants were also asked to participate in a structured interview. Although the additional aspects are corollary to testing the main hypothesis, they all form different units of analysis. Thus, the case studies in this project are considered as conforming to the embedded case study design.

In keeping with the initial desires of the project, the case studies were performed in the natural environment of the participants. A conscious attempt was made not to change the natural environment, within practical bounds. The investigator visited each subject at pre-arranged appointments. The study process was initiated by giving a written explanation of the activities to be performed by participants and privacy commitments undertaken. Consent was then sought to install the components of ADAPTOR on the desktop personal computers of the subjects. After the installation was completed, a training session was conducted to familiarise the participant with the use of ADAPTOR. Two example decision scenarios were modelled during the training session. A comprehensive user manual was also provided. The subjects were then asked to use the system in their usual decision-making tasks as they saw fit. The researcher had no input in the selection of decision situations modelled using the system. The indicators required to monitor the error terms were built into the system. Explicit note taking was required from the participants only if they find decision scenarios that they thought were particularly peculiar. This was left to their discretion. The period of the case study was designed to give the subjects an opportunity to use ADAPTOR for a sufficient number of times. This was an essential part of the design, as adaptation requires decision variables to be re-used for a number of instances. A period of one and a half months was considered a reasonable period to collect the required information. The only contact between the subjects and the investigator during this period was a casual progress inquiry.

The investigator visited the subjects at the end of the agreed time period to collect the data accumulated internally by the system and to conduct a structured interview. Most interview questions were open-ended. If the participants had any peculiar decision situation that they wished to discuss in detail, an opportunity was given at the interview.

7.2.3 Measures and analysis method

As mentioned in the earlier section, the hypothesis was tested through the error terms associated with the comparison approximations provided by the system and the actual preferences given by the decision-maker. To achieve this, the system should keep record of the error term for each pair of variable comparisons, for all decision instances. Similar records must be kept for all the levels of profiles that are relevant to the personality type of the subject, the subject and decisions that have been made. This functionality is not only necessary for testing the hypothesis, but an integral part of how the system adapts with use. Hence, there is no additional overhead imposed on the system to keep track of this data.

Time-series analysis can be performed on the error data recorded in the system. Simple graphical analysis is expected to show trends in this case study. The observations can be compared with the hypothesis. If the overall trend shows a decline in error (convergence towards zero) over time, the hypothesis could be confirmed. This is one of the major objectives of performing time-series analysis (Yin, 1989). If the collected data does not fit in to the pattern postulated in the hypothesis, it could be explained either as the rejection of the hypothesis or a result of a threat to internal validity of the study. In either scenario, explanations have to be provided based on the other information collected through interviewing the subjects. The information gathered from the structured interviews was used to develop a case description.

The other embedded unit of interest is how the active decision support components of ADAPTOR were used by the decision-makers. The number of times the subject has looked at warnings provided by the system is recorded in the database. In addition, the number of times the criteria preference trend graph has been accessed is also recorded. Together, these measures give an estimate on how useful the subject has found the active support components. This information was also compared with the information obtained at the interview.

The final analysis task is to perform secondary analysis across cases. Since there are only two cases, statistical analysis is not possible. However, similar observations in the two cases can lead to literal replication and greater confidence in the results. If the observations are different, those differences should be explained through the data collected or the possible confounding factors that may have been present.

7.3 Case X

The subject of this case study belonged to personality type ST, while he held the position of a Chief Executive Officer at a medium-sized technology sales and support company. The background of the subject reduced the anxiety that may be present in confronting a computer-based decision support tool.

Subject X used ADAPTOR over a six-week period for four distinct decisions. Although the number of instances was low, he used the system for decisions that had serious implications for his organisation and himself. He believed that ADAPTOR had a place in supporting strategic decisions and not in supporting routine operational decisions. He therefore only used the system for decisions that he believed were strategic and were candidates for benefiting from a methodical approach.

Formalising the thought process and the resulting exploration and learning of the decision situation were seen as major advantages of using the system. Comments were forthcoming on how the system promoted critical questioning of steps in the decision process and the general analytic regime that was promoted by using the system.

Questioned on the best candidates to use this system, subject X responded that senior managers may have benefits by directly using the system. He saw benefits for senior managers even when they have access to people who can provide them good information to make decisions. He saw ADAPTOR has a tool that may allow final analysis of that information. He also believed that used for long-term (strategic) decisions, even operational managers might gain some benefits from similar systems.

Ability to use the adaptive capability in the system was seen as a major advantage of personally using ADAPTOR. Emphasising personal preferences is possible only when the system is used hands-on. Further, subject X saw the need for improvement of the system to build a profile of 'corporate culture'. In this case, whoever uses the system, the decisions are congruent with the central ethos rather than any single person.

One of the decision processes supported by the system was seen as a major strategic decision that would affect the subject's company in the next two to three years. Both short and long term consequences were very important. The decision concerned the change to the company structure. The decision was contemplated over a few days before ADAPTOR was used. Important aspects were also noted down on paper. He believed that the time taken over the decision allowed a more formal structured approach. When the decision was defined in the system, not many suggestions for decision criteria were proposed by the system. Where the criteria that had been used previously were used for this decision, the system gave constant warnings on inconsistency in preference comparisons. The subject believed that although those criteria had been used previously, it was under different circumstance, such as for a personal decision. Hence, the warnings were misplaced. However, he also acknowledges that personal preferences have influence in organisational settings.

Given the importance of this decision, the company engaged the services of one of the "big six" consulting companies to advise them on the choices that should be made. The process of using ADAPTOR to evaluate alternatives and engaging external consultants were done completely independently. However, the choice made by the CEO using ADAPTOR and the suggestions made by the consultants were congruent. The subject felt that the outcome was also compatible with his "gut-feel". He was pleased that the system confirmed his intuitive decision, at the same time introducing structure to the decision process.

Other decisions that the system was used for were done in retrospect, ie. the decision had already been made, but the inputs were provided to the system to check its compatibility with the course of action already chosen. The subject was pleased with the outcomes proposed by system as they met the expected results.

He reported that some aspects of the system were limiting. For instance, not being able to change the description of a variable was seen as a shortcoming. The ability of the system in promoting understanding of the decision was seen as a major advantage in using the system. The preference allocation to criteria had direct appeal to the decision as the subject was able to compare what he perceived to be long term-criteria against short-term criteria.

He had difficulties in understanding how the consistency of preference comparisons was evaluated. He believed that to obtain a good decision outcome, he always had to be consistent in his comparisons, and conscious attempt was made to get the indicator built into ADAPTOR to the "green area". However, he was also of the opinion that there may be occasions where being inconsistent is unavoidable. He found the consistency indicator in ADAPTOR limiting, as sometimes he deviated from his natural inclination to extreme criteria comparisons. He acknowledged that this may be part of the process of making a "good decision".

Overall, subject X saw process improvement as the major benefit of using ADAPTOR. He also found preference expression and need for consistency in those preferences as a way of better understanding the decision situation. He was very keen to continually use the system for his decision-making tasks.

Although the subject found the system very useful, it was not possible to evaluate the adaptive capability of the system with the small number of decision instances. The researcher did not attempt to prolong the experimental period of this subject given the significance of the type of decision made using the system and the related comments provided by him. The use of a "expert" consultant by the subject to verify the results suggested by the system was seen as a valuable validation of the system. No attempt was made to analyse the trends in adaptation, as the data was not sufficient.

From the records kept within the database, it was observed that the subject has viewed the variable history trend graph on 12 occasions. Since the system was used only on a few occasions, this is significant. As this graph is generally highlighted when there is inconsistency in importance attached to criteria, it is clear that the subject has been conscious of the warnings provided by the system. Given his satisfaction with the decisions proposed by the system, it is plausible to conclude that the warnings were useful in his decision making process.

7.4 Case Y

Subject Y belonged to type NT and was a Director of a Tertiary college. She was also very familiar with computer-based tools and therefore found little anxiety in using ADAPTOR for decision support.

The usage pattern of ADAPTOR by this subject was very different to subject Y. In this case, the system was used to support a decision that was repeatedly made for different circumstances. The researcher saw an experimental advantage of using the system in this mode, as it was likely that the same set of decision criteria belonging to the same domain would be repeatedly used. The likelihood of measurable data patterns that would permit the testing of H4 was greater for this subject.

Unlike subject X, the analysis of the data collected from subject Y is biased towards actual data recorded in the system. The expectation of greater usage was realised as the subject had used the system to support 19 decision instances. 13 distinct sets of decision criteria were compared at least 5 times. Some pairs of criteria were compared up to 19 times. The system recorded the preference structure in all four types of Profiles - *Decision-Maker-General* (1), *Decision-Maker-*

Domain (2), *Stereotype-Domain* (5), *Decision-Domain* (6). As articulated in the description of the system, the profiles are maintained as matrices of criteria preference comparisons. The frequency of the comparison values allocated to sets of criteria have been tabulated in Appendix F. The symbols 1 to 17 in the histograms represent the comparison values 1 to 9 and 1/2 to 1/9. The comparison pairs have been named A_n to D_n representing profiles 1 , 2 , 5 and 6 respectively.

As expected, all profiles have identical comparison values for the same set of criteria. This is a result of the same person (therefore same personality type) repeatedly using the system to support the same decision, with criteria belonging to the same domain. In this circumstance, it is plausible to assume that the preference predictions are determined solely by the predictive ability of system components.

Examination of the histograms of all 13 sets of criteria preferences show that the maximum standard deviation is 3.85. Considering the range of 17, this is considered relatively low. However, only three sets of criteria display standard deviation of less than one. Although the subject has generally been consistent with comparison of criteria, the consistency has been within a range and not by allocating the same preference value all the time. Another interesting observation is that most histograms indicate multiple clusters of preference values for the same set of criteria. On inquiry, the subject conceded that this observation may be a result of the way the system was used. The subject had used the system in number of sessions, with few decisions attempted at each sitting. It is possible that greater variation of preference allocation occurred between sessions, rather than within sessions.

Tables 5 to 8 in Appendix F tabulate the prediction errors recorded by the system. The X-axis of these sequence charts contain the comparison instance (time), while the Y-axis contain the *Error* value. The error recorded is the difference between the prediction made by the system and the actual comparison that the subject made when using a given set of criteria. The error may be either positive or negative depending on the direction of the variation. For each of the 13 sets of criteria within the four profiles, errors were recorded by ADAPTOR. Although the different profiles have exact same values for a given set of criteria, there may be slightly different prediction errors. This is because each of the profiles is fed into an independent neural network. The predictions made by the different networks may be slightly different based on the previous learning that they have undergone. The data collected from this subject show small variation of error values between the profiles, for the same set of criteria.

Examination of the sequence charts indicates that there is a general trend towards zero for most sets of criteria. This trend is prominent for criteria set 2 and 13. However, this trend is contradicted by other sets of criteria such as 1 and 12 that show a trend away from zero. Criteria sets 6 and 10 have remained constant at zero on three profiles. This can be explained by the constant preference values allocated to the sets of criteria by the subject, as shown in the histograms in Tables 1 to 4. Other sets of criteria such as 4 and 9 oscillate around zero. This is encouraging as these two cases have a high number of comparison instances. However, no common patterns on the trend are observable in the number of cases recorded by this subject.

The subject expressed general satisfaction with the system behaviour. The database had recorded 16 occasion where the subject had inquired the criteria history graph. This indicates that she had made an attempt to take notice of the warnings provided by the system. As evident from the recorded data, the subject had been generally consistent in preference allocation. This is also confirmed by the fact that inconsistent preference warnings were given only on 20 occasions, even when the system had been used for 19 decisions with 13 sets of different criteria.

7.5 Discussion of the findings

The two case studies conducted to evaluate the impact of the system were more disparate than anticipated. As the researcher had no control over the manner in which the system was put to use, this has to be accepted as a possible artefact of field research. An advantage of the disparate nature is the ability to get a rich picture of practical use of the system. The system was used in realistic decision situations, contributing to external validity of the findings.

It was clear from both case studies that the system succeeded as a decision support tool at several levels. The subjects did not report any problems in using the system. They reported that the system promoted greater learning of the decision situation through exploration and formalisation. This is a major aim of building decision support systems (Keen, 1987).

Unexpected validation of the decision support capability of ADAPTOR was received through "expert" confirmation of a "major" decision supported by using the system. The active support components of ADAPTOR were useful to the case study subjects. The subjects acted upon the warnings provided by the system, and consistency of criteria comparison was consciously pursued. They used the facility of exploring the preference history of criteria, which is provided as means of understanding changes to their preferences over time.

However, the hypothesis that ADAPTOR provides better approximations of the decision-makers' preferences to criteria with increased use of the system, cannot be confirmed through these two case studies. Only one case study provided sufficient data to attempt testing the hypothesis. Although encouraging patterns were observed within that data, it did not clearly support the hypothesis.

The time allocated for the conducting these case studies was insufficient to produce conclusive results, though it must be stated that gaining longer-term experimental commitment from the target sample is difficult. As this stage of the project falls into theory refinement, valuable empirical evidence was gathered in these case studies to refine the concepts proposed within this thesis.

Analytic generalisation or theoretical replication of the findings cannot be claimed as the case studies were disparate in nature. Further longitudinal studies are required to observe the behaviour of the system.

Chapter 8

Summary and Conclusions

8.1 Summary of the project

Within this dissertation I postulated the major proposition that decision-makers' personality preferences can be used to provide active decision support to senior mangers. The project was approached as a number of steps that were not limited to theoretical foundations, but practical use of theoretical knowledge. The steps involved:

- analysing past literature to understand the need and feasibility of using personality as means of adapting decision support system generators;
- through the study of literature, select candidate theories for articulating decision-maker personality in the context of decision support systems;
- the selection of assessment tools, that would suit the target population of senior managerial users, to measure personality characteristics;
- conducting experiments to clarify and confirm the validity of using personality as a means of distinguishing between criteria preferences of decision-makers;
- determining an architecture in which criteria preferences of individuals may be incorporated in to formally expressed decision models and the selection of decision models that are candidates for such input;
- investigate and build a computer-based system that is based on the architecture developed to use personality preferences in decision models; and
- evaluate the ability of the computer-based system to actually adapt to its users in practical situations.

The project was conducted within the positivist research paradigm. The steps were seen as parts of the *concept-development-impact* model of information systems research. While the initial stages of the project were literature based, the aims of the project included conducting both *basic* and *applied* research. Hence, as is common in the information systems discipline, the *concept* was not merely borrowed from past literature, but validated within this project. A differential study was conducted to investigate the differences of decision criteria preferences between different personality types in the concept validation stage. The implications of this study are not limited to this research project, and may be applied elsewhere. Hence, that stage falls into the *basic* research category. However, the aim of the project was to produce results that may be practically beneficial to the target community of senior managers in organisations. The latter stages of the project are therefore *development* activities where a computer-based decision support generator, ADAPTOR, was built. It must be acknowledged that ADAPTOR is only one possible implementation of the findings of the prior stages. The practical impact of the concept was tested using ADAPTOR as the vehicle.

8.2 Findings

The questions proposed for the project were systematically addressed using appropriate research techniques. The questions and the findings are summarised in this section.

Qa. **What theory/theories provide an adequate basis for the articulation of decision-maker personality for decision support?**

Qb. **What is the personality assessment tool that resembles the selected theory and can be used in a computerised implementation for managerial use?**

The search for answers for these questions required the study of literature in personality psychology and its relevance to our discipline of information systems. It was also important to understand the current context of the reference discipline. Personality psychology is a complex area in which numerous dominant schools of thought exist. Affiliation to one school may result in ignoring other important elements within the discipline. My aim in understanding the different points of view was to select theories that have broad acceptance within its discipline, while still being applicable for building decision support tools for senior executives.

The study of literature covered a broad spectrum of competing personality theories. Personality psychology primarily deals with dimensional structures. Whether a particular construct is an extreme end of a dimension or whether it is a discrete type is a major issue in understanding personality assessment (the *type* vs. *trait* argument). While *trait* theories have wide acceptance in clinical assessment, it is clear that *type* theories have similar relevance to industrial settings. The Myers-Briggs Type Indicator (MBTI) is one such instrument, based on Jungian type theory, which is increasingly used for assessing individuals in the senior management category. This instrument has also been subject to scrutiny on its theoretical soundness. Research has also shown that senior executives are more agreeable to assessing their *type* than other psychological indicators.

Hence, the MBTI was selected as the most appropriate and valid tool for personality type assessment in this research project. It is also particularly useful in automated implementations of personality assessment.

Q1. Is there a relationship between the personality and the decision criteria preferences of a decision-maker?

Although some evidence was available in the literature on this relationship, the search for answers to this question required a major step in the project. This was necessitated because a concept that can be directly used (in a computer-based system) was not forthcoming. This step was approached as a basic research effort in the positivist paradigm.

Thirty-nine senior managers participated in the differential study that involved undertaking a hypothetical decision-making exercise. Analysis of the sample showed that it was well selected and homogenous. The sample distribution between personality types was similar to other research. However, the small overall sample resulted in only two personality types being adequately represented.

Statistical analysis using multivariate discriminant analysis showed that discriminant function is significant at the .05 level. As the statistical significance may have some deficiencies in evaluating the efficacy of the function to distinguish between personality types, further testing was done using multiple hold-out samples. This showed that given the criteria preferences of a person, the discriminant function is able to predict the personality type of the person. This predictive ability is significantly greater than that expected by chance.

The experimental data was also fed through a set of trained artificial neural networks that had comparable success in predicting personality types. This acted as a triangulation mechanism to answer the research question and confirm the hypothesis *that individuals with different personalities will attach different importance to decision criteria in a given situation.*

Q2. **How can the distinct criteria preferences of individuals belonging to different personality types be used as the basis of building decision support systems that adapt to individuals?**

This question formed part of the *development* stage of the research project. Given that the *concept* was confirmed in the previous stage, the effort at this stage was to develop an architecture for decision support system generators. This architecture had to fulfil the normal functionality expected of decision support systems while being able to adapt to individuals.

The architecture proposed has a multi-criteria decision model as its central component. The *Model* is the representation of the decision situation. The precise model to be used in a given situation can be selected from a collection of multi-criteria models held in a *Model Base*. On each instance a decision is supported, the decision-makers are required to express their preferences to the criteria through pair-wise comparisons. These preferences are transformed into weights before using them in a decision model.

The criteria preferences of the decision-maker are held in the *Profiles* as criteria comparison matrices. The *Inference Mechanism* included in the architecture has the task of building Profiles and enhancing existing ones, as specified in a number of predefined rules. In building profiles, the Inference Mechanism performs abstractions and generalisations on preferences expressed by decision-makers when they use the system for decision-making. These generalisations are stored in Profiles.

The various profiles are organised into a hierarchy. The hierarchy is based on the relevance and the level of abstraction of the preferences stored in the profiles. When a decision-maker uses the system, criteria and preference approximations are retrieved from the most relevant, least abstracted profile. These preference approximations give the decision-maker a starting point to understand the current decision situation. The decision-maker is also able to discard or change approximations given by the system.

Using these components of the architecture, it was expected that decision support system generators can be built. However, active support is possible only if there is a way in which the activities of the decision-maker are monitored and guidelines are provided as feedback. The *Active Monitor* component of the architecture is introduced to achieve this aim.

Hence, I *was able to propose an adaptive decision support system generator architecture that is able to use criteria preferences of individuals belonging to different personality types*. The architecture supports adaptiveness through the provision of preference approximations and active decision support through feedback to the decision-maker.

Q3. How can a prototype computer-based system be built to implement the Adaptive Decision Support System Generator Architecture?

One way of demonstrating viability of an architecture is to build a system that is based on that architecture. It was important in this research project to show that the proposed architecture can practically be used to build systems that can directly be used by senior managers.

Hence, a system named ADAPTOR, was built for the Microsoft® Windows™ platform. Every component of the architecture can be distinctly identified in this system. All appropriate software technologies, regardless of their philosophical underpinning were considered for implementing the system. This was seen as appropriate as this research project was making a conscious attempt at moving away from the traditional 'passive' decision support approach. As a result, ADAPTOR uses programming language, database, commonly used spreadsheet and artificial neural network technologies to fulfil its requirements. The system has a graphical interface and was developed with ease-of-use as a major aim.

ADAPTOR provides access to two types of multi-criteria decision models; binary and multiple alternative. The model evaluation is achieved through the linear weighted sum approach. Decision-makers are required to express their criteria preferences on a comparison scale similar to Saaty's (1980) semantic scale. The Inference Mechanism consists of a series of IF..THEN rules as well as a set of artificial neural networks. Neural networks are employed to perform abstractions and to provide predictions on the decision-makers' criteria preferences.

Thorough building ADAPTOR, I was able to implement the Adaptive Decision Support System Generator Architecture. This is an indication that the proposed architecture is a viable one. This system can also be used to evaluate the *concept* behi[illegible] [illegible]arch project.

Q4. Is the implemented decision support system generator (ADAPTOR) capable of incrementally adapting to individuals' decision making preferences based on their personality?

Falling into the theory refinement category, this research question is a surrogate to evaluating the impact of the concept of adapting decision support systems to their users, based on their personality characteristics. It is considered as a surrogate, as the same concept could have been implemented in a manner different to how it is implemented in ADAPTOR. The operational definition of the research question required the observation of the error term associated with predicting decision-makers' preferences. The case study technique was considered most appropriate to investigate this question because of the need to maintain external validity of the project and information richness of the technique. The longitudinal nature was also important in selecting this technique.

Two case studies were performed over a six-week period with individuals holding senior managerial responsibility. Each was given a copy of the system to use in their normal decision-making tasks. No attempt was made to control the environment. The participants belonged to two personality types.

It was clear from both case studies that the system succeeded as a decision support tool at several levels. The subjects did not report any problems in using the system. They reported that the system promoted greater learning of the decision situation through exploration and formalisation. The active support facilities built into the system were regularly used. However, the two cases were disparate; the usage patterns were very different and the instances of system use were not sufficient for formal testing of the hypothesis.

Hence, the hypothesis that ADAPTOR *provides better approximations of the decision-makers' preferences to criteria with increased use of the system* cannot be confirmed at this stage. Analytic generalisation or theoretical replication of the findings cannot be claimed as the case studies were disparate in nature.

8.3 Limitations

Although it was possible to complete the research steps successfully, this project had to contend with a number of difficulties. The primary causes of these difficulties are the *pursuance of external validity* and the *time limitations* imposed on a doctoral research program. While care was taken to avoid these being threats to the internal validity of the steps in the project, avoidance of some of the difficulties would have led to increased overall validity.

The major thrust of the research is aimed at supporting the decision-making needs of senior executives. Hence, conducting experiments to establish or to test theories with other populations is unlikely to provide valid outcomes that contribute to the thesis.

In testing hypothesis 1, that individuals with different personalities will attach different importance to decision criteria in a given situation, it was necessary to select participants from the target population. As personality types naturally occur, it is not possible to condition already selected subjects to display behaviour of types that are foreign to them. It was also not possible to select individuals whose personality types were already known to the researcher, as such a list of known people was not available. Being a privacy issue, such a list is unlikely to be available to any researcher. Therefore, the mechanism used for sample selection is to seek consent from a list of senior executives, whose personality types were not initially known. While it is possible to expect certain distributions of personality types based on similar experiments reported in literature, the researcher had no real control over the distribution of types in the pool of respondents.

Among the respondents for the differential study in this project, only two groups of interest were adequately present. The differential study was limited to these two types. Clearly, this is only the minimum acceptable standard for testing the hypothesis. The presence of more groups and larger samples within the groups can add to the validity of the findings. Obtaining such samples within the population of senior executives is extremely difficult. These individuals have busy schedules that prevent them from participating in any exercise that takes a considerable length of time. The privacy of the personality information collected can also be an important issue.

The time available to complete steps in a doctoral project was also a problem that impacted this project. The research project was aimed at building an adaptive decision support system generator. Adaptation is based on learning about decision criteria preferences of individuals and groups of individuals over time. This implies that the system built for testing the adaptive capability of the concept has to be used for a considerable time before the adaptiveness is tested. In the final stage of this project, case studies were carried-out over a six-week period to test the system's ability to adapt. This period proved inadequate and the results were inconclusive. While not taking away from the primary contributions of my thesis, this shows that a longitudinal study over a larger time span is needed. Such extended study periods is a facility not available in a project that has a number of distinct steps.

Compounding the need for a much longer period is the need for commitment from senior executives to use the system for their decision-making. Though it is clear from the case studies performed that after using the system for some time, the participants were willing to use it further, obtaining initial consent from a large number of people is difficult.

Another problem identified in this project is the complexity of its reference disciplines. Especially in the study of personality psychology for the selection of a suitable mechanism for classifying individuals, competing theories were readily available. It is not possible to resolve some of the complexities of the reference disciplines within a project of this nature. Hence, a pragmatic approach of selecting a theoretically valid suitable theory was used. This is considered a problem because my research could have been performed with an alternative personality theory as the basis of classifying people. It was however not possible to evaluate such multiple classifications within this project.

The problems encountered in this project relate to the nature of the research work itself and not externally imposed. To build an accepted theory in this area, it is important that these inherent problems are overcome through research design.

8.4 Potential impact on the discipline

My doctoral research project was aimed at building an adaptive decision support system generator for senior decision-makers. Adaptation is primarily based on personality types of individuals as classified by the Myers-Briggs Type Indicator (MBTI), a Jungian type classification instrument. The research project was carried-out with due consideration to suitable research methods and has both theoretical and practical impact on the discipline of information systems, particularly decision support systems. The findings of this project with potential impact to the discipline are outlined below:

- Showed through an analysis of previous literature and argument, that the decision-makers' personality characteristics are important in decision-making by senior executives.
- Through a reasoned analysis of personality psychology, selected a theory and an assessment instrument, MBTI, which can readily be used in decision support environments involving senior executives.
- Through a differential study, showed that there are differences between decision criteria preferences of individuals belonging to different personality types.

- Proposed a method in which unique personal preferences of individuals can be captured and stored in decision support system generators in the form of composite criteria preference models (Profiles).

- Proposed and demonstrated how criteria preferences of individuals stored in criteria preference models (Profiles) can be adaptively re-used in multi-criteria decision models as appropriate in given decision situations.

- Demonstrated that a viable architecture is available to build adaptive systems that use prior criteria preferences of decision-makers to adapt systems to current decision situations.

- Showed that the adaptive capability of a decision support system generator can be used to provide active decision support where the system attempts to influence the decision making process.

8.5 Future work

Having carried-out the research program outlined in this dissertation, I am in a position to see a number of research directions that can arise from this project. Some of these can contribute to increasing the validity of the findings of this project while others can make enhanced contributions to the discipline.

8.5.1 Increasing validity of the findings

One major shortcoming of the current project is the lack of representation of some personality types in the sample used to test the first hypothesis. Any future research should attempt to test this hypothesis with increased representation of types and larger samples in each cohort. Achieving this goal may be more practical outside of a doctoral project.

The learning mechanism built into ADAPTOR is based on a single design of a neural network. This arrangement of the network is unlikely to be the best possible design, as its learning capabilities have not been evaluated. With multiple experiments, it would be possible to investigate different network layouts. Such improved networks may lead to better overall adaptive capability of the system.

The final stage of this project was designed to test the adaptive capability of the system for individuals. To evaluate the adaptive capability as applicable to personality types, it is important that many people of same and different types use the system over an extended time period. This may only be achieved in an organisational setting with a longitudinal study.

This stage did not confirm the hypothesis that the system will improve its adaptive capability with increased use. The major contributing factor to this conclusion is the short time period (six weeks) allocated for the case studies. Hence, there is a need to conduct longitudinal case studies that will span a greater time period. Sufficiently large number of decision instances will lead to either confirmation or rebuttal of the hypothesis. The participation of multiple individuals from the same personality type and also different types will enable analytic generalisation and theoretical replication of the findings.

Currently the implementation of the architecture, ADAPTOR, is limited to two multi-criteria decision representations. Although not a threat to validity, it is a limitation when the system has to be used in practical situations. This is especially important when the efficacy of the system is tested through case studies. The availability of a greater variety of models may lead to increased use of the system. This can be helpful in reducing the length of longitudinal studies by collecting more data in a shorter time period.

The Active Monitor component of ADAPTOR is implemented as an illustration of the active support components in an adaptive system. Hence, the rules implemented are simple and limited to monitoring only few actions by the decision-maker. However, a fully-fledged active support component can be more sophisticated. More complex series of rules that provide useful guidance to the user may be built. Implementing such an active component can increase the usefulness of the system.

8.5.2 Enhanced contributions to the discipline

As indicated throughout this dissertation, the Myers-Briggs Type Indicator is one of many candidates for classification of individuals. In this project, the differential study was performed to evaluate a relationship between MBTI types and the criteria preferences of individuals. However, it would also be useful to investigate whether there are differences between preferences when individuals are classified on a different personality theory or instrument. It may be possible that classifications on some instruments will have a greater relationship with distinct criteria preferences. Within the scope of this study, we should focus on instruments that will lead to greater differentiation in the senior executive sample.

The relationship between personality types and criteria preferences may also be applicable in other information system endeavours. Personality differences have received some attention in the information system discipline. The outcomes of this project may have some relevance to that body of knowledge, and may be considered in building systems other than decision support systems.

The scope of this project limited the use of decision criteria preferences in multi-criteria decision models. This form of model is one of a plethora as outlined in this dissertation. It may be a worthwhile exercise to investigate how criteria preferences can be usefully employed in other types of models to enable adaptability. If there is success in this, it may be possible to enhance the Model Base in adaptive systems such as ADAPTOR, thereby increasing their usefulness.

ADAPTOR implemented a series of neural networks as an adaptive mechanism. While this may prove useful, there may be other learning paradigms that may have greater success in learning from criteria preferences. Hence, it would be useful to investigate such alternative mechanisms.

As alluded to by one of the case study participants, having external feedback mechanisms within adaptive systems can be useful. The architecture proposed in this project implements an internal feedback mechanism where the system learns from changes that the decision-maker makes to preference approximations provided by the system. This may be further enhanced through external feedback mechanisms, where outcomes of decisions are fed-back into the system. This may be used as another input to the prediction process.

8.6 Concluding comments

In this doctoral research project I attempted to address the issue of supporting senior executives' decision-making processes. The attempt was focussed on building adaptive decision support system generators that construct models of criteria preferences of individuals. These preferences are stored as profiles and are used as a way of adapting the system to an individual or a personality type. The adaptive capability is used as the basis of providing *active* decision support.

The project was carried-out with rigorous consideration of the research process as well as the subject matter. Within the limitations of a doctoral project, care was taken to uphold both internal and external validity of the findings. I believe that the findings of this project have useful impact on our discipline and future research directions on decision support systems for senior decision-makers.

Chapter 9

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Appendix A: Related Publications

List of Related Publications

Paranagama, P.C. Burstein, F.B. and Arnott, D.R. (1998). 'ADAPTOR: A Personality-Based Adaptive DSS Generator', *Proceedings of the 31st Hawaii International Conference on System Sciences*, University of Hawaii.

Paranagama, P.C. Burstein, F.B. and Arnott, D.R. (1997). 'Implementation of an Adaptive DSS Generator for Senior Managers', *Proceedings of the 4th International Conference on Decision Support Systems*, Ecole des HEC, University of Lausanne, Switzerland, July 21-22 1997.

Paranagama, P.C. Burstein, F.B. and Arnott, D.R. (1997). 'Adapting to Personality through the Use of DSS Generators', *Proceedings of the Sixth International Conference on User Modelling*, Chia Laguna, Sardinia, Italy, June 2-5 1997.

Paranagama, P.C. Burstein, F.B. and Arnott, D.R. (1996). 'Modelling Personality of Decision-Makers for Better Decision Support', *Proceedings of the Second Workshop on Intelligent Decision Support*, Melbourne, Australia, 9 September 1996.

Paranagama, P.C. and Burstein, F.B. (1996). 'A Preliminary Study of the Relationship between Decision Makers' Personality and Models of their Preferences', *Proceedings (supplement) of the 1996 Working Conference of Working Group 8.3 of the International Federation for Information Processing*. London School of Economics, 22-24 July 1996.

Paranagama, P.C., Burstein, F.B. and Arnott, D.R. (1995). 'DSS: How to Adapt Them to Managers', *Proceedings of the 6th Australasian Conference on Information Systems*, Perth, Australia, 26-29 September 1995.

Paranagama, P.C., Burstein, F.B. and Arnott, D.R. (1995). 'User Characteristics as a Basis for DSS Design', *Proceedings of the 3rd International Conference on Decision Support Systems*, HKUST, Hong Kong, 22-23 June 1995.

Paranagama, P.C. Burstein, F.B. and Arnott, D.R. (1994). 'Modelling Personality of the Decision Maker for Effective Decision Support', *Proceedings of the OzCHI'94 Conference of the Ergonomics Society of Australia*.

Appendix B: Experimental Instruments

Department of Information Systems
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FAX: (03) 9903 2005 TELEPHONE: (03) 9903 2208

AUSTRALIA

12 October, 1995

The «Position»
«Company»
«Address_1»
«Address_2»

Dear Sir/Madam

RE: CONSENT FOR PARTICIPATION IN RESEARCH STUDY

I refer to my recent letter addressed to «Full_Name», requesting consent for participation in a research study. Our mailing list was built from past survey responses, and indicated «Full_Name» as the «Position». We have received many responses that indicated changes in personnel since our mailing list was built. If this applies to you, please accept our sincere apologies. I also wish extend to you, the invitation addressed to «Full_Name».

Due to this reason we have decided to extend the response period until the 27th of October 1995. If you need us to provide you with more information or a new consent card, please do not hesitate to contact us at the address given below.

This research is project designed to investigate methods of better supporting senior managers such as you, through the development of computer-based information systems. If you did not receive our original letter, we will be glad to provide you with the details of the research project and other required material, if you are interested.

Thank you.

Professor D.R. Arnott

Contact details:
Mr. Priyanka Paranagama
Department of Information Systems
Monash University
Level 7, 26 Sir John Monash Drive
Caulfield East, VIC 3145
Tel: 9903 1065
Fax: 9903 2005

M O N A S H U N I V E R S I T Y

AUSTRALIA

Department of Information Systems
Level 7, 26 Sir John Monash Drive, Caulfield East, VIC 3145, Australia
FAX: (03) 9903 2005 TELEPHONE: (03) 9903 2208

ADAPTIVE DECISION SUPPORT SYSTEMS PROJECT

«Full_Name»

I, ______________________________(if new nominee, please write name) agree to participate in the above research project and understand that the information will be used in the strictest confidence by the researchers.

Position (if new nominee):______________________________

Signature:______________________ Date:____/____/____

Contact Phone Nos:

Email Address (if available): «Seq_No»

28 December, 1999

«Title» «Initials» «Name»
«Position»
«Company»
«Address_1»
«Address_2»

Dear «Title» «Name»,

ADAPTIVE DECISION SUPPORT SYSTEMS PROJECT

Thank you very much for your consent to participate in this research project. Your contribution will be invaluable in improving our research in the decision support systems area. As you may know, decision support systems are computer-based systems that help make decisions. They are not intended to replace human decision makers, but assist them. This research project is investigating the possibility of building decision support systems that are capable of adapting to the decision maker based on their personality. We believe that such systems will have the greatest utility in supporting senior decision makers.

While your contribution will help us refine certain concepts, the results will lead to computer-based systems. If you desire, we will make the resulting systems available for your use. We are also able to provide you with a personality profile based on your Myers-Briggs Type Indicator (MBTI) responses. Please indicate whether you are interested in receiving such on the demographic information sheet provided.

Please perform the following three tasks and return all three sections in the reply-paid envelope provided, at your earliest convenience before the 16th February 1996. If you are unable to complete the tasks by this date, please contact Mr. Priyanka Paranagama at the address below to arrange an alternative deadline.

Step 1: Complete the attached demographic information sheet. This information will only be used in our research reports to justify our sample selection procedures. You are not required to write your name on this form unless you want us to provide you with the results of this study.

Step 2: Complete the Myers-Briggs Type Indicator (MBTI) questionnaire. Circle the desired responses on the **question booklet itself.** This will save you time. Please attempt this questionnaire in a relaxed situation and think that you are doing it for yourself. Research has shown that most reliable results are generated in such circumstances. We will not be interested in answers to specific questions; we will only look at the whole personality type.

Step 3: The final task is to undertake the simple decision making exercise. This relates to a hypothetical situation and does not require much effort or time (approximately 10 mins.). Please do not delegate this task as the results will be meaningful only when your personality type is compared to the responses in the decision making exercise.

Let us once again thank you for your cooperation and assure you that all information that you provide will be held in the strictest confidence.

Yours sincerely,

Professor David Arnott

CONFIDENTIAL

Participant No.

AUSTRALIA

Department of Information Systems
Monash University
Level 7, 26 Sir John Monash Drive, Caulfield East, VIC 3145, Australia
FAX: (03) 9903 2005 TELEPHONE: (03) 9903 2208

Demographic Information Sheet

Please provide as much information as possible. That will allow us to justify our sample selection procedures. The information will not be used for any other purpose.

Are you interested in receiving results of this research project (tick more than one, if required)?

- Like to get my MBTI personality profile ☐
- Like to see research report ☐
- Will be interested in using resulting computer systems ☐

Name (optional): ....

Position: .... **No of levels between you and the CEO:** ....

Gender: Female ☐ Male ☐

Age:

25-30 ☐	46-50 ☐
31-35 ☐	51-55 ☐
36-40 ☐	56-60 ☐
41-45 ☐	over 60 ☐

Highest Educational Qualification:

High School ☐	Postgraduate Diploma ☐
Undergraduate Diploma ☐	Masters Degree ☐
Bachelors Degree ☐	Doctorate ☐

Other (please specify): ....

Average annual income (in $ thousands) :

Under 40 ☐	101-120 ☐
41-60 ☐	121-140 ☐
61-80 ☐	141-160 ☐
81-100 ☐	over 160 ☐

Have you ever purchased a house (this question is related to the exercise you are going to perform)?

Yes ☐ No ☐

If yes, how many times? .... **How long ago was the last occasion?** ....

CONFIDENTIAL

Participant No.

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AUSTRALIA

Decision Making Exercise

This exercise is designed to understand your preferences when buying an apartment. Senior decision makers, such as you, are believed to have highly developed preferences. The results will be used to evaluate the differences between groups of individuals. This is not intended as a test. There are no right or wrong answers and there will not be comparisons between individuals. Your preferences will remain confidential. The ultimate aim is to build computer-based decision support systems that can adapt to individuals.

Please read the following scenario carefully and perform the tasks required. **Although there are a number of pages, you only need to do a minimum amount of writing and would not take more than a few minutes of your time.** Please note that this exercise is printed on both sides of the paper.

The government of Victoria recently disclosed plans to offer the Melbourne docklands to private developers for commercial and residential development. The Melbourne docklands is the prime undeveloped water-front site in Australia. In the past, the site has only been used for industrial purposes although there has always been appeal as a prestigious residential development. Hence this is an opportunity that many people have been waiting for. The project is to be undertaken over the next five to ten years and when completed will constitute the newest suburb of Melbourne. The suburb will include commercial boulevards with high fashion boutiques and cafes, corporate offices, many boat piers and multi-story apartment buildings. The whole development is within a few kilometres of the Melbourne CBD and has the potential to be one of the most prestigious addresses in Melbourne.

One of the developers who has won the rights for residential development is a close friend of yours. They have drawn up plans for a low-rise water-front block of apartments. Each apartment includes spacious entertainment areas, three bedrooms, a kitchen, two bathrooms, a two-car basement lockup garage and a court yard facing the harbour. There is also provision and planning permission for a private boat pier. Naturally, the apartments contain all the trappings of a development of this class. Your friend's project will be one of the first to be undertaken and therefore will be completed before the end of 1998. Being close friends, you have been offered one of these apartments off the plan. The price quoted will remain fixed, but advance payments may have to be made. Needless to say, this is a rare opportunity either for investment purposes or dwelling.

You have to make a decision to buy this apartment or not. After the study of many sources of information, we have concluded the following as important factors in making this decision:

Factor	**Explanation**
• Cost	Amount of money you have to pay for the purchase (not affordability)
• Investment Value	Value of the apartment as an investment for future return
• Prestige	Social status value of owning/living in this development
• Convenience	Proximity to amenities
• Lifestyle	Match to your lifestyle (leisure, entertainment, self expression etc.)
• Design	The appearance and aesthetical design of house

OPTIONAL: You might feel that there are other factors that are important, but not listed above. You may add up to another four factors to the list. If there are such factors, please write them in the spaces provided below. A short statement of explanation for each additional factor may help us clarify the exact meaning and context. We have attached a list of possible factors at the end of this document. You may choose from that list or add your own factors.

Factor	**Explanation**
(1)	....
(2)	....
(3)	....
(4)	....

Your task now is to indicate how important each factor is to you, compared to the other factors, when making this decision. **You can do the comparisons by placing a circle on the scale to indicate your opinion, as in the example overleaf.** This enables us to build a clear picture of your preferences.

> Please be kind enough to write any comments you have on the tasks you have performed at the end of this document. Comments can include your opinion of the instructions provided, the time spent doing the tasks and any other general comments.

Example:

If there are two factors *Factor1* and *Factor2*, and you believe that *Factor2* is strongly more important than *Factor1* when deciding whether or not to buy the house, a circle should be placed as below.

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Factor1 important							◯			Factor2 important

The following pages provide you similar scales for each pair of factors. Place a circle on the scale to illustrate your opinion. Make sure that you keep the decision in mind when doing the comparison.

When deciding whether or not to buy this apartment,

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										Invest. Val. important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										Prestige important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										Convenience important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										Lifestyle important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										Design important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										Prestige important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										Convenience important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										Lifestyle important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										Design important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										Convenience important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										Lifestyle important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										Design important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Convenience important										Lifestyle important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Convenience important										Design important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Lifestyle important										Design important

If you did not have any additional factors, you have now finished the exercise. Else, you can compare the additional factors to other factors below. You can use the check list as a guide.

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										........(1) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										........(1) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										........(1) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Convenience important										........(1) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Lifestyle important										........(1) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Design important										........(1) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Convenience important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Lifestyle important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Design important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
(1).......... important										.........(2) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Convenience important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Lifestyle important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Design important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
(1)......... important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
(2)......... important										.........(3) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Cost important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Invest. Val. important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Prestige important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Convenience important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Lifestyle important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
Design important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
(1)......... important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
(2)......... important										.........(4) important

	Extremely More	Very Strongly More	Strongly More	Moderately More	Equal	Moderately More	Strongly More	Very Strongly More	Extremely More	
(3)......... important										.........(4) important

FEEDBACK

Please use the space below to give any comments you have on the tasks you have performed.

List of Additional Factors

Affordability
Car Parking Facilities
Convenience
Cost
Crime
Design of Development
Design of House
Design of Surroundings
Distance from Shopping Areas
Distance to Work
Distance to Schools
Diversity of Designs
Ease of Maintenance
Finances
Inconvenience in New Development
Inconvenience of Relocating
Investment Value
Leisure Facilities
Lifestyle Match
Locality
Monthly Repayment
Need for Self Expression
Neighbourhood
No of Bathrooms
Number of Bedrooms
Other Buying Expenses
Payment Terms

Personality Match
Pollution
Possibility of Expansion
Prestige
Pride of Ownership
Privacy
Public Transport
Quality of Fittings
Quietness
Rates
Rental Value
Repayment Period
Reputation of Builder
Resale Potential
Size of Formal/Informal Areas
Security
Size of Garden
Size of House
Size of Land
Status
Storage Space
Sturdy Construction
Symbol of Success
Tax Benefits
Time Saving
Trees

28 December, 1999

«Title» «Initials» «Name»
«Position»
«Company»
«Address_1»
«Address_2»

Dear «Title» «Name»

YOUR MYERS-BRIGGS TYPE INDICATOR DESCRIPTION

Thank you very much for participating in our research study. We are pleased to provide you with your Myers-Briggs Type Indicator (MBTI) personality description as requested by you. Your personality type according to the MBTI is **«Type»**.

As you might know, the MBTI is an increasingly popular personality instrument in organisations. It is being used for personnel selection, career counselling and team composition among other purposes. However, the results that it provides should not be interpreted as definitive personality descriptions. There is an error rate associated with assessments. Generally, about 80 percent of subjects agree with their descriptions. Approximately another 10 percent disagree with one of the four dimensions that are measured.

We have enclosed a booklet titled 'Introduction to Type' so that you may be able to study the description for your 'type'. You may also want to read the descriptions for other types as that will help you understand how those descriptions appeal to you. If you feel that another type describes you better, you may assume that that is your MBTI type.

I trust the information provided is of assistance to you.
Thank you.

Yours sincerely

Priyanka Paranagama
Doctoral Candidate

AUSTRALIA

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Explanatory Statement

Adaptive Decision Support Systems Project

This research project consists of three stages. In the first stage we investigated the relationship between the personality characteristics and their influence to senior managers' decision preferences. Since there was evidence of such a relationship, a decision support system generator that adapts to its users based on their personality was built in the second stage. We have named this system ADAPTOR.

The current stage of the project is aimed at investigating whether ADAPTOR is capable of successfully adapting to its users. Specifically, this investigation focuses on whether: ADAPTOR implementation is useable.

Your task is to use ADAPTOR for a given decision making situation. During this period, the ADAPTOR database will record your decision-making activity. Researchers will not try to re-construct complete decisions. The interest in collected data will be to investigate the above objectives. At the end of the exercise, you are expected to complete a questionnaire. Discussing any details of specific decision processes is left to your discretion.

No finding that could identify any individual participant will be published. The anonymity of your participation is assured by our reporting procedures. Access to data is restricted to the investigators. Coded data are stored for five years, as prescribed by university regulations.

Participation in this research is entirely voluntary, and if you agree to participate, you may withdraw your consent at any time by informing the investigators. You may also decline to participate in any section of the procedure.

If you have any queries or would like to be informed of the aggregate research finding, please contact the researchers at the above address. Should you have any complaint concerning the manner in which this research is conducted, please do not hesitate to contact the Standing Committee on Ethics in Research on Humans at the following address:

The Secretary
The Standing Committee on Ethics in Research on Humans
Monash University
Wellington Road
Clayton VIC 3163
Telephone: (03) 9905 2052 Fax: (03) 9905 1420

Thank you.

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Informed Consent Form

Adaptive Decision Support Systems Project

I agree to take part in the above Monash University research project. I have had the project explained to me, and I have read and understood the Explanatory Statement, which I retain for my records.

I understand that any information I provide is confidential, and that no information that could lead to the identification of any individual or organisation will be disclosed in any reports on the project, or to any other party.

I also understand that my participation is voluntary, that I can choose not to participate, and that I can withdraw my participation at any stage of the project.

Name: .... (please print)

Signature: .... Date: ....

Participant No.

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Evaluation of Concepts in ADAPTOR

Please give detailed answers to these questions.

1. How do you think ADAPTOR suited the way you work? Do you consider it as an overhead or an assistant?

2. Overall, what is your impression of ADAPTOR and its usefulness for a senior manager like you?

3. How many times have you used ADAPTOR?

4. How many different decisions were assisted by ADAPTOR? How may repetitions?

5. How many of the decisions would you consider as significant organisational decisions?

6. Why do you consider these as significant?

7. Did ADAPTOR help in understanding these decisions better? How?

8. Do you feel that ADAPTOR assisted you in identifying the relevant variables (factors) needed for decisions?

9. Did you get a reasonable list of variables and estimates of your preferences when you used ADAPTOR for the first time?

10. If ADAPTOR assisted in identifying variables, was it getting better at giving you a list of variables that were relevant to the situation as you used the system more?

11. Did ADAPTOR give you reasonable estimates of your preferences to variables?

12. Do you feel that the estimates of preferences given by ADAPTOR were getting better as you used the system more?

13. How do you think ADAPTOR helped you in structuring decisions?

14. How do you think ADAPTOR helped you in evaluating possible alternative solutions to the decision situation?

15. Did you get any warnings while evaluating decisions?

16. Were the warnings useful and relevant?

17. Did you make any changes to the way you had defined the decision because of the warnings?

18. In what way did you make changes because of the warnings?

19. Did the warnings help you better understand the decisions, or the way you make decisions? How?

20. How do you think that getting assistance from ADAPTOR changed your decision making process?

21. What effect do you think ADAPTOR had on the outcome of decisions?

22. What other advantages did you get from using the system?

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Details of Significant Decision Assisted with ADAPTOR

1. What is the decision? Description/Binary-Multiple alternative etc.
2. Why was it considered significant?
3. What was its perceived impact on the organisation?
4. Did ADAPTOR help in understanding the decision better? How?
5. Did ADAPTOR help in structuring the decision? How?
6. What were the variables (factors) important in making the decision?
7. Did ADAPTOR identify some of the variables? What were they?
8. Did ADAPTOR give reasonable estimates of your preferences to these variables?
9. How did ADAPTOR help in evaluating the alternatives?
10. What warnings did ADAPTOR generate? Did you consider these as relevant?
11. How did you change the decision definition because of the warnings?
12. What difference do you think ADAPTOR made to the way you approached this decision?
13. Do you think that you were able to exercise control over the decision making process?
14. What difference do you think ADAPTOR made to the time spent the making this decision?
15. Are you satisfied with the outcome selected with the assistance of ADAPTOR?
16. What influence do you think ADAPTOR had on the outcome you selected?

Appendix C: Statistical Analysis (Stage 1)

Appendix C-1

1.2

```
    ***************************** 1.2 EXPLORE DATA
->  *****************************************
->
-> EXAMINE
->  VARIABLES=f_1 f_2 f_3 f_4 f_5 f_6 f_7 f_8 f_9 f_10 f_11 f_12 f_13 f_14
->   f_15 NUM_TYPE
->   /PLOT NONE
->   /PERCENTILES(5,10,25,50,75,90,95) HAVERAGE
->   /FREQUENCIES
->   /STATISTICS DESCRIPTIVES
->   /CINTERVAL 95
->   /MISSING REPORT
->   /NOTOTAL.
```

F_1 F 1

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	5.8667	Std Err	.3449	Min	2.0000	Skewness	-.4525
Median	6.0000	Variance	3.5678	Max	9.0000	S E Skew	.4269
5% Trim	5.9074	Std Dev	1.8889	Range	7.0000	Kurtosis	-.3750
95% CI for Mean (5.1614, 6.5720)				IQR	2.2500	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	3.0000	4.7500	6.0000	7.0000	8.0000
Tukey's Hinges			5.0000	6.0000	7.0000	

Percentiles	95.0000
	9.0000

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
2.0	2.00	6.67	6.67	6.67
3.0	2.00	6.67	6.67	13.33
4.0	3.00	10.00	10.00	23.33
5.0	4.00	13.33	13.33	36.67
6.0	6.00	20.00	20.00	56.67
7.0	8.00	26.67	26.67	83.33
8.0	3.00	10.00	10.00	93.33
9.0	2.00	6.67	6.67	100.00

F_2 F 2

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	3.9000	Std Err	.2685	Min	1.0000	Skewness	.3235
Median	4.0000	Variance	2.1621	Max	7.0000	S E Skew	.4269
5% Trim	3.8889	Std Dev	1.4704	Range	6.0000	Kurtosis	-.5208
95% CI for Mean (3.3509, 4.4491)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.5500	2.0000	3.0000	4.0000	5.0000	6.0000
Tukey's Hinges			3.0000	4.0000	5.0000	

Percentiles	95.0000
	6.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
1.0	1.00	3.33	3.33	3.33
2.0	3.00	10.00	10.00	13.33
3.0	10.00	33.33	33.33	46.67
4.0	7.00	23.33	23.33	70.00
5.0	3.00	10.00	10.00	80.00
6.0	5.00	16.67	16.67	96.67
7.0	1.00	3.33	3.33	100.00

F_3 F 3

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	5.2333	Std Err	.3205	Min	1.0000	Skewness	-.9147
Median	6.0000	Variance	3.0816	Max	8.0000	S E Skew	.4269
5% Trim	5.3333	Std Dev	1.7555	Range	7.0000	Kurtosis	.4450
95% CI for Mean (4.5778, 5.8888)				IQR	2.2500	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	3.0000	4.0000	6.0000	6.2500	7.0000
Tukey's Hinges			4.0000	6.0000	6.0000	

Percentiles	95.0000
	7.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
1.0	2.00	6.67	6.67	6.67
3.0	3.00	10.00	10.00	16.67
4.0	4.00	13.33	13.33	30.00
5.0	4.00	13.33	13.33	43.33
6.0	10.00	33.33	33.33	76.67
7.0	6.00	20.00	20.00	96.67
8.0	1.00	3.33	3.33	100.00

F_4 F 4

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	5.5333	Std Err	.3313	Min	1.0000	Skewness	-.7256
Median	6.0000	Variance	3.2920	Max	8.0000	S E Skew	.4269
5% Trim	5.6296	Std Dev	1.8144	Range	7.0000	Kurtosis	-.0615
95% CI for Mean (4.8558, 6.2108)				IQR	3.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.5500	3.0000	4.0000	6.0000	7.0000	7.9000
Tukey's Hinges			4.0000	6.0000	7.0000	

Percentiles	95.0000
	8.0000

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
1.0	1.00	3.33	3.33	3.33
2.0	1.00	3.33	3.33	6.67
3.0	2.00	6.67	6.67	13.33
4.0	5.00	16.67	16.67	30.00
5.0	3.00	10.00	10.00	40.00
6.0	7.00	23.33	23.33	63.33
7.0	8.00	26.67	26.67	90.00
8.0	3.00	10.00	10.00	100.00

F_5 F 5

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	5.5667	Std Err	.3169	Min	2.0000	Skewness	-.2896
Median	6.0000	Variance	3.0126	Max	9.0000	S E Skew	.4269
5% Trim	5.5926	Std Dev	1.7357	Range	7.0000	Kurtosis	-.3345
95% CI for Mean (4.9185, 6.2148)				IQR	3.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	3.1000	4.0000	6.0000	7.0000	7.9000
Tukey's Hinges			4.0000	6.0000	7.0000	

Percentiles	95.0000
	8.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
2.0	2.00	6.67	6.67	6.67
3.0	1.00	3.33	3.33	10.00
4.0	6.00	20.00	20.00	30.00
5.0	4.00	13.33	13 33	43.33
6.0	7.00	23.33	23.33	66.67
7.0	7.00	23.33	23.33	90.00
8.0	2.00	6.67	6.67	96.67
9.0	1.00	3.33	3.33	100.00

F_6 F 6

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	3.3667	Std Err	.2733	Min	1.0000	Skewness	.9703
Median	3.0000	Variance	2.2402	Max	8.0000	S E Skew	.4269
5% Trim	3.2778	Std Dev	1.4967	Range	7.0000	Kurtosis	1.8939
95% CI for Mean (2.8078, 3.9256)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	2.0000	2.0000	3.0000	4.0000	5.0000
Tukey's Hinges			2.0000	3.0000	4.0000	

Percentiles	95.0000
	6.9000

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
1.0	2.00	6.67	6.67	6.67
2.0	7.00	23.33	23.33	30.00
3.0	8.00	26.67	26.67	56.67
4.0	8.00	26.67	26.67	83.33
5.0	3.00	10.00	10.00	93.33
6.0	1.00	3.33	3.33	96.67
8.0	1.00	3.33	3.33	100.00

F_7 F 7

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	4.3000	Std Err	.3113	Min	1.0000	Skewness	.3900
Median	4.0000	Variance	2.9069	Max	8.0000	S E Skew	.4269
5% Trim	4.2593	Std Dev	1.7050	Range	7.0000	Kurtosis	.0484
95% CI for Mean (3.6634, 4.9366)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.5500	2.0000	3.0000	4.0000	5.0000	6.9000
Tukey's Hinges			3.0000	4.0000	5.0000	

Percentiles	95.0000
	8.0000

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
1.0	1.00	3.33	3.33	3.33
2.0	3.00	10.00	10.00	13.33
3.0	6.00	20.00	20.00	33.33
4.0	7.00	23.33	23.33	56.67
5.0	7.00	23.33	23.33	80.00
6.0	3.00	10.00	10.00	90.00
7.0	1.00	3.33	3.33	93.33
8.0	2.00	6.67	6.67	100.00

F_8 F 8

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	4.7000	Std Err	.3395	Min	1.0000	Skewness	-.3557
Median	5.0000	Variance	3.4586	Max	8.0000	S E Skew	.4269
5% Trim	4.7222	Std Dev	1.8597	Range	7.0000	Kurtosis	-.9603
95% CI for Mean (4.0056, 5.3944)				IQR	3.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.5500	2.0000	3.0000	5.0000	6.0000	7.0000
Tukey's Hinges			3.0000	5.0000	6.0000	

Percentiles	95.0000
	7.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
1.0	1.00	3.33	3.33	3.33
2.0	4.00	13.33	13.33	16.67
3.0	5.00	16.67	16.67	33.33
4.0	1.00	3.33	3.33	36.67
5.0	6.00	20.00	20.00	56.67
6.0	9.00	30.00	30.00	86.67
7.0	3.00	10.00	10.00	96.67
8.0	1.00	3.33	3.33	100.00

F_9 F 9

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	4.6333	Std Err	.3088	Min	2.0000	Skewness	-.1089
Median	5.0000	Variance	2.8609	Max	8.0000	S E Skew	.4269
5% Trim	4.6111	Std Dev	1.6914	Range	6.0000	Kurtosis	-.9812
95% CI for Mean (4.0017, 5.2649)				IQR	3.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.0000	3.0000	5.0000	6.0000	6.9000
Tukey's Hinges			3.0000	5.0000	6.0000	

Percentiles	95.0000
	7.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
2.0	4.00	13.33	13.33	13.33
3.0	6.00	20.00	20.00	33.33
4.0	2.00	6.67	6.67	40.00
5.0	7.00	23.33	23.33	63.33
6.0	8.00	26.67	26.67	90.00
7.0	2.00	6.67	6.67	96.67
8.0	1.00	3.33	3.33	100.00

F_10 F 10

Valid cases: 30.0 Misring cases: 3.0 Percent missing: 9.1

Mean	6.4000	Std Err	.2378	Min	3.0000	Skewness	-.6179
Median	6.5000	Variance	1.6966	Max	9.0000	S E Skew	.4269
5% Trim	6.4444	Std Dev	1.3025	Range	6.0000	Kurtosis	.8060
95% CI for Mean (5.9136, 6.8864)				IQR	1.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.5500	4.1000	6.0000	6.5000	7.0000	8.0000
Tukey's Hinges			6.0000	6.5000	7.0000	

Percentiles	95.0000
	8.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
3.0	1.00	3.33	3.33	3.33
4.0	2.00	6.67	6.67	10.00
5.0	2.00	6.67	6.67	16.67
6.0	10.00	33.33	33.33	50.00
7.0	10.00	33.33	33.33	83.33
8.0	4.00	13.33	13.33	96.67
9.0	1.00	3.33	3.33	100.00

F_11 F 11

Valid cases:	30.0	Missing cases:	3.0	Percent missing:	9.1

Mean	6.8333	Std Err	.1982	Min	5.0000	Skewness	-.1669
Median	7.0000	Variance	1.1782	Max	9.0000	S E Skew	.4269
5% Trim	6.8333	Std Dev	1.0854	Range	4.0000	Kurtosis	-.7265
95% CI for Mean (6.4280, 7.2386)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	5.0000	5.0000	6.0000	7.0000	8.0000	8.0000
Tukey's Hinges			6.0000	7.0000	8.0000	

Percentile	95.0000
	8.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
5.0	4.00	13.33	13.33	13.33
6.0	7.00	23.33	23.33	36.67
7.0	10.00	33.33	33.33	70.00
8.0	8.00	26.67	26.67	96.67
9.0	1.00	3.33	3.33	100.00

F_12 F 12

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	6.6333	Std Err	.2372	Min	4.0000	Skewness	.0394
Median	6.5000	Variance	1.6885	Max	9.0000	S E Skew	.4269
5% Trim	6.6296	Std Dev	1.2994	Range	5.0000	Kurtosis	-.7724
95% CI for Mean (6.1481, 7.1185)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	4.5500	5.0000	6.0000	6.5000	8.0000	8.0000
Tukey's Hinges			6.0000	6.5000	8.0000	

Percentiles	95.0000
	9.0000

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
4.0	1.00	3.33	3.33	3.33
5.0	5.00	16.67	16.67	20.00
6.0	9.00	30.00	30.00	50.00
7.0	6.00	20.00	20.00	70.00
8.0	7.00	23.33	23.33	93.33
9.0	2.00	6.67	6.67	100.00

F_13 F 13

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	5.0333	Std Err	.2061	Min	2.0000	Skewness	.0848
Median	5.0000	Variance	1.2747	Max	8.0000	S E Skew	.4269
5% Trim	5.0185	Std Dev	1.1290	Range	6.0000	Kurtosis	1.6832
95% CI for Mean (4.6117, 5.4549)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.1000	4.0000	4.0000	5.0000	6.0000	6.0000
Tukey's Hinges			4.0000	5.0000	6.0000	

Percentiles	95.0000
	7.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
2.0	1.00	3.33	3.33	3.33
4.0	8.00	26.67	26.67	30.00
5.0	12.00	40.00	40.00	70.00
6.0	7.00	23.33	23.33	93.33
7.0	1.00	3.33	3.33	96.67
8.0	1.00	3.33	3.33	100.00

F_14 F 14

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	4.8667	Std Err	.2525	Min	2.0000	Skewness	.0036
Median	5.0000	Variance	1.9126	Max	8.0000	S E Skew	.4269
5% Trim	4.8519	Std Dev	1.3830	Range	6.0000	Kurtosis	-.1113
95% CI for Mean (4.3503, 5.3831)				IQR	2.0000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.5500	3.0000	4.0000	5.0000	6.0000	6.9000
Tukey's Hinges			4.0000	5.0000	6.0000	

Percentiles	95.0000
	7.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
2.0	1.00	3.33	3.33	3.33
3.0	5.00	16.67	16.67	20.00
4.0	4.00	13.33	13.33	33.33
5.0	11.00	36.67	36.67	70.00
6.0	6.00	20.00	20.00	90.00
7.0	2.00	6.67	6.67	96.67
8.0	1.00	3.33	3.33	100.00

F_15 F 15

Valid cases: 30.0 Missing cases: 3.0 Percent missing: 9.1

Mean	4.6333	Std Err	.2372	Min	3.0000	Skewness	.5446
Median	5.0000	Variance	1.6885	Max	8.0000	S E Skew	.4269
5% Trim	4.5556	Std Dev	1.2994	Range	5.0000	Kurtosis	.0608
95% CI for Mean (4.1481, 5.1185)				IQR	1.5000	S E Kurt	.8327

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.0000	3.0000	3.7500	5.0000	5.2500	6.0000
Tukey's Hinges			4.0000	5.0000	5.0000	

Percentiles	95.0000
	7.4500

Frequency Table

Bin Center	Freq	Pct	Valid Pct	Cum Pct
3.0	7.00	23.33	23.33	23.33
4.0	7.00	23.33	23.33	46.67
5.0	9.00	30.00	30.00	76.67
6.0	5.00	16.67	16.67	93.33
7.0	1.00	3.33	3.33	96.67
8.0	1.00	3.33	3.33	100.00

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-> FREQUENCIES
->   VARIABLES=num_type
->   /STATISTICS=MODE
->   /BARCHART  FREQ.

>Warning # 44
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NUM_TYPE

Value Label	Value	Frequency	Percent	Valid Percent	Cum Percent
	1	17	51.5	51.5	51.5
	3	16	48.5	48.5	100.0
	Total	33	100.0	100.0	

Hi-Res Chart # _0:Bar chart of num_type

Mode 1.000

Valid cases 33 Missing cases 0

Preceding task required 5.11 seconds elapsed.

Appendix C-2

```
-> * ***************************** 3.2 EXAMINING GROUP DIFFERENCES
->   ***************************
->
->
-> EXAMINE
->   VARIABLES=f_1 f_2 f_3 f_4 f_5 f_6 f_7 f_8 f_9 f_10 f_11 f_12 f_13 f_14
->   f_15 BY num_type
->   /PLOT BOXPLOT
->   /COMPARE GROUP
->   /MESTIMATORS  HUBER(1.339) ANDREW(1.34) HAMPEL(1.7,3.4,8.5) TUKEY(4.685)
->   /PERCENTILES(5,10,25,50,75,90,95) HAVERAGE
->   /STATISTICS DESCRIPTIVES
->   /CINTERVAL 95
->   /MISSING LISTWISE
->   /NOTOTAL.
```

3.2

F_1 F 1
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	5.2500	Std Err	.4610	Min	2.0000	Skewness	-.4922
Median	5.5000	Variance	3.4000	Max	8.0000	S E Skew	.5643
5% Trim	5.2778	Std Dev	1.8439	Range	6.0000	Kurtosis	-.6981
95% CI for Mean (4.2675, 6.2325)				IQR	3.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	5.4182	Tukey (4.685)	5.3910
Hampel (1.700, 3.400, 8.500)	5.3458	Andrew (1.340 * pi)	5.3903

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.0000	4.0000	5.5000	7.0000	7.3000
Tukey's Hinges			4.0000	5.5000	7.0000	

Percentiles	95.0000
	.

F_1 F 1
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	6.5714	Std Err	.4654	Min	3.0000	Skewness	-.5472
Median	7.0000	Variance	3.0330	Max	9.0000	S E Skew	.5974
5% Trim	6.6349	Std Dev	1.7415	Range	6.0000	Kurtosis	.0287
95% CI for Mean (5.5659, 7.5770)				IQR	2.2500	S E Kurt	1.1541

M-Estimators

Huber (1.339)	6.7305	Tukey (4.685)	6.8643
Hampel (1.700, 3.400, 8.500)	6.7097	Andrew (1.340 * pi)	6.8730

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.0000	3.5000	5.7500	7.0000	8.0000	9.0000
Tukey's Hinges			6.0000	7.0000	8.0000	

Percentiles	95.0000
	.

Hi-Res Chart # 26:Boxplot of f_1 by num_type

F_2 F 2
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	3.6250	Std Err	.3966	Min	1.0000	Skewness	.4831
Median	3.5000	Variance	2.5167	Max	7.0000	S E Skew	.5643
5% Trim	3.5833	Std Dev	1.5864	Range	6.0000	Kurtosis	.0320
95% CI for Mean (2.7797, 4.4703)				IQR	2.5000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	3.5000	Tukey (4.685)	3.4451
Hampel (1.700, 3.400, 8.500)	3.5112	Andrew (1.340 * pi)	3.4444

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	1.7000	2.2500	3.5000	4.7500	6.3000
Tukey's Hinges			2.5000	3.5000	4.5000	

Percentiles	95.0000
Haverage	.

F_2 F 2
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	4.2143	Std Err	.3505	Min	3.0000	Skewness	.4970
Median	4.0000	Variance	1.7198	Max	6.0000	S E Skew	.5974
5% Trim	4.1825	Std Dev	1.3114	Range	3.0000	Kurtosis	-1.6022
95% CI for Mean (3.4571, 4.9715)				IQR	3.0000	S E Kurt	1.1541

M-Estimators

Huber (1.339)	4.0359	Tukey (4.685)	4.0921
Hampel (1.700, 3.400, 8.500)	4.1781	Andrew (1.340 * pi)	4.0921

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.0000	3.0000	3.0000	4.0000	6.0000	6.0000
Tukey's Hinges			3.0000	4.0000	6.0000	

Percentiles	95.0000
	.

Hi-Res Chart # 27:Boxplot of f_2 by num_type

F_3 F 3
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	4.9375	Std Err	.4956	Min	1.0000	Skewness	-.8995
Median	5.5000	Variance	3.9292	Max	7.0000	S E Skew	.5643
5% Trim	5.0417	Std Dev	1.9822	Range	6.0000	Kurtosis	-.0003
95% CI for Mean (3.8813, 5.9937)				IQR	2.7500	S E Kurt	1.0908

M-Estimators

Huber (1.339)	5.2293	Tukey (4.685)	5.2397
Hampel (1.700, 3.400, 8.500)	5.1379	Andrew (1.340 * pi)	5.2372

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	1.0000	4.0000	5.5000	6.7500	7.0000
Tukey's Hinges			4.0000	5.5000	6.5000	

Percentiles	95.0000

F_3 F 3
By NUM_TYPE 3

Valid cases:	14.0	Missing cases:	2.0	Percent missing:	12.5

Mean	5.5714	Std Err	.3882	Min	3.0000	Skewness	-.5163
Median	6.0000	Variance	2.1099	Max	8.0000	S E Skew	.5974
5% Trim	5.5794	Std Dev	1.4525	Range	5.0000	Kurtosis	-.0727
95% CI for Mean (4.7328, 6.4101)				IQR	1.5000	S E Kurt	1.1541

M-Estimators

Huber (1.339)	5.7306	Tukey (4.685)	5.7262
Hampel (1.700, 3.400, 8.500)	5.6597	Andrew (1.340 * pi)	5.7247

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.0000	3.0000	4.7500	6.0000	6.2500	7.5000
Tukey's Hinges			5.0000	6.0000	6.0000	

Percentiles	95.0000

Hi-Res Chart # 28:Boxplot of f_3 by num_type

F_4 F 4
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	5.1250	Std Err	.5072	Min	1.0000	Skewness	-.4669
Median	5.5000	Variance	4.1167	Max	8.0000	S E Skew	.5643
5% Trim	5.1944	Std Dev	2.0290	Range	7.0000	Kurtosis	-.3353
95% CI for Mean (4.0438, 6.2062)				IQR	2.7500	S E Kurt	1.0908

M-Estimators

Huber (1.339)	5.2750	Tukey (4.685)	5.2974
Hampel (1.700, 3.400, 8.500)	5.2521	Andrew (1.340 * pi)	5.2958

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	1.7000	4.0000	5.5000	6.7500	8.0000
Tukey's Hinges			4.0000	5.5000	6.5000	

Percentiles	95.0000
	.

```
   F_4        F 4
By NUM_TYPE         3

Valid cases:        14.0   Missing cases:       2.0   Percent missing:    12.5


Mean        6.0000  Std Err      .3922  Min        3.0000  Skewness    -.8517
Median      6.5000  Variance    2.1538  Max        8.0000  S E Skew     .5974
5% Trim     6.0556  Std Dev     1.4676  Range      5.0000  Kurtosis    -.2532
95% CI for Mean (5.1526, 6.8474)        IQR        2.2500  S E Kurt    1.1541

                              M-Estimators
                              ------------

Huber  ( 1.339)                 6.4448   Tukey  ( 4.685)              6.7305
Hampel ( 1.700, 3.400, 8.500)   6.5078   Andrew ( 1.340 * pi )        6.7312


                              Percentiles
                              -----------

Percentiles          5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage             3.0000    3.5000    4.7500    6.5000    7.0000    7.5000
Tukey's Hinges                           5.0000    6.5000    7.0000

Percentiles         95.0000
```

Hi-Res Chart # 29:Boxplot of f_4 by num_type

F_5 F 5
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	5.0625	Std Err	.5039	Min	2.0000	Skewness	.1821
Median	4.5000	Variance	4.0625	Max	9.0000	S E Skew	.5643
5% Trim	5.0139	Std Dev	2.0156	Range	7.0000	Kurtosis	-.6983
95% CI for Mean (3.9885, 6.1365)				IQR	3.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	5.0799	Tukey (4.685)	4.9963
Hampel (1.700, 3.400, 8.500)	5.0327	Andrew (1.340 * pi)	4.9969

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.0000	4.0000	4.5000	7.0000	7.6000
Tukey's Hinges			4.0000	4.5000	7.0000	

Percentiles	95.0000

```
   F_5        F 5
By NUM_TYPE         3

Valid cases:         14.0   Missing cases:        2.0   Percent missing:    12.5


Mean         6.1429  Std Err       .3120  Min          4.0000  Skewness      .0207
Median       6.0000  Variance     1.3626  Max          8.0000  S E Skew      .5974
5% Trim      6.1587  Std Dev      1.1673  Range        4.0000  Kurtosis     -.4390
95% CI for Mean (5.4689, 6.8168)          IQR          2.0000  S E Kurt     1.1541

                              M-Estimators
                              ------------

Huber  ( 1.339)               6.1229   Tukey  ( 4.685)               6.1403
Hampel ( 1.700, 3.400, 8.500) 6.1562   Andrew ( 1.340 * pi )         6.1401


                              Percentiles
                              -----------

Percentiles           5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage              4.0000    4.5000    5.0000    6.0000    7.0000    8.0000
Tukey's Hinges                            5.0000    6.0000    7.0000

Percentiles          95.0000
```

Hi-Res Chart # 30:Boxplot of f_5 by num_type

F_6 F 6
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	3.7500	Std Err	.4233	Min	1.0000	Skewness	.9183
Median	3.5000	Variance	2.8667	Max	8.0000	S E Skew	.5643
5% Trim	3.6667	Std Dev	1.6931	Range	7.0000	Kurtosis	1.5569
95% CI for Mean (2.8478, 4.6522)				IQR	1.7500	S E Kurt	1.0908

M-Estimators

Huber (1.339)	3.5148	Tukey (4.685)	3.4107
Hampel (1.700, 3.400, 8.500)	3.4450	Andrew (1.340 * pi)	3.4105

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	1.7000	3.0000	3.5000	4.7500	6.6000
Tukey's Hinges			3.0000	3.5000	4.5000	

Percentiles	95.0000
	.

```
   F_6         F 6
By NUM_TYPE          3

Valid cases:        14.0   Missing cases:       2.0   Percent missing:    12.5


Mean        2.9286  Std Err      .3050  Min         1.0000  Skewness     .1590
Median      3.0000  Variance    1.3022  Max         5.0000  S E Skew     .5974
5% Trim     2.9206  Std Dev     1.1411  Range       4.0000  Kurtosis   -.8651
95% CI for Mean (2.2697, 3.5874)        IQR         2.0000  S E Kurt    1.1541

                                M-Estimators
                                ------------

Huber  ( 1.339)                 2.9153  Tukey  ( 4.685)             2.9064
Hampel ( 1.700, 3.400, 8.500)   2.9154  Andrew ( 1.340 * pi )       2.9064


                                Percentiles
                                -----------

Percentiles           5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage              1.0000    1.5000    2.0000    3.0000    4.0000    4.5000
Tukey's Hinges                            2.0000    3.0000    4.0000

Percentiles          95.0000


Hi-Res Chart  # 31:Boxplot of f_6 by num_type
```

F_7 F 7
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	4.3125	Std Err	.4539	Min	1.0000	Skewness	.2313
Median	4.5000	Variance	3.2958	Max	8.0000	S E Skew	.5643
5% Trim	4.2917	Std Dev	1.8154	Range	7.0000	Kurtosis	.0259
95% CI for Mean (3.3451, 5.2799)				IQR	2.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	4.2516	Tukey (4.685)	4.2612
Hampel (1.700, 3.400, 8.500)	4.2739	Andrew (1.340 * pi)	4.2618

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	1.7000	3.0000	4.5000	5.0000	7.3000
Tukey's Hinges			3.0000	4.5000	5.0000	

Percentiles	95.0000

```
   F_7         F 7
By NUM_TYPE         3

Valid cases:       14.0   Missing cases:      2.0   Percent missing:    12.5


Mean       4.2857  Std Err     .4376  Min        2.0000  Skewness     .6908
Median     4.0000  Variance   2.6813  Max        8.0000  S E Skew     .5974
5% Trim    4.2063  Std Dev    1.6375  Range      6.0000  Kurtosis     .7245
95% CI for Mean (3.3403, 5.2312)      IQR        2.2500  S E Kurt    1.1541

                              M-Estimators
                              ------------

Huber  ( 1.339)               4.1515  Tukey  ( 4.685)               4.0415
Hampel ( 1.700, 3.400, 8.500) 4.1795  Andrew ( 1.340 * pi )         4.0302


                              Percentiles
                              -----------

Percentiles       5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage          2.0000    2.0000    3.0000    4.0000    5.2500    7.0000
Tukey's Hinges                        3.0000    4.0000    5.0000

Percentiles      95.0000


Hi-Res Chart  # 32:Boxplot of f_7 by num_type
```

F_8 F 8
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	4.5000	Std Err	.5000	Min	1.0000	Skewness	-.1143
Median	5.0000	Variance	4.0000	Max	8.0000	S E Skew	.5643
5% Trim	4.5000	Std Dev	2.0000	Range	7.0000	Kurtosis	-.8879
95% CI for Mean (3.4343, 5.5657)				IQR	3.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	4.5494	Tukey (4.685)	4.5507
Hampel (1.700, 3.400, 8.500)	4.5000	Andrew (1.340 * pi)	4.5508

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	1.0000	1.7000	3.0000	5.0000	6.0000	7.3000
Tukey's Hinges			3.0000	5.0000	6.0000	

Percentiles	95.0000

F_8 F 8
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	4.9286	Std Err	.4625	Min	2.0000	Skewness	-.7041
Median	5.5000	Variance	2.9945	Max	7.0000	S E Skew	.5974
5% Trim	4.9762	Std Dev	1.7305	Range	5.0000	Kurtosis	-.8631
95% CI for Mean (3.9294, 5.9277)				IQR	3.0000	S E Kurt	1.1541

M-Estimators

Huber (1.339)	5.4591	Tukey (4.685)	5.5712
Hampel (1.700, 3.400, 8.500)	5.6501	Andrew (1.340 * pi)	5.8721

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.0000	3.0000	5.5000	6.0000	7.0000
Tukey's Hinges			3.0000	5.5000	6.0000	

Percentiles	95.0000

Hi-Res Chart # 33:Boxplot of f_8 by num_type

F_9 F 9
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	4.8125	Std Err	.4584	Min	2.0000	Skewness	-.0559
Median	5.0000	Variance	3.3625	Max	8.0000	S E Skew	.5643
5% Trim	4.7917	Std Dev	1.8337	Range	6.0000	Kurtosis	-.9510
95% CI for Mean (3.8354, 5.7896)				IQR	3.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	4.8186	Tukey (4.685)	4.8291
Hampel (1.700, 3.400, 8.500)	4.7997	Andrew (1.340 * pi)	4.8294

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.0000	3.0000	5.0000	6.0000	7.3000
Tukey's Hinges			3.0000	5.0000	6.0000	

Percentiles	95.0000

F_9 F 9
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	4.4286	Std Err	.4156	Min	2.0000	Skewness	-.4180
Median	5.0000	Variance	2.4176	Max	6.0000	S E Skew	.5974
5% Trim	4.4762	Std Dev	1.5549	Range	4.0000	Kurtosis	-1.4768
95% CI for Mean (3.5308, 5.3263)				IQR	3.0000	S E Kurt	1.1541

M-Estimators

Huber (1.339)	4.6997	Tukey (4.685)	4.6384
Hampel (1.700, 3.400, 8.500)	4.5485	Andrew (1.340 * pi)	4.6364

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.0000	3.0000	5.0000	6.0000	6.0000
Tukey's Hinges			3.0000	5.0000	6.0000	

Percentiles	95.0000

Hi-Res Chart # 34:Boxplot of f_9 by num_type

```
   F_10       F 10
By NUM_TYPE          1

Valid cases:        16.0   Missing cases:       1.0   Percent missing:    5.9


Mean        6.3125  Std Err      .3381  Min         3.0000  Skewness   -1.0228
Median      6.0000  Variance    1.8292  Max         8.0000  S E Skew     .5643
5% Trim     6.4028  Std Dev     1.3525  Range       5.0000  Kurtosis    1.4811
95% CI for Mean (5.5918, 7.0332)        IQR         1.0000  S E Kurt    1.0908

                                M-Estimators
                                ------------

Huber  ( 1.339)                6.4885   Tukey  ( 4.685)               6.5226
Hampel ( 1.700, 3.400, 8.500)  6.4754   Andrew ( 1.340 * pi )         6.5227


                                Percentiles
                                -----------

Percentiles         5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage            3.0000    3.7000    6.0000    6.0000    7.0000    8.0000
Tukey's Hinges                          6.0000    6.0000    7.0000

Percentiles        95.0000
```

F_10 F 10
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	6.5000	Std Err	.3437	Min	4.0000	Skewness	-.1266
Median	7.0000	Variance	1.6538	Max	9.0000	S E Skew	.5974
5% Trim	6.5000	Std Dev	1.2860	Range	5.0000	Kurtosis	.3592
95% CI for Mean (5.7575, 7.2425)				IQR	1.2500	S E Kurt	1.1541

M-Estimators

Huber (1.339)	6.5124	Tukey (4.685)	6.5245
Hampel (1.700, 3.400, 8.500)	6.4969	Andrew (1.340 * pi)	6.5247

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	4.0000	4.5000	5.7500	7.0000	7.0000	8.5000
Tukey's Hinges			6.0000	7.0000	7.0000	

Percentiles	95.0000

Hi-Res Chart # 35:Boxplot of f_10 by num_type

```
    F_11      F 11
By  NUM_TYPE        1

Valid cases:        16.0   Missing cases:        1.0   Percent missing:     5.9


Mean         6.8125  Std Err      .2276  Min         5.0000  Skewness     -.1916
Median       7.0000  Variance     .8292  Max         8.0000  S E Skew      .5643
5% Trim      6.8472  Std Dev      .9106  Range       3.0000  Kurtosis     -.6752
95% CI for Mean (6.3273, 7.2977)         IQR         1.7500  S E Kurt     1.0908

                                M-Estimators
                                ------------

Huber  ( 1.339)                 6.8439   Tukey  ( 4.685)                6.8225
Hampel ( 1.700, 3.400, 8.500)   6.8197   Andrew ( 1.340 * pi )          6.8225


                                Percentiles
                                -----------

Percentiles           5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage              5.0000    5.7000    6.0000    7.0000    7.7500    8.0000
Tukey's Hinges                            6.0000    7.0000    7.5000

Percentiles          95.0000
```

F_11 F 11
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	6.8571	Std Err	.3454	Min	5.0000	Skewness	-.1934
Median	7.0000	Variance	1.6703	Max	9.0000	S E Skew	.5974
5% Trim	6.8413	Std Dev	1.2924	Range	4.0000	Kurtosis	-1.0040
95% CI for Mean (6.1109, 7.6034)				IQR	2.2500	S E Kurt	1.1541

M-Estimators

Huber (1.339)	6.9300	Tukey (4.685)	6.9003
Hampel (1.700, 3.400, 8.500)	6.8577	Andrew (1.340 * pi)	6.9004

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	5.0000	5.0000	5.7500	7.0000	8.0000	8.5000
Tukey's Hinges			6.0000	7.0000	8.0000	

Percentiles	95.0000

Hi-Res Chart # 36:Boxplot of f_11 by num_type

F_12 F 12
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	6.5625	Std Err	.3287	Min	4.0000	Skewness	-.0542
Median	6.5000	Variance	1.7292	Max	9.0000	S E Skew	.5643
5% Trim	6.5694	Std Dev	1.3150	Range	5.0000	Kurtosis	-.2501
95% CI for Mean (5.8618, 7.2632)				IQR	1.7500	S E Kurt	1.0908

M-Estimators

Huber (1.339)	6.5144	Tukey (4.685)	6.5067
Hampel (1.700, 3.400, 8.500)	6.5285	Andrew (1.340 * pi)	6.5072

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	4.0000	4.7000	6.0000	6.5000	7.7500	8.3000
Tukey's Hinges			6.0000	6.5000	7.5000	

Percentiles	95.0000

F_12 F 12
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	6.7143	Std Err	.3544	Min	5.0000	Skewness	.1508
Median	6.5000	Variance	1.7582	Max	9.0000	S E Skew	.5974
5% Trim	6.6825	Std Dev	1.3260	Range	4.0000	Kurtosis	-1.2603
95% CI for Mean (5.9487, 7.4799)				IQR	2.2500	S E Kurt	1.1541

M-Estimators

Huber (1.339)	6.6923	Tukey (4.685)	6.6979
Hampel (1.700, 3.400, 8.500)	6.7143	Andrew (1.340 * pi)	6.6977

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	5.0000	5.0000	5.7500	6.5000	8.0000	8.5000
Tukey's Hinges			6.0000	6.5000	8.0000	

Percentiles	95.0000
	.

Hi-Res Chart # 37:Boxplot of f_12 by num_type

F_13 F 13
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	4.9375	Std Err	.3350	Min	2.0000	Skewness	.1284
Median	5.0000	Variance	1.7958	Max	8.0000	S E Skew	.5643
5% Trim	4.9306	Std Dev	1.3401	Range	6.0000	Kurtosis	1.5859
95% CI for Mean (4.2234, 5.6516)				IQR	2.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	4.9285	Tukey (4.685)	4.9088
Hampel (1.700, 3.400, 8.500)	4.9284	Andrew (1.340 * pi)	4.9087

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	3.4000	4.0000	5.0000	6.0000	6.6000
Tukey's Hinges			4.0000	5.0000	6.0000	

Percentiles	95.0000

F_13 F 13
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	5.1429	Std Err	.2310	Min	4.0000	Skewness	.5274
Median	5.0000	Variance	.7473	Max	7.0000	S E Skew	.5974
5% Trim	5.1032	Std Dev	.8644	Range	3.0000	Kurtosis	.2433
95% CI for Mean (4.6437, 5.6420)				IQR	1.2500	S E Kurt	1.1541

M-Estimators

Huber (1.339)	5.1044	Tukey (4.685)	5.0275
Hampel (1.700, 3.400, 8.500)	5.1241	Andrew (1.340 * pi)	5.0201

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	4.0000	4.0000	4.7500	5.0000	6.0000	6.5000
Tukey's Hinges			5.0000	5.0000	6.0000	

Percentiles	95.0000

Hi-Res Chart # 38:Boxplot of f_13 by num_type

F_14 F 14
By NUM_TYPE 1

Valid cases:	16.0	Missing cases:	1.0	Percent missing:	5.9

Mean	4.7500	Std Err	.4133	Min	2.0000	Skewness	.1517
Median	5.0000	Variance	2.7333	Max	8.0000	S E Skew	.5643
5% Trim	4.7222	Std Dev	1.6533	Range	6.0000	Kurtosis	-.5140
95% CI for Mean (3.8690, 5.6310)				IQR	3.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	4.7690	Tukey (4.685)	4.7042
Hampel (1.700, 3.400, 8.500)	4.6693	Andrew (1.340 * pi)	4.7045

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	2.0000	2.7000	3.0000	5.0000	6.0000	7.3000
Tukey's Hinges			3.0000	5.0000	6.0000	

Percentiles	95.0000
	.

```
   F_14      F 14
By NUM_TYPE        3

Valid cases:        14.0   Missing cases:       2.0   Percent missing:    12.5


Mean        5.0000  Std Err      .2774  Min         3.0000  Skewness     .0000
Median      5.0000  Variance    1.0769  Max         7.0000  S E Skew     .5974
5% Trim     5.0000  Std Dev     1.0377  Range       4.0000  Kurtosis     .1688
95% CI for Mean (4.4008, 5.5992)        IQR         2.0000  S E Kurt    1.1541

                                  M-Estimators
                                  ------------

Huber  ( 1.339)                   5.0000   Tukey  ( 4.685)               5.0000
Hampel ( 1.700, 3.400, 8.500)     5.0000   Andrew ( 1.340 * pi )         5.0000


                                  Percentiles
                                  -----------

Percentiles          5.0000   10.0000   25.0000   50.0000   75.0000   90.0000
Haverage             3.0000    3.5000    4.0000    5.0000    6.0000    6.5000
Tukey's Hinges                           4.0000    5.0000    6.0000

Percentiles         95.0000
```

Hi-Res Chart # 39:Boxplot of f_14 by num_type

F_15 F 15
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Mean	5.0000	Std Err	.3536	Min	3.0000	Skewness	.3232
Median	5.0000	Variance	2.0000	Max	8.0000	S E Skew	.5643
5% Trim	4.9444	Std Dev	1.4142	Range	5.0000	Kurtosis	.0275
95% CI for Mean (4.2464, 5.7536)				IQR	2.0000	S E Kurt	1.0908

M-Estimators

Huber (1.339)	4.9668	Tukey (4.685)	4.9176
Hampel (1.700, 3.400, 8.500)	4.9325	Andrew (1.340 * pi)	4.9187

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.0000	3.0000	4.0000	5.0000	6.0000	7.3000
Tukey's Hinges			4.0000	5.0000	6.0000	

Percentiles	95.0000
	.

F_15 F 15
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Mean	4.2143	Std Err	.2809	Min	3.0000	Skewness	.4355
Median	4.0000	Variance	1.1044	Max	6.0000	S E Skew	.5974
5% Trim	4.1825	Std Dev	1.0509	Range	3.0000	Kurtosis	-.8121
95% CI for Mean (3.6075, 4.8211)				IQR	2.0000	S E Kurt	1.1541

M-Estimators

Huber (1.339)	4.1406	Tukey (4.685)	4.1722
Hampel (1.700, 3.400, 8.500)	4.2015	Andrew (1.340 * pi)	4.1722

Percentiles

Percentiles	5.0000	10.0000	25.0000	50.0000	75.0000	90.0000
Haverage	3.0000	3.0000	3.0000	4.0000	5.0000	6.0000
Tukey's Hinges			3.0000	4.0000	5.0000	

Percentiles	95.0000

Hi-Res Chart # 40:Boxplot of f_15 by num_type

Preceding task required 16.37 seconds elapsed.

Appendix C-3

```
-> * ************************** 5.1 UNIVARIATE OUTLIERS
->   ********************************
->
->
-> LIST
->   VARIABLES=zf_1 zf_2 zf_3 zf_4 zf_5 zf_6 zf_7 zf_8 zf_9 zf_10 zf_11 zf_12
->   zf_13 zf_14 zf_15
->   /CASES= BY 1
->   /FORMAT=  WRAP  NUMBERED .


1,036 bytes of memory required for the LIST procedure.
496 bytes have already been acquired.
540 bytes remain to be acquired.

The variables are listed in the following order:

      LINE   1: ZF_1 ZF_2 ZF_3 ZF_4 ZF_5

      LINE   2: ZF_6 ZF_7 ZF_8 ZF_9 ZF_10

      LINE   3: ZF_11 ZF_12 ZF_13 ZF_14 ZF_15
```

1	ZF_1:	-1.03465	-.61825	-.75053	-.91003	-.95832
	ZF_6:	-.24089	-.83040	-.91257	-1.02062	-.32640
	ZF_11:	.11506	-1.18769	.00000	-1.20515	-.45064
2	ZF_1:	.61746	.69802	.90063	.18201	.23506
	ZF_6:	1.79570	.31140	.65184	.81650	.44297
	ZF_11:	.11506	1.11783	.87287	-.51946	-1.19420
3	ZF_1:	.61746	-.61825	.90063	.18201	-.36163
	ZF_6:	-.24089	.31140	-.91257	.20412	-.32640
	ZF_11:	-.83417	-.41919	-.87287	.16623	.29292
4	ZF_1:	-1.58536	-.61825	-.20014	-.36401	-.95832
	ZF_6:	.43797	.88230	.65184	.81650	-.32640
	ZF_11:	-.83417	-.41919	.87287	.85192	.29292
5	ZF_1:	.06675	-.61825	.90063	1.27404	.83175
	ZF_6:	.43797	2.02410	1.17331	1.42887	1.21234
	ZF_11:	1.06428	.34932	.00000	-1.20515	-1.19420
6	ZF_1:	.61746	.03989	.35025	.72803	.83175
	ZF_6:	-.24089	.31140	.13037	-.40825	-.32640
	ZF_11:	-.83417	-.41919	-.87287	-1.20515	.29292
7	ZF_1:	-1.03465	.03989	-.75053	-.91003	-.95832
	ZF_6:	1.11684	.31140	.13037	.20412	.44297
	ZF_11:	.11506	.34932	-.87287	.16623	.29292
8	ZF_1:	-2.13606	-1.27638	-1.30092	-.91003	-2.15169
	ZF_6:	-.91975	-.83040	-1.43404	-1.63299	.44297
	ZF_11:	.11506	-1.18769	-.87287	-1.20515	-.45064
9	ZF_1:	-.48395	-1.93452	-2.40169	-2.54809	-1.55500
	ZF_6:	-1.59861	-1.97220	-1.95551	-1.02062	1.21234
	ZF_11:	1.06428	1.11783	.00000	2.22329	2.52359
10	ZF_1:	-.48395	2.01429	.90063	1.27404	2.02512
	ZF_6:	3.15342	1.45320	1.69477	2.04124	.44297
	ZF_11:	1.06428	1.88634	.00000	.16623	.29292
11	ZF_1:	-2.13606	-1.27638	-2.40169	-2.00207	-2.15169
	ZF_6:	1.11684	-.83040	.13037	.20412	-2.63451
	ZF_11:	1.06428	1.11783	2.61861	1.53761	1.78003
12	ZF_1:	.06675	.69802	.35025	.18201	-.95832
	ZF_6:	.43797	-.25950	.65184	.81650	-.32640
	ZF_11:	.11506	.34932	.87287	.85192	1.03648
13	ZF_1:	.06675	.03989	.35025	-.36401	.23506
	ZF_6:	-.24089	-.25950	-.39110	.20412	-.32640
	ZF_11:	-.83417	-.41919	-.87287	.85192	1.03648

14	ZF_1:	.61746	1.35616	-.20014	.18201	.83175
	ZF_6:	-.24089	-.83040	-.91257	-1.02062	-1.86514
	ZF_11:	-1.78339	-1.95620	.87287	.16623	-1.19420
15	ZF_1:	.06675	-.61825	1.45102	1.27404	-.36163
	ZF_6:	.	2.02410	1.69477	.20412	1.21234
	ZF_11:	1.06428	-1.18769	.00000	-1.89084	-1.93776
16	ZF_1:	-.48395	.03989	.35025	.72803	.83175
	ZF_6:	.43797	.31140	.65184	1.42887	-.32640
	ZF_11:	-.83417	-.41919	.00000	.16623	.29292
17	ZF_1:	1.16816	-1.27638	-.75053	-1.45605	-.95832
	ZF_6:	-.91975	-1.40130	-1.43404	-1.63299	1.21234
	ZF_11:	.11506	.34932	-2.61861	-1.89084	1.03648
20	ZF_1:	-.48395	.03989	.35025	1.27404	1.42843
	ZF_6:	.43797	-.25950	1.17331	.81650	.44297
	ZF_11:	1.06428	1.11783	1.74574	1.53761	.29292
21	ZF_1:	.61746	2.01429	1.45102	1.27404	.83175
	ZF_6:	.	.31140	-.91257	-.40825	-1.09577
	ZF_11:	.11506	-1.18769	-1.74574	-1.20515	.29292
22	ZF_1:	-.48395	-.61825	-.75053	-.36401	.23506
	ZF_6:	-.24089	.31140	.	.81650	.44297
	ZF_11:	.11506	.34932	.87287	.85192	1.03648
23	ZF_1:	.06675	-.61825	-.20014	.72803	.23506
	ZF_6:	-.91975	.31140	.65184	.81650	.44297
	ZF_11:	1.06428	-.41919	.87287	-.51946	-1.19420
24	ZF_1:	.61746	-.61825	1.45102	.72803	.83175
	ZF_6:	-.24089	.88230	.65184	.81650	.44297
	ZF_11:	.11506	.34932	.00000	.16623	-.45064
25	ZF_1:	1.71886	.69802	.35025	.72803	1.42843
	ZF_6:	-1.59861	-1.40130	-1.43404	-1.63299	1.98171
	ZF_11:	2.01350	1.88634	.00000	.16623	.29292
26	ZF_1:	1.16816	-.61825	-.75053	-.91003	-.36163
	ZF_6:	-.91975	-.83040	-.91257	-1.02062	.44297
	ZF_11:	1.06428	1.11783	.00000	.85192	1.03648
27	ZF_1:	-1.03465	.03989	.35025	-.36401	.23506
	ZF_6:	.43797	.31140	.13037	-.40825	-1.09577
	ZF_11:	-1.78339	-.41919	-.87287	.85192	1.03648
28	ZF_1:	.61746	.03989	35025	.72803	.83175
	ZF_6:	-.24089	-.25950	.13037	-1.63299	.44297
	ZF_11:	1.06428	.34932	.00000	-.51946	-1.19420
29	ZF_1:	1.71886	-.61825	-1.30092	-1.45605	-.36163

	ZF_6:	-.91975	-1.40130	-1.43404	-1.02062	-1.09577
	ZF_11:	-1.78339	-1.18769	.00000	.16623	.29292
30	ZF_1:	.06675	1.35616	.35025	.72803	.23506
	ZF_6:	.43797	-.25950	.65184	.81650	-.32640
	ZF_11:	.11506	-.41919	.87287	.16623	-.45064
31	ZF_1:	.06675	-.61825	-.20014	.18201	.23506
	ZF_6:	-.91975	-.25950	.65184	.20412	.44297
	ZF_11:	.11506	1.11783	.00000	.85192	-.45064
32	ZF_1:	.61746	1.35616	.90063	.72803	-.36163
	ZF_6:	.43797	2.02410	1.17331	.20412	1.21234
	ZF_11:	.11506	-1.18769	-.87287	-1.20515	-1.19420
33	ZF_1:	1.16816	1.35616	.90063	.18201	-.95832
	ZF_6:	-.91975	-.25950	.13037	-1.02062	-.32640
	ZF_11:	-.83417	1.11783	.00000	.16623	-1.19420
34	ZF_1:	-1.58536	1.35616	.35025	.18201	.23506
	ZF_6:	1.11684	.88230	.65184	.81650	-.32640
	ZF_11:	-1.78339	-1.18769	-.87287	-.51946	-.45064
35	ZF_1:	.61746	-.61825	-1.30092	-.91003	.83175
	ZF_6:	-.24089	-.83040	-.91257	.20412	-1.86514
	ZF_11:	-.83417	-.41919	.87287	.16623	-.45064

Number of cases read: 33 Number of cases listed: 33

Preceding task required 1.21 seconds elapsed.

Appendix C-4

```
-> * *************************** 5.3 MULTIVARIATE OUTLIERS
->   ******************************
->
-> REGRESSION
->    /DEPENDENT=NUM
->    /METHOD=ENTER F_1 f_2 f_3 f_4 f_5 f_6 f_7 f_8 f_9 f_10 f_11 f_12 f_13
->   f_14 F_15
->    /RESIDUALS=OUTLIERS(MAHAL) NORMPROB ID(NUM).

   8012 bytes of memory required for REGRESSION procedure.
  80671 more bytes may be needed for Residuals plots.
```

* * * * M U L T I P L E   R E G R E S S I O N * * * *

Listwise Deletion of Missing Data

Equation Number 1   Dependent Variable..   NUM

Block Number 1. Method: Enter

```
   F_1      F_2      F_3      F_4      F_5      F_6      F_7      F_8
   F_9      F_10     F_11     F_12     F_13     F_14     F_15
```

Variable(s) Entered on Step Number

```
   1..    F_15     F 15
   2..    F_13     F 13
   3..    F_6      F 6
   4..    F_11     F 11
   5..    F_5      F 5
   6..    F_1      F 1
   7..    F_2      F 2
   8..    F_9      F 9
   9..    F_12     F 12
  10..    F_3      F 3
  11..    F_14     F 14
  12..    F_10     F 10
  13..    F_8      F 8
  14..    F_7      F 7
  15..    F_4      F 4
```

Multiple R	.79248
R Square	.62803
Adjusted R Square	.22948
Standard Error	89.29385

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	15	188467.49478	12564.49965
Residual	14	111627.47189	7973.39085

F = 1.57580   Signif F = .2008

* * * * M U L T I P L E R E G R E S S I O N * * * *

Equation Number 1 Dependent Variable.. NUM

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
F_1	10.277270	17.193002	.190831	.598	.5595
F_2	.885129	23.731626	.012794	.037	.9708
F_3	-80.705153	34.315245	-1.392707	-2.352	.0338
F_4	49.859076	47.226203	.889285	1.056	.3090
F_5	-7.190405	23.070376	-.122687	-.312	.7599
F_6	8.456016	33.474905	.124418	.253	.8042
F_7	-32.305365	28.519832	-.541451	-1.133	.2764
F_8	24.687281	28.189592	.451330	.876	.3959
F_9	17.260146	23.500361	.286990	.734	.4748
F_10	-47.967136	31.249051	-.614182	-1.535	.1471
F_11	9.681481	44.619029	.103303	.217	.8314
F_12	28.926025	28.491795	.369496	1.015	.3272
F_13	-95.436930	43.175853	-1.059235	-2.210	.0442
F_14	11.315975	30.840187	.153843	.367	.7192
F_15	-12.558531	28.495717	-.160420	-.441	.6661
(Constant)	758.999842	255.698638		2.968	.0102

End Block Number 1 All requested variables entered.

* * * * MULTIPLE REGRESSION * * * *

Equation Number 1 Dependent Variable.. NUM

Residuals Statistics:

	Min	Max	Mean	Std Dev	N
*PRED	33.4997	333.8233	189.3667	80.6156	30
*ZPRED	-1.9335	1.7919	.0000	1.0000	30
*SEPRED	44.4918	79.8611	64.5825	9.1867	30
*ADJPRED	-39.5440	381.6825	193.4428	106.8270	30
*RESID	-143.4704	102.8505	.0000	62.0421	30
*ZRESID	-1.6067	1.1518	.0000	.6948	30
*SRESID	-2.3255	1.6644	-.0117	1.0120	30
*DRESID	-300.5583	231.5252	-4.0761	137.8851	30
*SDRESID	-2.8606	1.7907	-.0284	1.0839	30
*MAHAL	6.2330	22.2300	14.5000	4.2551	30
*COOK D	.0001	.5107	.0823	.1188	30
*LEVER	.2149	.7666	.5000	.1467	30

Total Cases = 33

* *

Outliers - Mahalanobis' Distance

Case #	NUM	*MAHAL
11	340	22.22999
33	90	21.24205
3	60	20.37895
25	163	20.16267
2	49	19.98963
32	33	19.19629
17	308	18.59476
8	269	18.04162
10	280	17.79459
9	271	17.17238

Hi-Res Chart # 1:Normal p-p plot of *zresid

Appendix C-5

Preceding task required 5.38 seconds elapsed.

```
-> REGRESSION
->    /DEPENDENT=NUM
->    /METHOD=ENTER F_1 f_2 f_3 f_4 f_5 f_6 f_7 f_8 f_9 f_10 f_11 f_12 f_13
->  f_14 F_15
->    /CASEWISE=ALL PLOT(ZRESID).
```

8012 bytes of memory required for REGRESSION procedure.
0 more bytes may be needed for Residuals plots.

* * * * M U L T I P L E   R E G R E S S I O N * * * *

Listwise Deletion of Missing Data

Equation Number 1   Dependent Variable..   NUM

Block Number 1. Method: Enter

F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
F_9	F_10	F_11	F_12	F_13	F_14	F_15	

Variable(s) Entered on Step Number

1..	F_15	F 15
2..	F_13	F 13
3..	F_6	F 6
4..	F_11	F 11
5..	F_5	F 5
6..	F_1	F 1
7..	F_2	F 2
8..	F_9	F 9
9..	F_12	F 12
10..	F_3	F 3
11..	F_14	F 14
12..	F_10	F 10
13..	F_8	F 8
14..	F_7	F 7
15..	F_4	F 4

Multiple R	.79248
R Square	.62803
Adjusted R Square	.22948
Standard Error	89.29385

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	15	188467.49478	12564.49965
Residual	14	111627.47189	7973.39085

F =   1.57580   Signif F = .2008

* * * * M U L T I P L E   R E G R E S S I O N * * * *

Equation Number 1   Dependent Variable..   NUM

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
F_1	10.277270	17.193002	.190831	.598	.5595
F_2	.885129	23.731626	.012794	.037	.9708
F_3	-80.705153	34.315245	-1.392707	-2.352	.0338
F_4	49.859076	47.226203	.889285	1.056	.3090
F_5	-7.190405	23.070376	-.122687	-.312	.7599
F_6	8.456016	33.474905	.124418	.253	.8042
F_7	-32.305365	28.519832	-.541451	-1.133	.2764
F_8	24.687281	28.189592	.451330	.876	.3959
F_9	17.260146	23.500361	.286990	.734	.4748
F_10	-47.967136	31.249051	-.614182	-1.535	.1471
F_11	9.681481	44.619029	.103303	.217	.8314
F_12	28.926025	28.491795	.369496	1.015	.3272
F_13	-95.436930	43.175853	-1.059235	-2.210	.0442
F_14	11.315975	30.840187	.153843	.367	.7192
F_15	-12.558531	28.495717	-.160420	-.441	.6661
(Constant)	758.999842	255.698638		2.968	.0102

End Block Number   1   All requested variables entered.

```
              * * * *   M U L T I P L E   R E G R E S S I O N   * * * *

Equation Number 1    Dependent Variable..   NUM


Casewise Plot of Standardized Residual

*: Selected   M: Missing

          -3.0      0.0     3.0
Case #    O:........:........:O      NUM       *PRED      *RESID
     1    .     *   .         .       26    136.0394   -110.0394
     2    .        *.         .       49     65.7115    -16.7115
     3    .       * .         .       60    111.9480    -51.9480
     4    .         *         .       81     77.4953      3.5047
     5    .         .*        .      135     91.2203     43.7797
     6    .       * .         .      190    238.4990    -48.4990
     7    .       * .         .      243    288.5160    -45.5160
     8    .         . *       .      269    206.7521     62.2479
     9    .         .*        .      271    249.4703     21.5297
    10    .         *         .      280    281.5137     -1.5137
    11    .         *         .      340    333.8233      6.1767
    12    .         .  *      .      265    169.9110     95.0890
    13    .      *  .         .      100    181.9616    -81.9616
    14    .        *.         .      129    154.3673    -25.3673
    15    .         .         .      144        .           .
    16    .         *         .      241    230.0632     10.9368
    17    .         *         .      308    320.1018    -12.1018
    20    .    *    .         .       30    173.4704   -143.4704
    21    .         .         .       62        .           .
    22    .         .         .       86        .           .
    23    .       * .         .      110    182.9387    -72.9387
    24    .         .  *      .      124     33.4997     90.5003
    25    .         .*        .      163    123.2863     39.7137
    26    .        *.         .      178    218.8254    -40.8254
    27    .         . *       .      231    183.2705     47.7295
    28    .         .  *      .      273    177.6020     95.3980
    29    .         .*        .      292    248.9211     43.0789
    30    .         .  *      .      294    191.1495    102.8505
    31    .         .*        .      326    301.8058     24.1942
    32    .        *.         .       33     62.0578    -29.0578
    33    .       * .         .       90    158.3069    -68.3069
    34    .         .*        .      217    185.5728     31.4272
    35    .         .*        .      333    302.8993     30.1007
Case #    O:........:........:O      NUM       *PRED      *RESID
          -3.0      0.0     3.0
```

* * * * M U L T I P L E R E G R E S S I O N * * * *

Equation Number 1 Dependent Variable.. NUM

Residuals Statistics:

	Min	Max	Mean	Std Dev	N
*PRED	33.4997	333.8233	189.3667	80.6156	30
*RESID	-143.4704	102.8505	.0000	62.0421	30
*ZPRED	-1.9335	1.7919	.0000	1.0000	30
*ZRESID	-1.6067	1.1518	.0000	.6948	30

Total Cases = 33

Preceding task required 9.00 seconds elapsed.

Appendix C-6

```
-> * ************************* 6.1.UNIVARIATE NORMALITY
->   ******************************
->
->
-> EXAMINE
->   VARIABLES=f_1 f_2 f_3 f_4 f_5 f_6 f_7 f_8 f_9 f_10 f_11 f_12 f_13 f_14
->   f_15 BY num_type
->   /PLOT  NPPLOT
->   /STATISTICS NONE
->   /CINTERVAL 95
->   /MISSING LISTWISE
->   /NOTOTAL.
```

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F_1 F 1
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 1:Normal q-q plot of f_1 for num_type: 1
Hi-Res Chart # 2:Detrended normal q-q plot of f_1 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9298	16	.3071
K-S (Lilliefors)	.1088	16	> .2000

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F_1 F 1
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 3:Normal q-q plot of f_1 for num_type: 3
Hi-Res Chart # 4:Detrended normal q-q plot of f_1 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9454	14	.4880
K-S (Lilliefors)	.1171	14	> .2000

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F_2 F 2
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 5:Normal q-q plot of f_2 for num_type: 1
Hi-Res Chart # 6:Detrended normal q-q plot of f_2 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9575	16	.5916
K-S (Lilliefors)	.1566	16	> .2000

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F_2 F 2
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 7:Normal q-q plot of f_2 for num_type: 3
Hi-Res Chart # 8:Detrended normal q-q plot of f_2 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.7826	14	< .0100
K-S (Lilliefors)	.2513	14	.0167

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F_3 F 3
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 9:Normal q-q plot of f_3 for num_type: 1
Hi-Res Chart # 10:Detrended normal q-q plot of f_3 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.8724	16	.0317
K-S (Lilliefors)	.1491	16	> .2000

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F_3 F 3
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 11:Normal q-q plot of f_3 for num_type: 3
Hi-Res Chart # 12:Detrended normal q-q plot of f_3 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9094	14	.2109
K-S (Lilliefors)	.1697	14	> .2000

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F_4 F 4
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 13:Normal q-q plot of f_4 for num_type: 1
Hi-Res Chart # 14:Detrended normal q-q plot of f_4 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9538	[illegible]	.5297
K-S (Lilliefors)	.0854	16	> .2000

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F_4 F 4
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 15:Normal q-q plot of f_4 for num_type: 3
Hi-Res Chart # 16:Detrended normal q-q plot of f_4 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8723	14	.0482
K-S (Lilliefors)	.1764	14	> .2000

F_5 F 5
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 17:Normal q-q plot of f_5 for num_type: 1
Hi-Res Chart # 18:Detrended normal q-q plot of f_5 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9358	16	.3592
K-S (Lilliefors)	.2010	16	.0835

F_5 F 5
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 19:Normal q-q plot of f_5 for num_type: 3
Hi-Res Chart # 20:Detrended normal q-q plot of f_5 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9369	14	.4219
K-S (Lilliefors)	.1916	14	.1747

F_6 F 6
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 21:Normal q-q plot of f_6 for num_type: 1
Hi-Res Chart # 22:Detrended normal q-q plot of f_6 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9291	16	.3006
K-S (Lilliefors)	.1913	16	.1205

F_6 F 6
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 23:Normal q-q plot of f_6 for num_type: 3
Hi-Res Chart # 24:Detrended normal q-q plot of f_6 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9171	14	.2702
K-S (Lilliefors)	.2207	14	.0631

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F_7 F 7
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 25:Normal q-q plot of f_7 for num_type: 1
Hi-Res Chart # 26:Detrended normal q-q plot of f_7 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9621	16	.6691
K-S (Lilliefors)	.1650	16	> .2000

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F_7 F 7
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 27:Normal q-q plot of f_7 for num_type: 3
Hi-Res Chart # 28:Detrended normal q-q plot of f_7 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9316	14	.3819
K-S (Lilliefors)	.2121	14	.0878

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F_8 F 8
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 29:Normal q-q plot of f_8 for num_type: 1
Hi-Res Chart # 30:Detrended normal q-q plot of f_8 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9559	16	.5655
K-S (Lilliefors)	.1484	16	> .2000

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F_8 F 8
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 31:Normal q-q plot of f_8 for num_type: 3
Hi-Res Chart # 32:Detrended normal q-q plot of f_8 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8614	14	.0365
K-S (Lilliefors)	.1532	14	> .2000

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F_9 F 9
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 33:Normal q-q plot of f_9 for num_type: 1
Hi-Res Chart # 34:Detrended normal q-q plot of f_9 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9461	16	.4491
K-S (Lilliefors)	.1510	16	> .2000

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F_9 F 9
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 35:Normal q-q plot of f_9 for num_type: 3
Hi-Res Chart # 36:Detrended normal q-q plot of f_9 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8483	14	.0224
K-S (Lilliefors)	.1780	14	> .2000

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F_10 F 10
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 37:Normal q-q plot of f_10 for num_type: 1
Hi-Res Chart # 38:Detrended normal q-q plot of f_10 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.8552	16	.0159
K-S (Lilliefors)	.1539	16	> .2000

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F_10 F 10
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 39:Normal q-q plot of f_10 for num_type: 3
Hi-Res Chart # 40:Detrended normal q-q plot of f_10 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9362	14	.4173
K-S (Lilliefors)	.2059	14	.1109

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F_11 F 11
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 41:Normal q-q plot of f_11 for num_type: 1
Hi-Res Chart # 42:Detrended normal q-q plot of f_11 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.8832	16	.0453
K-S (Lilliefors)	.1889	16	.1303

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F_11 F 11
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 43:Normal q-q plot of f_11 for num_type: 3
Hi-Res Chart # 44:Detrended normal q-q plot of f_11 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9112	14	.2245
K-S (Lilliefors)	.1389	14	> .2000

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F_12 F 12
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 45:Normal q-q plot of f_12 for num_type: 1
Hi-Res Chart # 46:Detrended normal q-q plot of f_12 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9577	16	.5954
K-S (Lilliefors)	.1656	16	> .2000

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F_12 F 12
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 47:Normal q-q plot of f_12 for num_type: 3
Hi-Res Chart # 48:Detrended normal q-q plot of f_12 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9042	14	.1711
K-S (Lilliefors)	.2049	14	.1145

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F_13 F 13
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 49:Normal q-q plot of f_13 for num_type: 1
Hi-Res Chart # 50:Detrended normal q-q plot of f_13 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9178	16	.2023
K-S (Lilliefors)	.1689	16	> .2000

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F_13 F 13
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 51:Normal q-q plot of f_13 for num_type: 3
Hi-Res Chart # 52:Detrended normal q-q plot of f_13 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8722	14	.0480
K-S (Lilliefors)	.2799	14	.0040

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F_14 F 14
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 53:Normal q-q plot of f_14 for num_type: 1
Hi-Res Chart # 54:Detrended normal q-q plot of f_14 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9450	16	.4387
K-S (Lilliefors)	.1676	16	> .2000

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F_14 F 14
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 55:Normal q-q plot of f_14 for num_type: 3
Hi-Res Chart # 56:Detrended normal q-q plot of f_14 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9334	14	.3955
K-S (Lilliefors)	.2143	14	.0808

F_15 F 15
By NUM_TYPE 1

Valid cases: 16.0 Missing cases: 1.0 Percent missing: 5.9

Hi-Res Chart # 57:Normal q-q plot of f_15 for num_type: 1
Hi-Res Chart # 58:Detrended normal q-q plot of f_15 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9284	16	.2950
K-S (Lilliefors)	.1875	16	.1359

F_15 F 15
By NUM_TYPE 3

Valid cases: 14.0 Missing cases: 2.0 Percent missing: 12.5

Hi-Res Chart # 59:Normal q-q plot of f_15 for num_type: 3
Hi-Res Chart # 60:Detrended normal q-q plot of f_15 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8789	14	.0616
K-S (Lilliefors)	.2236	14	.0560

Preceding task required 77.17 seconds elapsed.

Appendix C-7

```
-> EXAMINE
->   VARIABLES=f2_Norm f13_Norm
->   f_15 BY num_type
->   /PLOT  NPPLOT
->   /STATISTICS NONE
->   /CINTERVAL 95
->   /MISSING LISTWISE
->   /NOTOTAL.
```

F2_NORM
By NUM_TYPE 1

Valid cases: 17.0 Missing cases: .0 Percent missing: .0

Hi-Res Chart # 61:Normal q-q plot of f2_norm for num_type: 1
Hi-Res Chart # 62:Detrended normal q-q plot of f2_norm for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9257	17	.2429
K-S (Lilliefors)	.1051	17	> .2000

F2_NORM
By NUM_TYPE 3

Valid cases: 16.0 Missing cases: .0 Percent missing: .0

Hi-Res Chart # 63:Normal q-q plot of f2_norm for num_type: 3
Hi-Res Chart # 64:Detrended normal q-q plot of f2_norm for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8091	16	< .0100
K-S (Lilliefors)	.1890	16	.1298

F13_NORM
By NUM_TYPE 1

Valid cases: 17.0 Missing cases: .0 Percent missing: .0

Hi-Res Chart # 65:Normal q-q plot of f13_norm for num_type: 1
Hi-Res Chart # 66:Detrended normal q-q plot of f13_norm for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.8885	17	.0455
K-S (Lilliefors)	.1759	17	.1691

F13_NORM
By NUM_TYPE 3

Valid cases: 16.0 Missing cases: .0 Percent missing: .0

Hi-Res Chart # 67:Normal q-q plot of f13_norm for num_type: 3
Hi-Res Chart # 68:Detrended normal q-q plot of f13_norm for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.9242	16	.2581
K-S (Lilliefors)	.2063	16	.0672

F_15 F 15
By NUM_TYPE 1

Valid cases: 17.0 Missing cases: .0 Percent missing: .0

Hi-Res Chart # 69:Normal q-q plot of f_15 for num_type: 1
Hi-Res Chart # 70:Detrended normal q-q plot of f_15 for num_type: 1

	Statistic	df	Significance
Shapiro-Wilks	.9557	17	.5297
K-S (Lilliefors)	.1606	17	> .2000

F_15 F 15
By NUM_TYPE 3

Valid cases: 16.0 Missing cases: .0 Percent missing: .0

Hi-Res Chart # 71:Normal q-q plot of f_15 for num_type: 3
Hi-Res Chart # 72:Detrended normal q-q plot of f_15 for num_type: 3

	Statistic	df	Significance
Shapiro-Wilks	.8819	16	.0436
K-S (Lilliefors)	.1974	16	.0963

Preceding task required 16.58 seconds elapsed.

Appendix C-8

```
-> * ************************ 8 Homoscedasticity ****************************
    **
->
-> EXAMINE
->   VARIABLES=f_1 f_3 f_4 f_5 f_7 f_9 f_10 f_11 f_12 f_14 f_15 f2_norm
->   f13_norm f_6_1 f_8_1 BY num_type
->   /PLOT  SPREADLEVEL(1)
->   /STATISTICS NONE
->   /MISSING LISTWISE
->   /NOTOTAL.
```

Hi-Res Chart # 73:Spread vs. level plot of f_1 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.1685	1	31	.6843

Hi-Res Chart # 74:Spread vs. level plot of f_3 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	1.3337	1	31	.2570

Hi-Res Chart # 75:Spread vs. level plot of f_4 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	2.0411	1	31	.1631

Hi-Res Chart # 76:Spread vs. level plot of f_5 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	5.7897	1	31	.0223

Hi-Res Chart # 77:Spread vs. level plot of f_7 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	1.0897	1	31	.3046

Hi-Res Chart # 78:Spread vs. level plot of f_9 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.0933	1	31	.7621

Hi-Res Chart # 79:Spread vs. level plot of f_10 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.0034	1	31	.9536

Hi-Res Chart # 80:Spread vs. level plot of f_11 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.6675	1	31	.4202

Hi-Res Chart # 81:Spread vs. level plot of f_12 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.0277	1	31	.8689

Hi-Res Chart # 82:Spread vs. level plot of f_14 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	4.1663	1	31	.0498

Hi-Res Chart # 83:Spread vs. level plot of f_15 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.8092	1	31	.3753

Hi-Res Chart # 84:Spread vs. level plot of f2_norm by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.2598	1	31	.6139

Hi-Res Chart # 85:Spread vs. level plot of f13_norm by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	.3458	1	31	.5608

Hi-Res Chart # 86:Spread vs. level plot of f_6_1 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	1.3553	1	31	.2532

Hi-Res Chart # 87:Spread vs. level plot of f_8_1 by num_type

Test of homogeneity of variance		df1	df2	Significance
Levene Statistic	1.1990	1	31	.2820

Preceding task required 22.03 seconds elapsed.

Appendix C-9

Final Discriminant

```
-> * ************************* DISCRIMINANT ANALYSIS
->   ****************************54321
->
-> SET SEED RANDOM.
-> COMPUTE RANDZ=UNIFORM(1)>.8.
-> DISCRIMINANT
->   /GROUPS=num_type(1 3)
->   /VARIABLES=f_1 f_3 f_4 f_5 f_7 f_9 f_10 f_11 f_12 f_14 f_15 f_6_1 f_8_1
->   f2_norm f13_norm
->   /SELECT=RANDZ(0)
->   /ANALYSIS ALL
->   /PRIORS  SIZE
->   /STATISTICS=MEAN STDDEV UNIVF BOXM COEFF RAW CORR COV GCOV TCOV TABLE
->   /PLOT=COMBINED SEPARATE MAP CASES
->   /CLASSIFY=NONMISSING POOLED .
```

```
This DISCRIMINANT analysis requires 12604 bytes of memory.

>Warning # 43
>MXMEMORY (the maximum amount of memory that can be allocated dynamically)
>has been reached.  To increase this value, use the SET MXMEMORY command.
```

- - - - - - - - D I S C R I M I N A N T   A N A L Y S I S - - - - - - - -

On groups defined by NUM_TYPE

33 (Unweighted) cases were processed.
5 of these were excluded from the analysis.
0 had missing or out-of-range group codes.
5 were excluded by the select= variable.
28 (Unweighted) cases will be used in the analysis.

Number of cases by group

	Number of cases		
NUM_TYPE	Unweighted	Weighted	Label
1	14	14.0	
3	14	14.0	
Total	28	28.0	

Group means

NUM_TYPE	F_1	F_3	F_4	F_5
1	4.85714	5.14286	5.28571	4.85714
3	6.50000	5.85714	6.14286	6.14286
Total	[illegible].67857	5.50000	5.71429	5.50000

NUM_TYPE	F_7	F_9	F_10	F_11
1	4.78571	5.21429	6.50000	7.07143
3	4.42857	4.35714	6.57143	6.85714
Total	4.60714	4.78571	6.53571	6.96429

NUM_TYPE	F_12	F_14	F_15	F_6_1
1	6.64286	4.85714	4.85714	3.94981
3	6.71429	5.00000	4.50000	3.02124
Total	6.67857	4.92857	4.67857	3.48552

NUM_TYPE	F_8_1	F2_NORM	F13_NORM
1	5.00000	2.53130	2.18776
3	4.84398	2.32467	2.24134
Total	4.92199	2.42799	2.21455

Group standard deviations

NUM_TYPE	F_1	F_3	F_4	F_5
1	1.65748	2.24832	2.16364	1.99450
3	1.78670	1.46009	1.46009	1.16732
Total	1.88657	1.89541	1.86304	1.73205

NUM_TYPE	F_7	F_9	F_10	F_11
1	2.00686	1.67233	1.28602	.82874
3	1.60357	1.54955	1.15787	1.23146
Total	1.79174	1.64107	1.20130	1.03574

NUM_TYPE	F_12	F_14	F_15	F_6_1
1	1.27745	1.70326	1.61041	1.71998
3	1.38278	1.17670	1.09193	1.11224
Total	1.30678	1.43833	1.36228	1.49785

NUM_TYPE	F_8_1	F2_NORM	F13_NORM
1	2.14834	.31561	.27626
3	1.70278	.32140	.22695
Total	1.90383	.32980	.24958

Pooled within-groups covariance matrix with 26 degrees of freedom

	F_1	F_3	F_4	F_5
F_1	2.9698			
F_3	1.2418	3.5934		
F_4	.7912	3.1429	3.4066	
F_5	.8352	1.9451	2.2418	2.6703
F_7	-.1319	2.4725	2.3462	1.2198
F_9	-.3874	1.3571	1.5549	1.4121
F_10	.7308	.5824	.7637	.6484
F_11	.3516	-.0934	.3846	.3626
F_12	.4725	-.3022	-.0385	.5714
F_14	-.3956	-1.4505	-1.3626	-.3187
F_15	-.4918	-1.6044	-1.5549	-.4341
F_6_1	-.6790	.9857	1.1017	1.0444
F_8_1	-.4894	2.0791	2.3652	1.3582
F2_NORM	-.0791	-.3576	-.3356	-.2240
F13_NORM	.0838	.1612	.0682	.0439

	F_7	F_9	F_10	F_11
F_7	3.2995			
F_9	1.9038	2.5989		
F_10	.4643	-.0907	1.4973	
F_11	-.1511	-.2115	.6786	1.1016
F_12	-.5907	.2115	.4148	.7995
F_14	-1.3626	.2088	-.4231	5.4945055E-03
F_15	-1.4396	-.1951	-.5769	-.0330
F_6_1	1.4966	1.6556	-.4047	-.1388
F_8_1	2.7981	2.4389	.2332	.1034
F2_NORM	-.2289	-.1932	.0150	.0233
F13_NORM	.0959	-.0978	.0775	-.0889

	F_12	F_14	F_15	F_6_1
F_12	1.7720			
F_14	1.0879	2.1429		
F_15	.5110	1.6429	1.8929	
F_6_1	.1786	-.2149	-.3401	2.0977
F_8_1	.2068	-.5071	-1.2799	1.9748
F2_NORM	2.3647380E-03	.1542	.1174	-.2879
F13_NORM	-.1558	-.1800	-.0729	-.0667

	F_8_1	F2_NORM	F13_NORM
F_8_1	3.7574		
F2_NORM	-.2364	.1015	
F13_NORM	-.1291	-.0191	.0639

Pooled within-groups correlation matrix

	F_1	F_3	F_4	F_5	F_7	F_9
F_1	1.00000					
F_3	.38012	1.00000				
F_4	.24875	.89828	1.00000			
F_5	.29657	.62791	.74327	1.00000		
F_7	-.04213	.71807	.69980	.41094	1.00000	
F_9	-.13943	.44410	.52259	.53602	.65015	1.00000
F_10	.34655	.25109	.33817	.32425	.20889	-.04596
F_11	.19441	-.04695	.19854	.21143	-.07925	-.12502
F_12	.20599	-.11976	-.01565	.26269	-.24428	.09857
F_14	-.15682	-.52274	-.50434	-.13322	-.51246	.08848
F_15	-.20741	-.61518	-.61234	-.19307	-.57604	-.08794
F_6_1	-.27205	.35904	.41213	.44128	.56886	.70905
F_8_1	-.14650	.56582	.66110	.42877	.79470	.78047
F2_NORM	-.14411	-.59227	-.57085	-.43030	-.39561	-.37634
F13_NORM	.19233	.33638	.14623	.10636	.20892	-.23988

	F_10	F_11	F_12	F_14	F_15	F_6_1
F_10	1.00000					
F_11	.52836	1.00000				
F_12	.25468	.57219	1.00000			
F_14	-.23620	.00358	.55830	1.00000		
F_15	-.34270	-.02283	.27901	.81573	1.00000	
F_6_1	-.22834	-.09134	.09266	-.10135	-.17070	1.00000
F_8_1	.09833	.05081	.08013	-.17871	-.47991	.70339
F2_NORM	.03850	.06971	.00558	.33076	.26796	-.62417
F13_NORM	.25066	-.33504	-.46292	-.48640	-.20946	-.18218

	F_8_1	F2_NORM	F13_NORM
F_8_1	1.00000		
F2_NORM	-.38285	1.00000	
F13_NORM	-.26347	-.23676	1.00000

Wilks' Lambda (U-statistic) and univariate F-ratio
with 1 and 26 degrees of freedom

Variable	Wilks' Lambda	F	Significance
F_1	.80342	6.3617	.0181
F_3	.96318	.9939	.3280
F_4	.94512	1.5097	.2302
F_5	.85714	4.3333	.0474
F_7	.98970	.2706	.6073
F_9	.92927	1.9789	.1714
F_10	.99908	.0239	.8785
F_11	.98890	.2918	.5937
F_12	.99923	.0202	.8882
F_14	.99744	.0667	.7983
F_15	.98218	.4717	.4983
F_6_1	.90036	2.8773	.1018
F_8_1	.99826	.0453	.8330
F2_NORM	.89822	2.9460	.0980
F13_NORM	.98805	.3145	.5798

Covariance matrix for group 1,

	F_1	F_3	F_4	F_5
F_1	2.7473			
F_3	2.7143	5.0549		
F_4	1.9670	4.5714	4.6813	
F_5	1.9780	3.4066	3.4286	3.9780
F_7	1.1978	3.6484	3.8352	2.6593
F_9	1.1099	2.3516	2.5495	2.6484
F_10	.9231	1.0769	1.0000	.8462
F_11	-.1429	-.3956	-.0989	-.0659
F_12	.2527	-.4066	-.2747	.7143
F_14	-.4066	-2.0549	-2.1868	-.7912
F_15	-.7143	-2.4396	-2.4176	-1.0989
F_6_1	.2459	1.4609	1.6994	1.9923
F_8_1	.9231	3.2308	3.6154	2.6923
F2_NORM	-.1965	-.4259	-.4190	-.4678
F13_NORM	.1476	.2058	.1518	.1511

	F_7	F_9	F_10	F_11
F_7	4.0275			
F_9	2.3571	2.7967		
F_10	.8846	-.0385	1.6538	
F_11	.1703	-.0165	.2692	.6868
F_12	-.0824	1.0055	-.1154	.4890
F_14	-1.8791	.1099	-.9231	-.1429
F_15	-2.2637	-.4286	-.9231	-.0659
F_6_1	1.7493	2.1654	-.3888	.2575
F_8_1	3.6923	3.0000	.2308	.3846
F2_NORM	-.2856	-.3743	-.0289	.0100
F13_NORM	.0660	-.0926	.2303	-.0742

	F_12	F_14	F_15	F_6_1
F_12	1.6319			
F_14	1.1758	2.9011		
F_15	.8681	2.5934	2.5934	
F_6_1	1.3196	-.1533	-.5379	2.9583
F_8_1	.6154	-1.1538	-1.6923	2.6840
F2_NORM	-.1727	.0490	.0946	-.4462
F13_NORM	-.1475	-.1684	-.1157	-.1514

	F_8_1	F2_NORM	F13_NORM
F_8_1	4.6154		
F2_NORM	-.4250	.0996	
F13_NORM	-.1530	-.0061	.0763

Covariance matrix for group 3,

	F_1	F_3	F_4	F_5
F_1	3.1923			
F_3	-.2308	2.1319		
F_4	-.3846	1.7143	2.1319	
F_5	-.3077	.4835	1.0549	1.3626
F_7	-1.4615	1.2967	.8571	-.2198
F_9	-1.8846	.3626	.5604	.1758
F_10	.5385	.0879	.5275	.4505
F_11	.8462	.2088	.8681	.7912
F_12	.6923	-.1978	.1978	.4286
F_14	-.3846	-.8462	-.5385	.1538
F_15	-.2692	-.7692	-.6923	.2308
F_6_1	-1.6040	.5105	.5040	.0965
F_8_1	-1.9018	.9274	1.1151	.0240

	F_1	F_3	F_4	F_5
F2_NORM	.0383	-.2893	-.2522	.0198
F13_NORM	.0199	.1166	-.0153	-.0633

	F_7	F_9	F_10	F_11
F_7	2.5714			
F_9	1.4505	2.4011		
F_10	.0440	-.1429	1.3407	
F_11	-.4725	-.4066	1.0879	1.5165
F_12	-1.0989	-.5824	.9451	1.1099
F_14	-.8462	.3077	.0769	.1538
F_15	-.6154	.0385	-.2308	.0000
F_6_1	1.2438	1.1457	-.4206	-.5352
F_8_1	1.9040	1.8778	.2357	-.1778
F2_NORM	-.1722	-.0122	.0589	.0366
F13_NORM	.1258	-.1030	-.0753	-.1036

	F_12	F_14	F_15	F_6_1
F_12	1.9121			
F_14	1.0000	1.3846		
F_15	.1538	.6923	1.1923	
F_6_1	-.9623	-.2765	-.1424	1.2371
F_8_1	-.2019	.1397	-.8674	1.2655
F2_NORM	.1774	.2594	.1402	-.1297
F13_NORM	-.1641	-.1916	-.0300	.0180

	F_8_1	F2_NORM	F13_NORM
F_8_1	2.8995		
F2_NORM	-.0477	.1033	
F13_NORM	-.1052	-.0321	.0515

Total covariance matrix with 27 degrees of freedom

	F_1	F_3	F_4	F_5
F_1	3.5595			
F_3	1.5000	3.5926		
F_4	1.1270	3.1852	3.4709	
F_5	1.3519	2.1111	2.4444	3.0000
F_7	-.2791	2.3148	2.1799	1.0556
F_9	-.7381	1.1481	1.3069	1.0741
F_10	.7341	.5741	.7513	.6481

	F_1	F_3	F_4	F_5
F_11	.2474	-.1296	.3228	.2778
F_12	.4854	-.2778	-.0212	.5741
F_14	-.3201	-1.3704	-1.2804	-.2593
F_15	-.6257	-1.6111	-1.5767	-.5370
F_6_1	-1.0494	.7773	.8546	.6962
F_8_1	-.5377	1.9732	2.2430	1.2558
F2_NORM	-.1642	-.3826	-.3691	-.2846
F13_NORM	.1035	.1652	.0776	.0602

	F_7	F_9	F_10	F_11
F_7	3.2103			
F_9	1.9127	2.6931		
F_10	.4405	-.1032	1.4431	
F_11	-.1257	-.1561	.6495	1.0728
F_12	-.5754	.1878	.4008	.7659
F_14	-1.3254	.1693	-.4048	-.0026
F_15	-1.3532	-.1085	-.5622	-.0119
F_6_1	1.5271	1.8006	-.4069	-.0821
F_8_1	2.7090	2.3832	.2217	.1082
F2_NORM	-.2013	-.1402	.0106	.0339
F13_NORM	.0874	-.1061	.0757	-.0886

	F_12	F_14	F_15	F_6_1
F_12	1.7077			
F_14	1.0503	2.0688		
F_15	.4854	1.5688	1.8558	
F_6_1	.1548	-.2413	-.2416	2.2436
F_8_1	.1962	-.4941	-1.2180	1.9392
F2_NORM	-.0015	.1409	.1322	-.2275
F13_NORM	-.1490	-.1714	-.0751	-.0771

	F_8_1	F2_NORM	F13_NORM
F_8_1	3.6246		
F2_NORM	-.2193	.1088	
F13_NORM	-.1265	-.0212	.0623

-------- D I S C R I M I N A N T   A N A L Y S I S --------

On groups defined by NUM_TYPE

Analysis number 1

Direct method: all variables passing the tolerance test are entered.

Minimum tolerance level.................. .00100

Canonical Discriminant Functions

Maximum number of functions.............. 1
Minimum cumulative percent of variance... 100.00
Maximum significance of Wilks' Lambda.... 1.0000

Prior probabilities

Group	Prior	Label
1	.50000	
3	.50000	
Total	1.00000	

Classification function coefficients
(Fisher's linear discriminant functions)

NUM_TYPE=	1	3
F_1	17.5050308	17.4049925
F_3	-1.5439473	-3.6585616
F_4	52.4780182	50.5913503
F_5	-48.3756361	-44.1665829
F_7	-45.7134501	-41.8695860
F_9	15.4157691	12.7639191
F_10	-.8749718	-2.5931483
F_11	19.2340328	19.3220345
F_12	4.9258263	3.4225330
F_14	-2.7724617	1.2674981
F_15	21.9191265	18.4421471
F_6_1	63.8040873	59.2305224
F_8_1	13.9280072	14.0123792
F2_NORM	273.9292539	254.7532698
F13_NORM	318.0521476	309.2834160
(Constant)	-974.7073499	-881.3796307

Canonical Discriminant Functions

Fcn	Eigenvalue	Pct of Variance	Cum Pct	Canonical Corr	:	After Fcn	Wilks' Lambda	Chi-square	df	Sig
					:	0	.231701	27.053	15	.0283 (< 0.05)
1*	3.3159	100.00	100.00	.8765	:					

* Marks the 1 canonical discriminant functions remaining in the analysis.

Standardized canonical discriminant function coefficients

	Func 1
F_1	.04912
F_3	1.14221
F_4	.99224
F_5	-1.95988
F_7	-1.98953
F_9	1.21816
F_10	.59907
F_11	-.02632
F_12	.57021
F_14	-1.68514
F_15	1.36308
F_6_1	1.88751
F_8_1	-.04660
F2_NORM	1.74043
F13_NORM	.63167

Structure matrix:

Pooled within-groups correlations between discriminating variables
and canonical discriminant functions
(Variables ordered by size of correlation within function)

	Func 1
F_1	-.27164
F_5	-.22419
F2_NORM	.18486
F_6_1	.18269
F_9	.15150
F_4	-.13233
F_3	-.10737
F_15	.07397
F13_NORM	-.06039
F_11	.05817
F_7	.05603
F_14	-.02781
F_8_1	.02293
F_10	-.01663
F_12	-.01529

Unstandardized canonical discriminant function coefficients

	Func 1
F_1	.0285054
F_3	.6025496
F_4	.5375973
F_5	-1.1993502
F_7	-1.0952913
F_9	.7556324
F_10	.4895864
F_11	-.0250757
F_12	.4283565
F_14	-1.1511679
F_15	.9907492
F_6_1	1.3032162
F_8_1	-.0240414
F2_NORM	5.4641080
F13_NORM	2.4986095
(Constant)	-26.5933020

Canonical discriminant functions evaluated at group means (group centroids)

Group	Func 1
1	1.75472
3	-1.75472

Test of Equality of Group Covariance Matrices Using Box's M

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Group Label	Rank	Log Determinant
1	< 14	(Too few cases to be non-singular)
3	< 14	(Too few cases to be non-singular)
Pooled within-groups covariance matrix	15	-11.579378

No test can be performed without at least two non-singular group covariance matrices.

```
>Warning # 43
>MXMEMORY (the maximum amount of memory that can be allocated dynamically)
>has been reached.  To increase this value, use the SET MXMEMORY command.
```

Case Number	Mis Val	Sel	Actual Group		Highest Probability Group	P(D/G)	P(G/D)	2nd Highest Group	P(G/D)	Discrim Scores
1		YES	1		1	.8452	.9958	3	.0042	1.5594
2		YES	1		1	.2746	1.0000	3	.0000	2.8473
3		YES	1		1	.5690	.9997	3	.0003	2.3242
4		YES	1		1	.1414	.7304	3	.2696	.2840
5		YES	1		1	.8375	.9957	3	.0043	1.5496
6		NO	1		1	.1421	.7323	3	.2677	.2868
7		YES	1		1	.2383	1.0000	3	.0000	2.9341
8		YES	1		1	.1260	1.0000	3	.0000	3.2848
9		YES	1		1	.7087	.9922	3	.0078	1.3811
10		YES	1		1	.5900	.9862	3	.0138	1.2159
11		YES	1		1	.6624	.9995	3	.0005	2.1914
12		YES	1		1	.2709	1.0000	3	.0000	2.8558
13		YES	1	**	3	.1213	.6727	1	.3273	-.2053
14		NO	1	**	3	.0000	1.0000	1	.0000	-9.0441
15		YES	1		1	.7254	.9928	3	.0072	1.4035
16		YES	1		1	.4154	.9644	3	.0356	.9403
17		NO	1		1	.0000	1.0000	3	.0000	7.6431
20		YES	3		3	.9336	.9972	1	.0028	-1.6714
21		YES	3		3	.8784	.9988	1	.0012	-1.9078
22		YES	3		3	.4245	.9663	1	.0337	-.9560
23		NO	3		3	.9602	.9975	1	.0025	-1.7048
24		YES	3	**	1	.0833	.5200	3	.4800	.0228
25		YES	3		3	.2366	1.0000	1	.0000	-2.9384
26		YES	3		3	.2289	.8739	1	.1261	-.5515
27		YES	3		3	.6483	.9896	1	.0104	-1.2986
28		YES	3		3	.2410	1.0000	1	.0000	-2.9273
29		YES	3		3	.4135	.9999	1	.0001	-2.5724
30		YES	3		3	.8409	.9957	1	.0043	-1.5539
31		YES	3		3	.9904	.9978	1	.0022	-1.7427
32		YES	3		3	.8854	.9987	1	.0013	-1.8989
33		YES	3		3	.0996	1.0000	1	.0000	-3.4017
34		YES	3		3	.5576	.9837	1	.0163	-1.1683
35		NO	3		3	.0068	1.0000	1	.0000	-4.4623

Symbols used in plots

Symbol	Group	Label
1	1	
2	3	

```
                 Histogram for group 1

                        Canonical Discriminant Function 1
        4 +                                                             +
          |                                                             |
          |                                                             |
 F        |                                                             |
 r      3 +                                                             +
 e        |                                                             |
 q        |                                                             |
 u        |                                                             |
 e      2 +                               1     11     1                +
 n        |                               1     11     1                |
 c        |                               1     11     1                |
 y        |                               1     11     1                |
        1 +1                            1 1   1111  11 111             1+
          |1                            1 1   1111  11 111             1|
          |1                            1 1   1111  11 111             1|
          |1                            1 1   1111  11 111             1|
           X---------+---------+---------+---------+---------+---------X
         out      -4.0      -2.0        .0       2.0       4.0       out
   Class   2222222222222222222222222222222111111111111111111111111111111
 Centroids                                        1

                 Histogram for group 3

                        Canonical Discriminant Function 1
        4 +                                                             +
          |                                                             |
          |                                                             |
 F        |                                                             |
 r      3 +                     2                                       +
 e        |                     2                                       |
 q        |                     2                                       |
 u        |                     2                                       |
 e      2 +               2     22 2                                    +
 n        |               2     22 2                                    |
 c        |               2     22 2                                    |
 y        |               2     22 2                                    |
        1 +        2    2 2 2  222 22 2  2                              +
          |        2    2 2 2  222 22 2  2                              |
          |        2    2 2 2  222 22 2  2                              |
          |        2    2 2 2  222 22 2  2                              |
           X---------+---------+---------+---------+---------+---------X
         out      -4.0      -2.0        .0       2.0       4.0       out
   Class   2222222222222222222222222222222111111111111111111111111111111
 Centroids                       2
```

All-groups Stacked Histogram

Canonical Discriminant Function 1

```
        4 +                                                             +
          |                                                             |
          |                                                             |
 F        |                                                             |
 r      3 +                     2                                       +
 e        |                     2                                       |
 q        |                     2                                       |
 u        |                     2                                       |
 e      2 +               2     22 2      1     11     1                +
 n        |               2     22 2      1     11     1                |
 c        |               2     22 2      1     11     1                |
 y        |               2     22 2      1     11     1                |
        1 +1       2    2 2 2  222 22 2 121   1111  11 111             1+
          |1       2    2 2 2  222 22 2 121   1111  11 111             1|
          |1       2    2 2 2  222 22 2 121   1111  11 111             1|
          |1       2    2 2 2  222 22 2 121   1111  11 111             1|
           X---------+---------+---------+---------+---------+---------X
         out      -4.0      -2.0        .0       2.0       4.0        out
   Class   2222222222222222222222222222222111111111111111111111111111111
 Centroids                       2                1
```

Classification results for cases selected for use in the analysis -

Actual Group		No. of Cases	Predicted Group Membership 1	Predicted Group Membership 3
Group	1	14	13 92.9%	1 7.1%
Group	3	14	1 7.1%	13 92.9%

Percent of "grouped" cases correctly classified: 92.86%

Classification results for cases not selected for use in the analysis -

Actual Group		No. of Cases	Predicted Group Membership 1	3
Group	1	3	2 66.7%	1 33.3%
Group	3	2	0 .0%	2 100.0%

Percent of "grouped" cases correctly classified: 80.00%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Preceding task required 4.34 seconds elapsed.

Appendix C-10

Classification results for cases not selected for use in the analysis -

Actual Group		No. of Cases	Predicted Group Membership 1	3
Group	1	5	3 60.0%	2 40.0%
Group	3	3	0 .0%	3 100.0%

Percent of "grouped" cases correctly classified: 75.00%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Classification results for cases not selected for use in the analysis -

Actual Group	No. of Cases	Predicted Group Membership 1	3
Group 1	6	4 66.7%	2 33.3%
Group 3	3	0 .0%	3 100.0%

Percent of "grouped" cases correctly classified: 77.78%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Classification results for cases not selected for use in the analysis -

Actual Group	No. of Cases	Predicted Group Membership 1	3
Group 1	6	5 83.3%	1 16.7%
Group 3	3	1 33.3%	2 66.7%

Percent of "grouped" cases correctly classified: 77.78%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Classification results for cases not selected for use in the analysis -

Actual Group	No. of Cases	Predicted Group Membership 1	3
Group 1	6	4 66.7%	2 33.3%
Group 3	2	0 .0%	2 100.0%

Percent of "grouped" cases correctly classified: 75.00%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Classification results for cases not selected for use in the analysis -

Actual Group		No. of Cases	Predicted Group Membership 1	3
Group	1	3	2 66.7%	1 33.3%
Group	3	3	1 33.3%	2 66.7%

Percent of "grouped" cases correctly classified: 66.67%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Classification results for cases not selected for use in the analysis -

Actual Group		No. of Cases	Predicted Group Membership 1	3
Group	1	6	4 66.7%	2 33.3%
Group	3	1	0 .0%	1 100.0%

Percent of "grouped" cases correctly classified: 71.43%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Classification results for cases not selected for use in the analysis -

Actual Group		No. of Cases	Predicted Group Membership 1	3
Group	1	6	4 66.7%	2 33.3%
Group	3	7	2 28.6%	5 71.4%

Percent of "grouped" cases correctly classified: 69.23%

Classification processing summary

33 (Unweighted) cases were processed.
0 cases were excluded for missing or out-of-range group codes.
0 cases had at least one missing discriminating variable.
33 (Unweighted) cases were used for printed output.

Appendix D: ADAPTOR Program Code

As program code for ADAPTOR consists of 220 printed pages, it has been excluded from this bound version of the dissertation. Code listing is available with the author and can be provided upon request.

Appendix E: ADAPTOR User Manual

ADAPTOR

Adaptive Decision Support System for Managers

Version 1.0

User's Guide

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This user guide was produced using Microsoft Word.

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INTRODUCTION

What ADAPTOR can do

ADAPTOR is a decision support system for individual decision makers that attempts to learn about its users for better decision support. Learning is based on research into the decision making behaviour of individuals. This research showed that individuals belonging to a particular personality type have distinct decision preferences to other personality types. ADAPTOR uses this finding to give distinct support for individuals of different personality types. The system is designed to be most useful for senior decision makers in organisations.

ADAPTOR can be used by many different users (one at a time) for assistance in many different decision situations. Such systems are called decision support system generators. ADAPTOR learns individually from each user of the system and generalises for personality types. Therefore it is capable of adapting to each user individually. Generalisations for personality types are useful as starting positions for new users. It also keeps records of each decision situation. You may therefore recall your own decisions or other decisions in the system. However, individual preferences can only be accessed by the owner of that decision. The learning capability in ADAPTOR is implemented using artificial neural networks. This form of technology attempts to imitate learning in humans.

ADAPTOR can model situations using different representations. You can select the notation best suited to the situation at hand. A Multi-criteria decision making model is utilised as the basis for these representations. Multi-criteria models are a simple way of conceptualising decision situations based on the factors to be considered when making the decision. Final decisions are arrived at by evaluating possible solutions against the factors to be considered.

ADAPTOR provides 'active' decision support by analysing your decision making behaviour. If a user deviates from the behaviour that the system has learned from previous situations, it prompts with messages indicating where the anomaly exists. You can select your own thresholds for these warnings. Although such warnings are provided, the system does not force users into specific normative behaviour. Each instance is regarded as a learning experience. The system also provides approximations of preferences for factors in a decision situation. These approximations are also based on learning from your previous decisions and your personality type. The approximations are expected to get better with use as there is opportunity for more learning.

Since this version of ADAPTOR has been developed for research purposes and not intended as a commercial product, a number of limitations exist. These limitations mainly concern the number of factors and the number of decision alternatives to be evaluated in a given situation. These do not affect the major functionality of the system.

User guide conventions

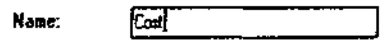
The conventions listed below are used throughout this user guide.

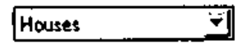
- Text printed in **bold** letters is what you type into the system.
- The word 'click' indicates that you have to point at the specified item in the system using the mouse pointer and press and release the left mouse button (assuming you have set the mouse with the left button as primary button).
- The word 'double-click' indicates that you have to point at the specified item in the system using the mouse pointer, press and release the left mouse button twice in quick succession.
- The word 'select' indicates that you have to highlight the specified item and click the specified button or double-click the item on the system.
- The term 'press ENTER' or means that you have to depress the ENTER key on your keyboard.
- The term 'press TAB' means that you have to depress the TAB key.
- Numbered lists (**1, 2, ...**) are used to indicate the order in which you should perform tasks.

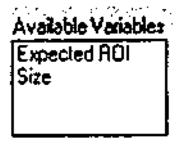
System conventions

The conventions listed below are used in ADAPTOR.

- Button: 

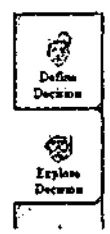
- Entry field: 

- Drop-down list: 

- List: 

- Score indicator: 

- Trash can: 

- Menu tabs: 

Getting Started

Requirements

You should install ADAPTOR on a computer with at least the following configuration:

- IBM PC compatible machine with a 486 processor
- 3½ inch floppy disk drive
- 6 Mega bytes free space on the hard disk drive
- 16 Mega bytes random access memory (RAM)
- VGA graphics card running at least 600 X 800 resolution.
- Microsoft Windows 95® operating system
- Microsoft Excel® spreadsheet
- Neuralyst™ neural network software (contact ADAPTOR developer for instructions on how to obtain this software or contact Neuralyst developers direct).

NOTE ADAPTOR will provide superior performance on systems with a better configuration.

Although ADAPTOR will run on systems with other members of the Microsoft Windows® family of operating systems, it has been optimised for Windows 95®.

ADAPTOR is capable of running without Microsoft Excel® spreadsheet and Neuralyst™ neural network software. However, the learning capabilities will be limited.

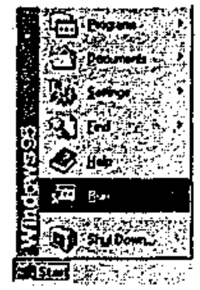
You should know your Myers-Briggs Type Indicator personality type to get best assistance from the system.

Installing the system

1. Before you install ADAPTOR onto the hard disk on your computer, make copies of the two installation disks. These can be used as a backup if disk errors occur in the installation disks.

2. Switch your machine on and start Microsoft Windows®.

3. Insert installation Disk 1 into a 3½ inch floppy disk drive.



4. From the Start menu in Widows 95® select Run.

5. Type **A:\Setup** or select A:\Setup from the drop-down list and press ENTER (if the floppy disk drive is labelled A).

6. The setup program should now start. Follow the instructions provided.

7. Before finishing the setup program, a dialogue box opens with instructions to locate Microsoft Excel® and Neuralyst™ neural network software. Follow instructions to locate these software products on your computer. You may also skip this part resulting in limited learning functionality of ADAPTOR.

If this dialogue box appears as a minimised icon, click on it to view the full dialogue box.

THE CONCEPTS

Decision Concepts

ADAPTOR can support two main types of decisions:

- Binary decisions
- Multiple-alternative decisions

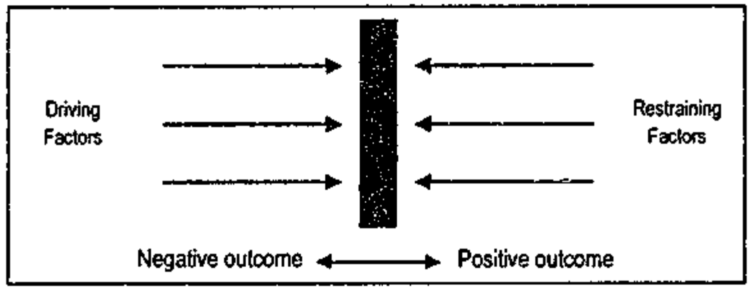
These two types of decisions have many common elements and together encompass most decision situations that you may encounter. The difference between the two types is that in a multiple-alternative situation, many possible solutions can be identified for the problem and in a binary situation only two outcomes can be identified.

Binary Decisions

In practical decision situations, binary decisions often are an important part of a larger decision process. It is common to decide between two alternative solutions or to decide whether to implement an alternative that has been decided through a multiple-alternative process. Hence, they take the form of *yes* or *no* decisions. This form of decision making is frequent towards the end of a longer process and determines the success of the complete process.

ADAPTOR provides support for binary decisions through a visual representation based model. The concept employed is a *bi-polar force-field*. The decision is represented as an equilibrium that maintains its position through forces acting on it from two opposite directions. In a decision situation, these forces are the factors that you should consider when making the decision. The stable position of the equilibrium is determined by the relative strengths of the factors. The opposing forces are termed *driving forces* and *restraining forces* .

The definition of driving and restraining forces depends on the way you perceive the solution. Factors that push you towards your perceived positive outcome are termed driving forces while the factors that may prevent you from achieving that positive outcome are termed restraining forces.



Multiple-alternative decisions

This type of situation has a number of possible solutions. The primary decision making task is to evaluate the alternatives against a set of important factors. Binary situations can be perceived as a multiple-alternative situation with only two possible outcomes.

The model

Regardless of the representation and the type of decision being supported, ADAPTOR uses a *linear-weighted sum* approach to modelling the decision. This is a useful and easily understood method of modelling decisions. This kind of model is used in *multiple-criteria decision situations*. Situations where the final decision is made by considering a number of factors (criteria) are called multiple-criteria decisions.

The important fact to be remembered here is that there are a number of possible solutions and that they will be evaluated using a number of factors. These factors are assumed to be independent of each other. Factor evaluation is done with a two-stage process.

First, we recognise that all factors may not be equally important in the given situation. Hence, a weight is given to each factor to indicate its importance. The weight allocation in ADAPTOR is done by comparing two factors at a time until all pairs of factors have been compared to each other. Comparisons are done with a semantic scale.

Once the weights have been established, a score is given to each possible alternative to indicate how well it performs on each factor. The scores thus given and the weights for the factors are combined for all factors to arrive at a final score for an alternative. The alternative with the best score is regarded as the most suitable solution to the problem. ADAPTOR uses adaptations of this model to provide you decision suggestions.

Domains

ADAPTOR uses the concept of decision domains to identify various possible subject areas for decision making. For example, a decision to purchase a house may belong to *purchasing* and *houses* domains.

This concept is important as ADAPTOR's learning mechanism performs generalisations. Some generalisation may not be valid across all possible decision domains. To ensure maximum validity of these generalisations, ADAPTOR aligns its learnt facts with domains.

NOTE Factors that affect the decision are identified by different names. Factors, criteria and variables are some of the notations. In ADAPTOR, we choose to call them **variables**, as you have the capability observing the effect of changing the values of these factors.

Interface concepts

ADAPTOR uses a graphical user interface. This is similar to most other programs in the Microsoft Windows® environment. The concepts of screen manipulation are also common with other programs in this environment..

ADAPTOR is designed in modular fashion, with a representation-based interface. There is minimum keyboard input required. The primary input device is a mouse. Graphical representations are used for both input and output where ever possible.

Objects that you see on the screen are called *controls* (buttons, lists etc.). When you move the mouse pointer over controls, an explanation of each control's action is displayed at the bottom of the screen. Some labels act as *hot-words* in ADAPTOR. Hot-words are elements on your screen that can be double-clicked with the mouse pointer to get more information.

USING ADAPTOR

Typical sequence of operations

1. Start ADAPTOR.

2. Identify yourself.

3. Define basic details of a new decision or recall a previously defined decision:

   - the name and the description of the decision
   - domains to which the decision belongs
   - the most suited representation- binary/multiple-alternative

4. Define the decision in detail:

   - the alternative solutions to the problem
   - the factors that may influence your choice between the alternatives
   - the importance of each factor to this decision
   - how each alternative measures against each factor

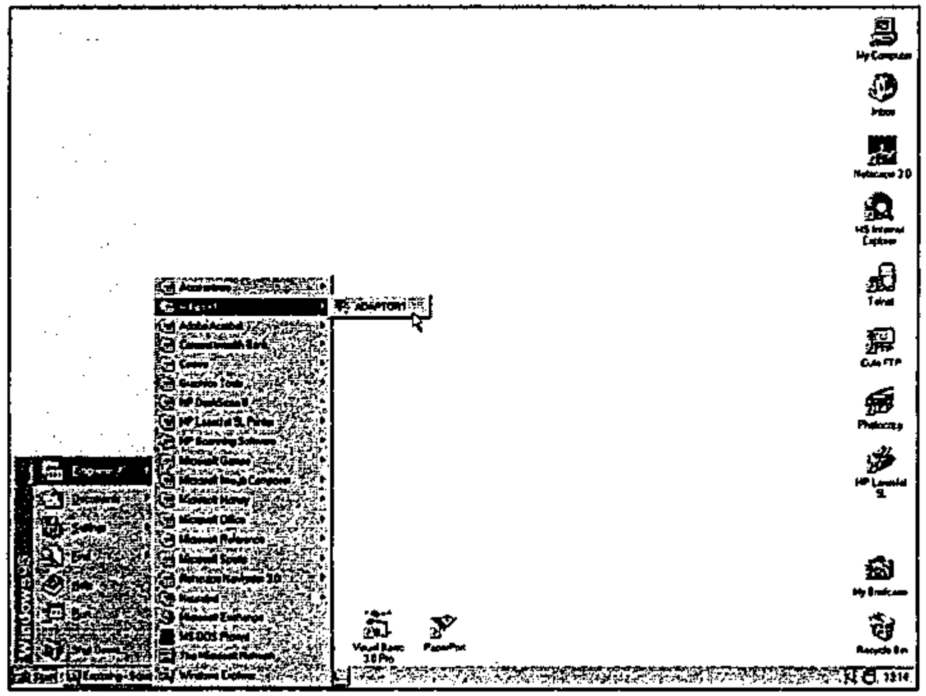
5. Explore the situation. Change characteristic of the model. Observe effect of changes on the final outcome.

6. When satisfied with decision solution, save the details.

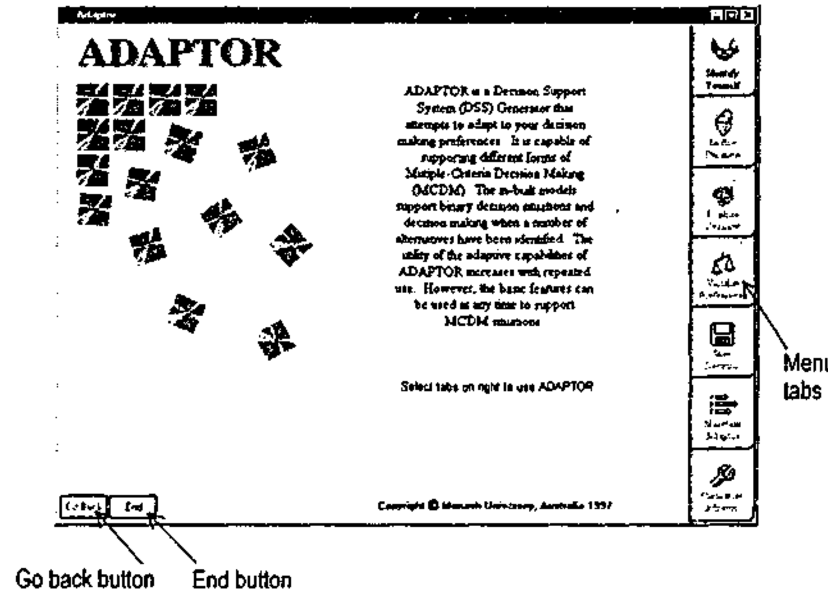
Starting ADAPTOR

To start ADAPTOR,

1. From the Start menu on your desk-top, select Programs.
2. Select Adaptor1 group and click on ADAPTOR1.



When you start ADAPTOR a window similar to the figure below should appear on your screen .



This is the ADAPTOR introduction screen. The menu tabs on the extreme right can be seen throughout the session on all major screens. The two buttons on the bottom-left corner also remain in that position on all screens.

The tabs available for selection at a given time are highlighted with blue fonts. Other tabs are displayed in a pale-grey font. Select tabs by clicking on them with the mouse pointer.

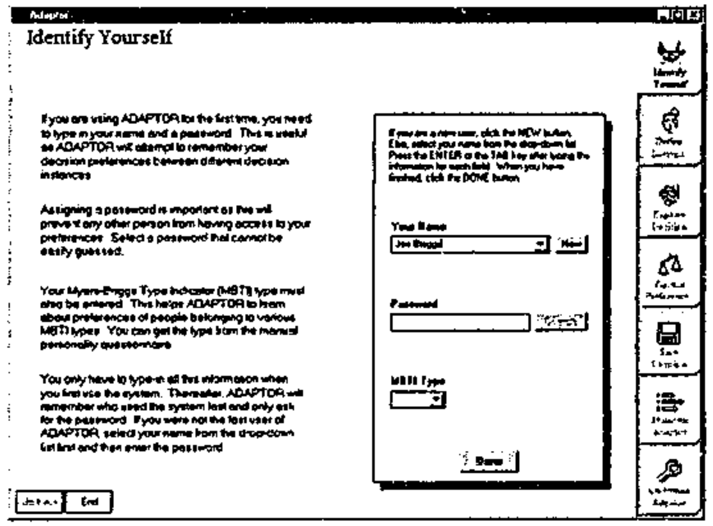
The *Go back* and *End* buttons are highlighted and disabled depending on their availability in a given situation.

Sometimes a pointer on the right margin of the screen will indicate the next action you should perform. You may either follow that sequence or select your own order in performing the tasks. This pointer can be switched off in the *Customise Adaptor* screen.

- To start using ADAPTOR select the *Identify Yourself* tab.
- To finish the session, select the *End* button at any time. Always save any changes made to the decision before you end the session as the learning facility in ADAPTOR is activated when saving. In addition to losing the work you have done, unsaved decisions deny ADAPTOR an opportunity to learn.
- To go back to your previous screen select the *Go back* button.

Using ADAPTOR for the first time

When you select the *Identify Yourself* tab the following screen is displayed.



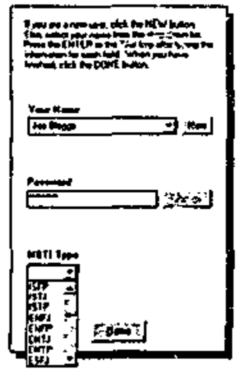
As ADAPTOR provides facilities for multiple users and decisions, privacy of the information is very important. This has been a major consideration when designing ADAPTOR. A password system has been used to prevent any other person from accessing your data. Please make sure that you use this facility.

1. Select the *Identify Yourself* tab after starting ADAPTOR.

2. Select the *New* button.

3. Type in your name or another name that will identify you in the *Your Name* entry field.

1. Enter a password in the *Password* entry field. Make sure that you enter a password that cannot be easily guessed by others.



2. Select your personality type from the drop-down list. The personality type should be based on the Myers-Briggs Type Indicator (MBTI). If you have not undertaken a personality test, please do so before using ADAPTOR.

3. Select the *Done* button.

4. You will be prompted to re-enter the password in a new dialogue box. Press ENTER or select the OK button after typing the password.

If your initial password and the re-entered one does not match, a message will indicate this to you. Please enter the password again and re-confirm if this happens.

When you have registered as a new user, a pointer on the right of the screen will indicate the next step you should perform.

NOTE Make sure that you enter the correct personality type. Once you have selected your personality type and selected the Done button, the system will align its learning with that personality type. You cannot change this type later. If you make a mistake, create a new user by following the above steps again.

Using ADAPTOR the next time

ADAPTOR has the capability to remember the details of the previous person who used it. This prevents you from having to select the name from the list if you are constantly using the system.

1. Select the *Identify Yourself* tab after starting ADAPTOR.

2. If your name is already displayed in the *Your Name* entry field, skip step 3.

3. Select your name from the *Your Name* drop-down list.

4. Enter your password.

5. Press the ENTER key or select the *Done* button

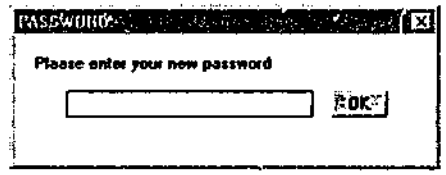
Note that you cannot change the name or the personality type on this screen.

Once you have been identified, a pointer on the right of the screen will indicate the next step you should perform.

Changing the Password

You may change the password at any time. Changing the password regularly is a good practice as this will prevent continued unauthorised access if your old password has been guessed by somebody.

1. Identify yourself following one of the two procedures described previously.



2. Select the Change button.

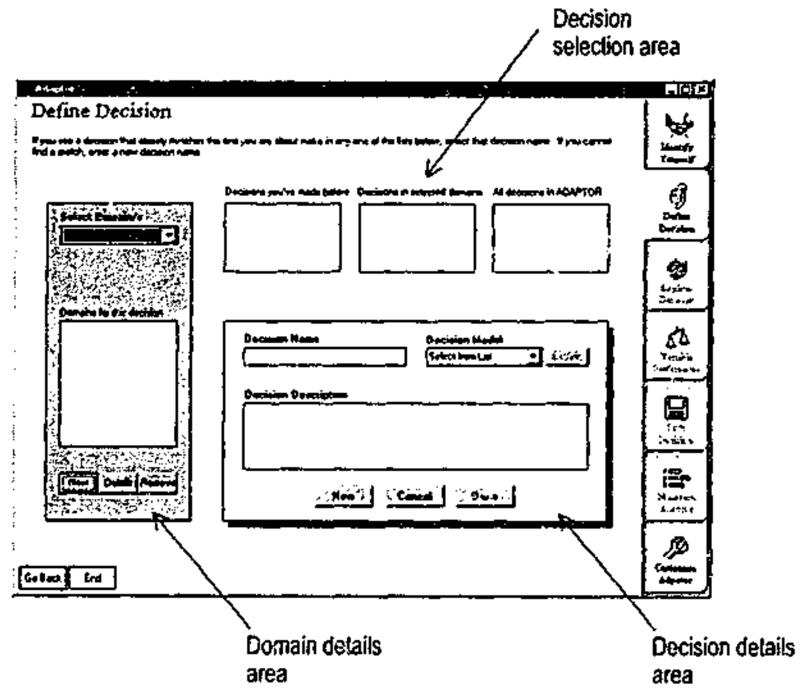
3. A dialogue box similar to the above will prompt you for the new password. Type the new password and press ENTER or select the OK button.

4. Now you will be prompted to re-enter the password. Re-type the new password and press ENTER or select the OK button.

If your two entries matched, that will be recorded as the new password. If not, a message will indicate that the entries did not match and no changes will be made. To attempt changing again, follow steps 1 to 4.

Adding a new decision

Select the *Define Decision* menu tab. The following screen is displayed.



The *Define Decision* screen consists of three main areas: decision selection area, domain details area and the decision details area. The decision selection area has three lists. The first lists the decisions that you have previously made using ADAPTOR. If you are using the system for the first time, this will remain blank. The second lists the other decisions that belong to the domains that you have selected for the current decision and the third lists all decisions that have been made using ADAPTOR. These lists can be used to recall details of previous decisions. How this can be done is explained in the next section.

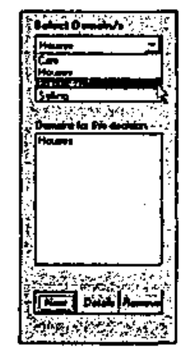
The second major area on the screen is the domain details area. The drop-down list has all the domains that have been defined in ADAPTOR. This list can be used to select domains for the current decision. The domains selected for the current decision are listed in the list box.

The decision details area is the input area for the details of the current decision.

To add a new decision the following procedure should be followed:

1. If there are details of a decision already displayed in the decision details area, click the *New* button. This will clear the entry fields on the screen. If the previous decision had not been saved, a message with a warning will be displayed.

2. Domains are subject areas to which the decision belongs. Click on the domain drop-down list and see whether the domains that the new decision belongs to are listed. If relevant domains can be found, select them by clicking on the list, one-at-a-time. Remember that a decision can belong to more than one domain.

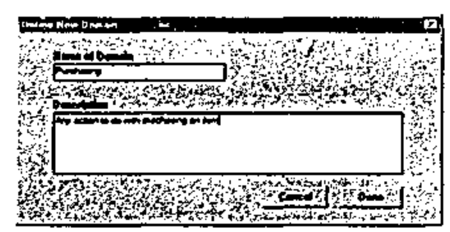


The domains you have selected appear on the domains list in the domain details area. Simultaneously, decisions that are aligned to the selected domains are added to the list in the decision selection area.

To view the details of domains, highlight (by clicking) a domain in the selected list and click the *Details* button or simply double-click on the domain name.

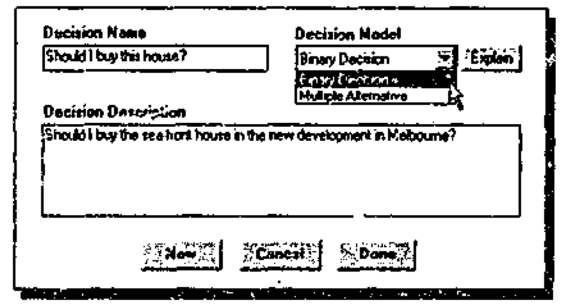
To remove domains that you have just added, select the domain name and then click the *Remove* button.

If you are not satisfied with the domains that are in the drop-down list, **add a new domain** by selecting the *New* button in the domain details area. When the new button is selected, the dialogue box on the right is displayed:



A domain name and a description can be entered in this box. The description is optional. However, you should always give a description as this domain may be used by you or other decision makers for other decision situations. Exact context and meaning can only be understood with a good description as the name is only a short representation. Selecting appropriate domains for decisions is very important as learning in ADAPTOR is aligned with decision domains.

1. Give the decision a name by typing in the *Decision Name* entry field in the decision details area. This should be a short name that identifies the decision well.



2. Select a model for this decision by selecting from the *Decision Model* drop-down list. The decision model should be selected to reflect the characteristics of the current decision situation.

   - If there are many possible solution to this problem, select the *Multiple-alternative model.*
   - If the decision is of yes/no type, select the *Binary model.*

Brief descriptions of these models can be obtained by selecting the model and then clicking the *Explain* button. These descriptions can be hidden by clicking on any part of the screen. Please read the decision concepts section for a detailed description.

3. Enter a description for the decision. A description is important as it will help identify whether the context in this instance can be applied for another situation. It will also serve as a reminder to you on the exact circumstances of this decision.

4. Select the *Done* button. If the information is incomplete, error messages will indicate missing information. If the information is complete you are now ready to explore the details of the new decision.

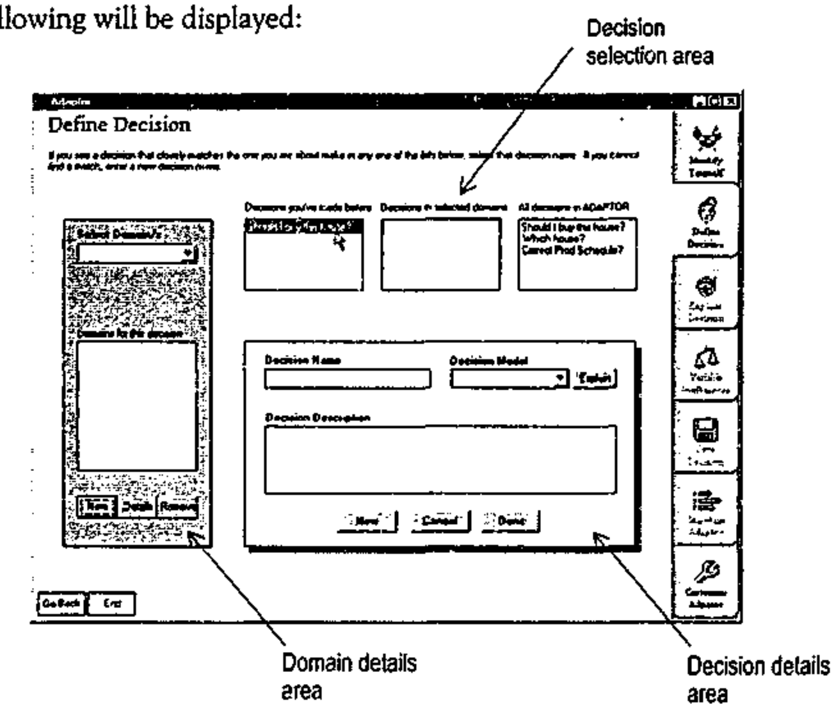
5. Select the *Explore Decision* menu tab.

NOTE Changes made to the decision definition can be discarded by clicking the *Cancel* button in the decision details area, at any time.

Retrieving a previously defined decision

You can recall a decision that you have previously defined or a decision defined by another user.

1. Select the *Define Decision* from menu tabs. A screen similar to the following will be displayed:



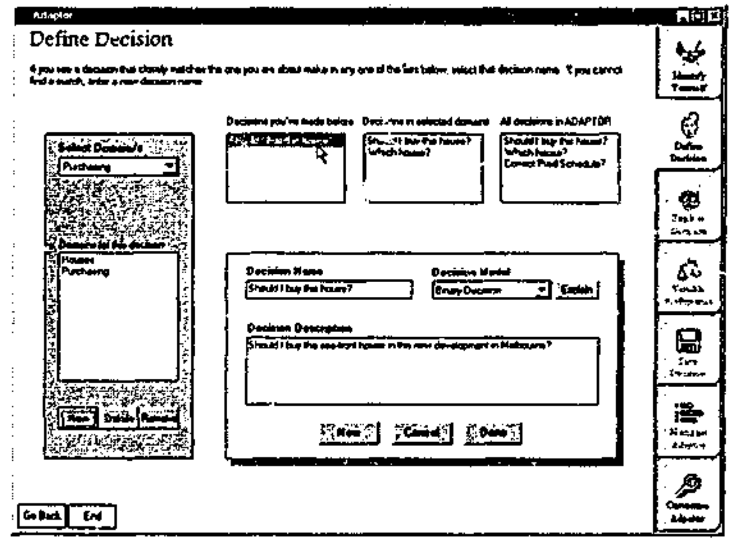
2. Double click on the name of the decision that you require from one of the decision lists in the decision selection area. For example, if you want to retrieve the 'Should I buy this house?' decision, double-click on the decision name as shown.

If there is an unsaved decision already defined, an error message will appear. You can choose to discard the changes to that decision or save that decision before selecting your new decision.

3. The details of the selected decision will be displayed as shown. Note that you cannot amend the decision name or the model. These two fields are disabled. The description may be changed. However, refrain

from deleting the existing description as another user may find it useful.

Details of domains for this decision are displayed in the domain details area. Other decisions that belong to the same domains are listed in the appropriate list in the decision selection area.



4. You can link this decision to more domains if you feel that it is appropriate to do so. However, you are not allowed to delete the domains that the decision has already been linked. To add domains or to get details of existing domains, follow the procedure described in the *Domains and your decision* section in this guide.

5. When you are satisfied with the definition of the decision, select the *Done* button. You are now ready to begin exploring the details of the selected decision.

6. Select the *Explore Decision* menu tab.

NOTE You can discard the changes made by selecting the *Cancel* button at any time. You may also start to define a new decision by selecting the *New* button in the decision details area.

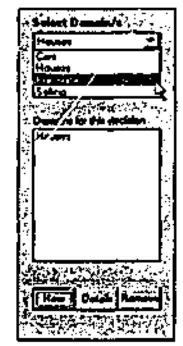
Domains and your decision

ADAPTOR uses the concept of decision domains to identify various possible subject areas for decision making. For example, a decision to purchase a house may belong to *purchasing* and *houses* domains.

Domains are important as ADAPTOR's learning mechanism performs generalisations. Some generalisation may not be valid across all possible decision domains. To ensure maximum validity of these generalisations, ADAPTOR aligns its learnt facts with domains.

Selecting an existing domain

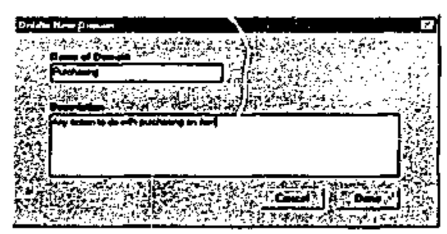
Click on the domain drop-down list on the Define Decision screen and see whether the domains that the decision should belong to are listed. If relevant domains can be found, select them by clicking on the list one-at-a-time. Remember that a decision can belong to more than one domain.



The domains you have selected appear on the domains list in the domain details area. Simultaneously, decisions that are aligned to the selected domains are added to the list in the decision selection area.

Adding a new domain

If you are not satisfied with the domains that are in the drop-down list, add a new domain by selecting the *New* button in the domain details area. When the new button is selected, a dialogue box is displayed.



A domain name and a description can be typed in this box. The description is optional. However, you should always give a description as this domain may be used by you or other decision makers for other decision situations. Exact context and meaning can only be understood with a good description as the name is only a short representation. Selecting appropriate domains for decisions is very important as learning in ADAPTOR is aligned with decision domains.

After you type a name and a description for the domain, select the *Done* button on the dialogue box. Selecting the *Cancel* button will close the dialogue box without adding a new domain.

Removing domains

To remove a domain that you have just added, select the domain name and then click the remove button.

Note that you are not allowed to remove domains that have been previously linked to this decision by you or other users of ADAPTOR.

Viewing details of domains

Select a domain in the list and click the *Details* button or simply double-click on the domain name. A dialogue box with the domain details is displayed.

Detailed definition of the decisions

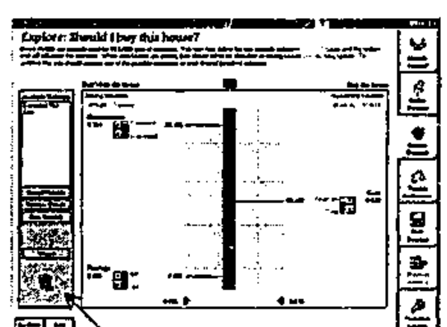
Unlike traditional computer systems, ADAPTOR does not require you to first define the inputs and then obtain the output, in two steps. The explore facility in ADAPTOR facilitates both these functions with the same interface. This concept is also useful in understanding a dynamically changing decision situation. You can visualise the effect that is caused by incrementally defining the decision details. In this user guide, we however divided the discussion into *detailed definition* and *exploring the decision* sections for ease of understanding.

You begin detailed definition of the decision once the basic details such as the name, description and model have been defined using *the Define Decision* section. By this stage, the decision is also linked to domains. ADAPTOR provides two visual representations based on the model that best fits your decision. These representations are discussed in detail under the *decision concepts* section of this guide.

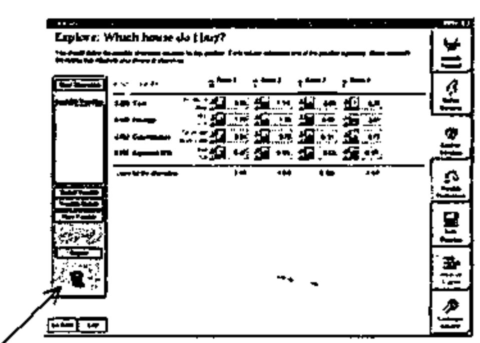
To start detailed definition, select the *Explore Decision* menu tab. Depending on the model selected for the decision, an exploration screen with the relevant visual representation is displayed.

Although the representations are different, common tools located in the *explore control panel* are used for detail definition of the decision in both models. As can be seen from the two screens below, the tool structures are similar in both representations.

Binary representation



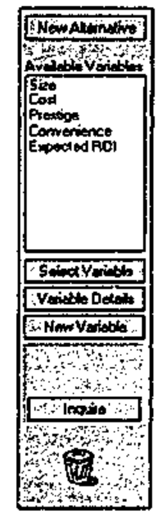
Multiple-alternative representation



Explore control panel

We will first discuss the common elements in the two representations.

In ADAPTOR, factors that affect the decision situation are called *variables*. As discussed in the concepts section, the two types of elements in a multiple-criteria decision situation are *alternatives* and *variables*. For a definition of a decision to be complete, both these types of elements should be defined. We begin with a discussion on defining variables.



The figure on the right is similar to the *explore control panel* in both binary and multiple-alternative explore routines. The only difference between the two is that the binary module does not have the *New Alternative* button. The reasons for this will be discussed later. All other operations on this panel are common to both types of representations.

The list box in this panel lists variables that you may consider when making the decision. ADAPTOR automatically generates a list of possible variables at the commencement of the explore session. It generates this by looking at the domains that this decision belongs and the variables the have been previously used for decision making.

Selecting an existing variable

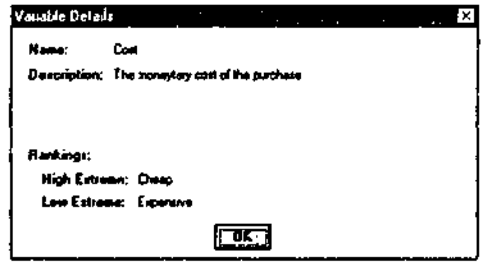
To use a variable that is in the list of available variables, select the name from the list and then click the *Select Variable* button. You can also use a variable by double-clicking on the variable name in the list.

NOTE Before using an existing variable always look at the details of its definition. If the variable is not defined exactly suited to the current situation, create a new variable.

Creating a new variable

To add a new variable that is not in the list, select the *New Variable* button. Details on how to define the details of the variable, please refer to the *defining a new variable* section in this guide.

Viewing details of a variable



To get details of an existing variable, select the variable from the list and click the *Variable Details* button. The details are displayed in a dialogue box similar to the one shown here. The name, description and the labels for the extremes of the measurement scale are displayed. The labels for the extremes are defined when the variable is first created. They are based on the perceived high and lower ends of the measurement scale when alternatives are assessed on this variable.

For example, as shown in the dialogue box, if *Cost* is a variable in a decision to purchase a house, each house that we evaluate can rate between *Expensive* and *Cheap* on this factor. Thus, we define Expensive as the low extreme and Cheap as the high extreme for this variable. In this situation, the high extreme can be perceived as 'good' and the low extreme as 'bad'. These labels should be understood in the context of the decision situation.

Deleting a variable

To delete a variable that you have included in the model but no longer require, drag the variable name displayed in your exploration screen to the trash can on the control panel. This variable is added to the list of available variables. You may reuse the variable if needed again later.

NOTE To drag the variable, point at the variable name and depress the left mouse button. Variable name transforms into a drag icon: While keeping the button pressed, move the mouse over the trash can icon. You will notice the trash can opening when the positioning is correct. Release the mouse button.

NOTE With this version of ADAPTOR, maximum of 12 variables can be used at any one time for both types of decisions.

The other control on the panel is a button labelled *Inquire*. This button is set in a small sub-panel. At most times you will notice that this button remains disabled. While using ADAPTOR, you may observe flashing icons on the sub-panel. When these icons are displayed, the *Inquire* button will be enabled.

Selecting the *Inquire* button will cause a message to be displayed warning you of some irregularity that ADAPTOR has observed in your decision making. This is ADAPTOR's 'active' support component. Details of these messages can be found in the *Active support with ADAPTOR* section of this guide.

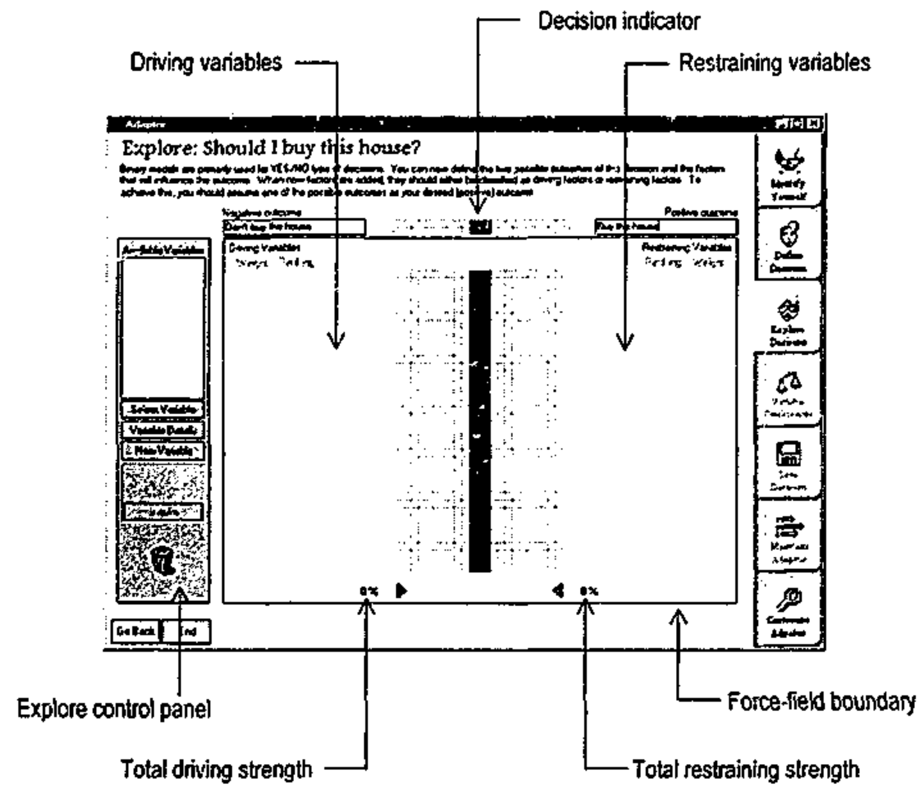
Once you have read the message, pressing the OK button will close the message window. However, the icons will remain visible until the anomaly has been rectified.

NOTE You can switch off ADAPTOR's active support facilities as described in the Customising ADAPTOR section.

So far we have discussed common elements to both binary and multiple-alternative decision representations. The operation of the two modules is discussed next.

Defining a new binary decision

When a binary model is selected as the most suitable for the decision, the binary exploration screen is displayed upon selection of the *Explore Decision* menu tab. This screen, reproduced below, graphically resembles a *bi-polar force field* discussed in the concepts chapter.



Before proceeding any further, carefully study the different areas on this screen. The decision indicator in the middle represents the equilibrium that exists between two opposing sets of factors. On the ADAPTOR screen, the driving variables (factors that push you towards the positive outcome) are on the left of the decision indicator. The restraining variables are therefore on the right hand side.

The equilibrium and the forces exist within the force field that is defined with a boundary. If the decision indicator is moved towards the right of the centre of the force field, the positive decision outcome is desired (as this direction indicates a bigger force from the driving factors as compared to the restraining factors). If the indicator moves left of the centre, the negative outcome is desired. The total forces generated by driving and restraining forces respectively are displayed at the bottom of the screen.

NOTE Driving variables are on the left while the positive outcome is achieved when the indicator moves to the right.

Restraining variables are on the right while the negative outcome is achieved when the indicator moves to the left.

Binary situations require a *yes* or *no* type of decision to be made. This can be regarded as two extremes of the same decision alternative. Therefore there is no need to generate a number of possible alternatives. By the stage that a binary decision has to be made, the decision process should be sufficiently developed to identify the alternative being subject to the binary decision.

It is common to approach a binary situation with a desired outcome already in mind. We term this as the *positive outcome*. The other end of the continuum should therefore be the other possible outcome. This can be regarded as the *negative outcome*. How you perceive the positive and negative outcomes is dependent on each situation.

Variables that should be considered when making the decision generally have a stronger pre-disposition as either a factor supporting you achieving the positive outcome or as a factor preventing you from achieving that outcome. When defining the details of the decision, all variables should be classified on this pre-disposition. Note that this is a subjective assessment that can be changed at any time.

To define details of a new binary decision,

1. Select the *Explore Decision* menu tab.

2. Indicate your positive and negative outcomes by typing-in labels in the entry fields on the top left and right corners of the force field. To change these labels, double-click on the fields.

3. Check the list of available variables to see whether variables appropriate to this decision are present.

If there are appropriate variables, select them one at a time.

If there are no suitable variables already available or you want to add additional variables, create new variables.

Read the preceding section on selecting and adding variables to achieve these tasks.

4. When a new variable is added or an existing one is selected for use in the current decision, it is displayed as a flashing icon in the top-centre of the force field. Drag this icon to the left or the right of the decision indicator. These placements can be changed later. The variables are shown with labels and *score indicators* associated with them.

   - To add a driving variable, drag the variable to the left.
   - To add a restraining variable, drag the variable to the right.
   - To discard the variable, drag it to the trash can. It is added back to the list of available variables.

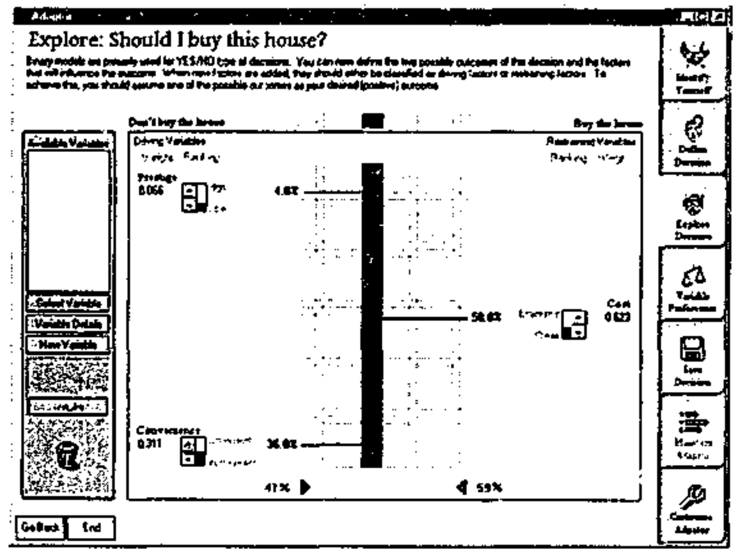
5. Start exploring the decision. Read *exploring the decision* section.

NOTE To drag the variable, point at the flashing icon and depress the left mouse button. The flashing icon transforms to a drag icon: 

While keeping the button pressed, move the mouse over the area you want to drop it. Release the mouse button.

Recalling a binary decision

If you had recalled a decision that had been previously defined by you, the binary exploration screen already consists of the force field as you defined it last. A screen similar to the one below will be displayed:



You may add or delete variables from this screen using procedures described previously. Please refer to the *exploring the decision* section for details on how to manipulate the model to evaluate the decision situation.

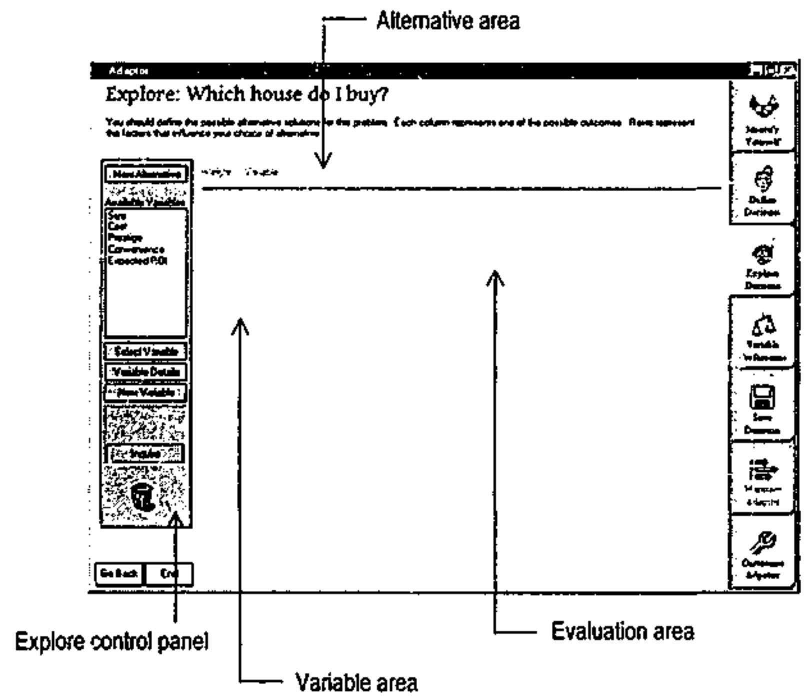
To delete an existing variable, drag it to the trash can on the control panel.

To change the direction of a variable, ie. To change a driving variable to a restraining one and visa-versa, drag the name of the variable to the opposite end of the force-field.

To change the names of the positive and negative outcomes, double-click on the label and then type-in the new name.

Defining a new multiple-alternative decision

When a multiple-alternative model is selected as the most suitable for the decision, the multiple-alternative exploration screen is displayed upon selection of the *Explore Decision* menu tab. This screen is similar the one reproduced below.

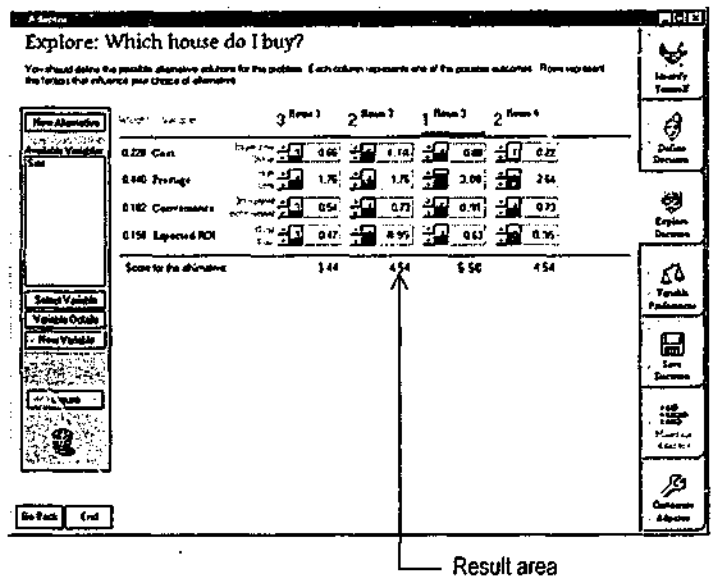


Before proceeding any further, carefully study the different areas on this screen. When this screen is first displayed, most areas appear as blank. However, specific areas are reserved for different purposes.

As discussed in the *concepts* chapter, a multiple-alternative decision situation consists of a number of possible solutions to the problem (alternatives) and a number of factors that are used to evaluate the alternatives (variables). The areas on this screen allow display of the alternatives and the variables.

The explore control panel is common to both binary and multiple-alternative explore screens, with one exception: a *New Alternative* button. This button is used to define a new alternative solution that is available in the decision situation. Alternative solutions that you define are placed above the horizontal line that is visible. This area is called the *alternative area*.

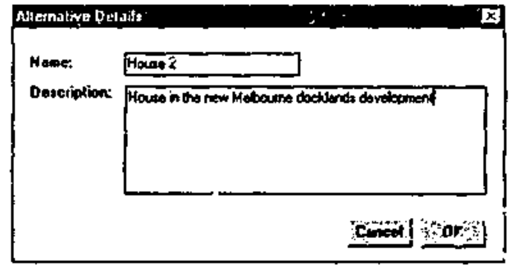
A column area below the variable label is reserved for listing the variables. Variable names and the weights that are associated with those variables are displayed in this area. How each alternative measures against the variables should also be shown. These measures are shown in the evaluation area. The final scores calculated for alternatives are shown below the evaluation area. Thus, a detailed multiple-alternative screen looks similar to the screen below :



To define details of a new multiple alternative decision,

1. Select the *Explore Decision* menu tab.

2. Click on the *New Alternative* button to define the different possible solutions available for this decision.



When this button is clicked, a dialogue box is displayed. Type a name for each alternative solution. Keep this name short. The details of this solution can typed in the description entry field. Although optional, it is strongly recommend that you should enter a description. When details are completed, click the OK button. If you do not want to go ahead with this alternative, click the *Cancel* button.

Repeat this process until all the alternatives have been defined.

To **delete an alternative** already defined, simply drag its name to the trash can in the control panel.

> **NOTE** With this version of ADAPTOR, the maximum number of alternatives that can be defined is five.

3. Check the list of available variables to see whether variables appropriate to this decision are present.

If there are appropriate variables, select them one at a time.

If there are no suitable variables already available or you want to add additional variables, create new variables.

Read the preceding section on selecting and adding variables to achieve these tasks.

New variables are shown with labels and *score indicators* associated with them. Each alternative has a *score indicator* for a given variable. The screen therefore takes the form of rows and columns.

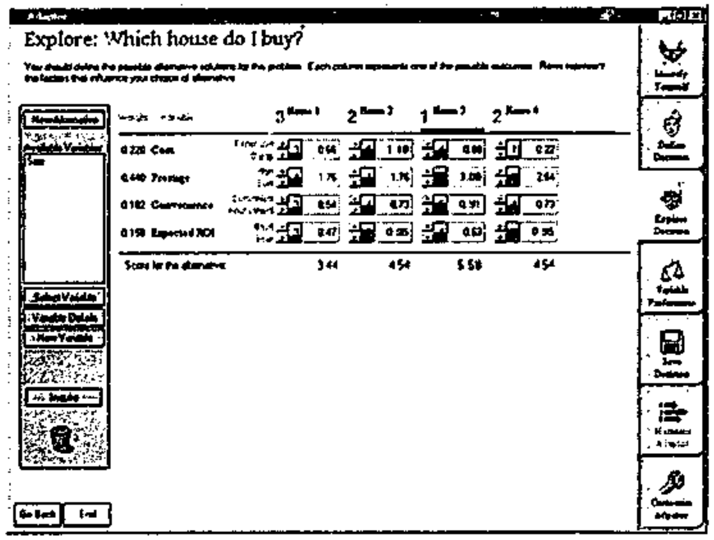
To **delete a variable** already defined, drag its name to the trash can on the control panel.

4. Start exploring the decision. Read *exploring the decision* section.

NOTE To drag a variable or an alternative to the trash can, point at the name and depress the left mouse button. The name transforms into a drag icon:  While keeping the button pressed, move the mouse over the trash can icon. You will notice the trash can opening when the positioning is correct. Release the mouse button.

Recalling a multiple-alternative decision

If you had recalled a decision that had been previously defined by you, the multiple-alternative exploration screen already consists of elements you defined it last. A screen similar to the one below will be displayed:



You may add or delete alternatives and variables from this screen using procedures described previously. Please refer to the *exploring the decision* section for details on how to manipulate the model to evaluate the decision situation.

To delete an existing variable, drag it to the trash can on the control panel.

To delete an alternative, drag it to the trash can on the control panel.

Exploring the decision

Once you have completed the detailed definition of the decision or have recalled a previously defined decision, you are ready to get ADAPTOR to help with your decision making task. We call the decision making session with ADAPTOR as *exploration*. The term exploration is used because the session with ADAPTOR is designed to assist you in further understanding and clarifying the decision situation before a decision is made.

As discussed previously, you do not have to do detailed definition and exploration in two distinct steps. Detailed definition and exploration are both done using the same interface. Thus decision exploration is an iterative task along with decision definition.

The discussion on exploration is divided into two sections for binary and multiple-alternative decisions although there are many common elements between them. One common feature is how the final decision suggestions are calculated.

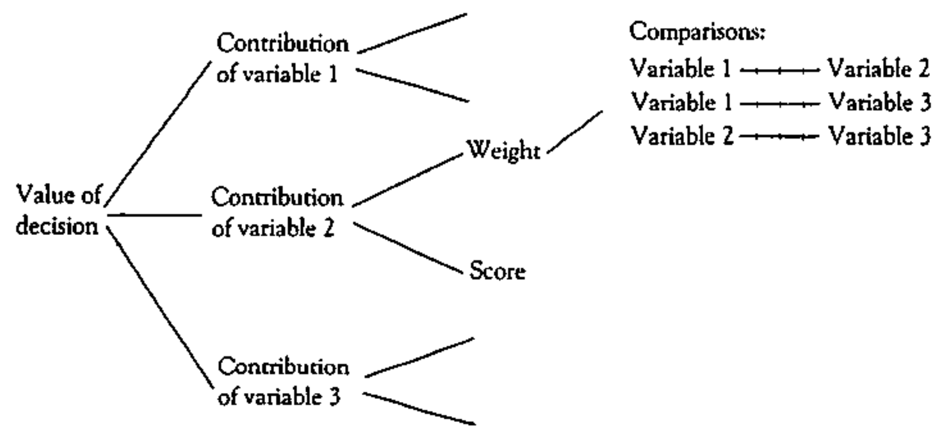
How decisions are derived

The force contributed by a variable is calculated using two elements: the *weight* and the *score* of the variable. The weight is a representation of the importance of this variable to the final decision. The weight of a variable is derived using the preferences that you indicate when comparing the sets of variables.

The score of a variable is a measure of how a given alternative fares on this variable. For example, if you were considering buying a house, the cost can be cheap to expensive on a scale that you define. The position of this house on the scale is its score for the cost variable.

To arrive at the final value for the decision, we add the forces contributed by all the variables. The alternative with the highest value is taken to be the most appropriate decision. The usefulness of decision aids such as ADAPTOR is that you can manipulate each element that contributes to the final value. 'What if' analysis is the term given to exploring the decision situation by changing the elements that make up the final decision values.

The diagram below shows the elements that you can manipulate in ADAPTOR to evaluate different scenarios:



Binary and multiple-alternative representations in ADAPTOR have different forms of presentation of the final decision outcome values although internal calculations are performed using the method described above.

Exploring a binary decision situation

A binary decision situation consists of two possible outcomes and a set of variables that influence the choice between the two outcomes. As the decision takes an yes or no form, the two outcomes are extreme ends of the same alternative.

When you evaluate the variables to assign scores, this should be kept in mind. For example, if you are deciding to purchase a particular house or not, your problem on which house has already been resolved. If you had variables called *cost* and *floor area*, the score for these two variables are decided by evaluating the house that you have in mind: how much does this house cost, how big is this house - there is no question of different houses.

The outcome of a binary decision can be changed by manipulating two entities in the model: the scores and weights associated with variables. In addition you can also change the direction of the influence of a variable, ie. Making a driving variable a restraining variable and visa-versa. Variables may also be eliminated or added to the model.

To change the score of a variable, click on the up and down symbols of the score indicator associated with the variable. As you change score, a coloured bar indicates the relative value on the measurement scale. This acts as a quick, visual guide to the score you have assigned.

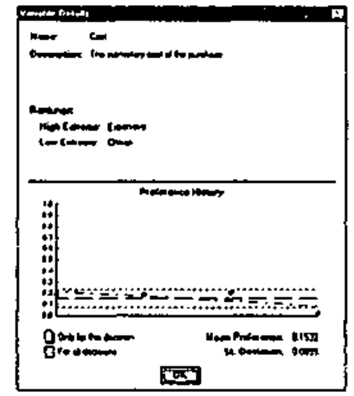
NOTE It is assumed that the scores of the variables are independent of each other.

As explained in the previous section, the weight for a variable is derived using all the variable comparisons you have performed. How you have compared variables to each other (when defining the decision) can be viewed by selecting the *Variable Preferences* menu tab. This is further explained in *the examining your preferences* section of this guide.

To change the weight of a variable, you have to review the pair-wise comparisons between variables. A change that you make to a single variable is also reflected in other variables as the weights are normalised. To review the comparisons that relate to a given variable, double-click on the weight displayed besides the variable name.

To change the direction of a variable, drag to the desired end of the force field. You can achieve this by depressing the left mouse button over the variable name and then moving the mouse pointer to the desired location. Release the mouse button to drop the variable. Notice how the score and the weight are preserved.

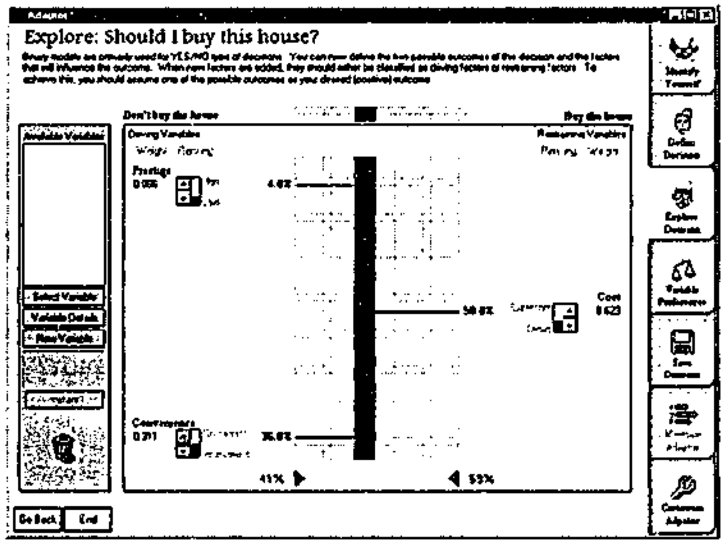
To get details of a variable, double click on the variable name. A window with variable details will be displayed. This window contains basic variable details such as the name, description and the domain that it belongs. In addition it may also contain a graph showing the history of weights given to this variable. This graph can be changed to either display the weight history of the variable on all occasions that it has been used, or just the occasions on which it has been used for the current decision. The mean weight and standard deviation are also displayed. A trend line of the weights on the graph allows you to learn how your preference to this variable has changed over time.



To delete a variable, drag it to the trash can on the control panel. You can achieve this by depressing the left mouse button over the variable name and then moving the mouse pointer over the trash can. Release the mouse button to drop the variable. Notice how the trash can opens when the mouse pointer is correctly over it.

To reuse a deleted variable, double-click on the variable name in the control panel. You can also achieve the same result by selecting the variable and then clicking the *Select Variable* button. Newly selected variable appears as a flashing icon in the centre of the force field. Drag the icon to the desired direction of the force field.

To add a new variable, click the New Variable button. A dialogue box prompting details of the new variable will appear. Please read *the defining a new variable* section of this guide for details.



A binary decision situation is represented on a screen similar to the above. The positioning of the decision indicator determines the final decision suggestion. The position is dependent on the total forces contributed by all the driving variables and the restraining variables. These totals are presented as percentages of the total force in the force field. The contribution of each variable is also displayed.

When you manipulate the elements on the screen, flashing icons may be visible on the control panel. This is ADAPTOR's active support component indicating various anomalies it has found in your decision making. Click on the flashing icon or the *Inquire* button on the control panel to get details. These messages are further explained in *active support with ADAPTOR* section of this guide.

After you are satisfied with the decision, save it by selecting the *Save Decision* menu tab.

NOTE Save the decision only after you are satisfied that the current formation of the model is your preferred decision.

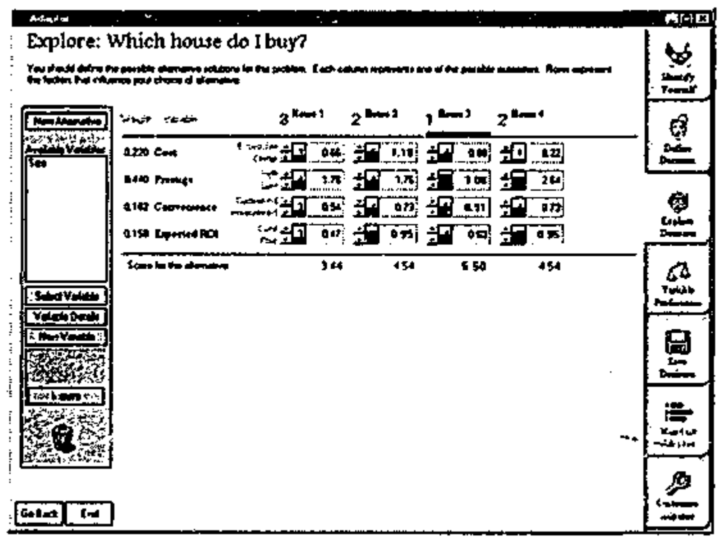
Exploring a multiple-alternative situation

A multiple-alternative decision has many possible outcomes and many factors on which the outcome is decided. The aim in exploration is to find the most attractive decision outcome. In addition, it is possible to see the rankings for all possible alternatives so that an informed decision can be made.

As with a binary decision, the outcome of a multiple alternative decision can be changed by manipulating two entities in the model: the scores and weights associated with variables. In this form of decision, the weight associated with a variable is common to all the decision alternatives, ie. Weight is perceived as the importance of a factor when making the decision. It is not aligned with alternatives.

The score for a variable is however aligned with the alternative. Therefore all alternatives should be measured against each variable. This results in a matrix of scores.

The final score for each alternative is displayed in the results area. As shown in the screen below, the ranking of an alternative is displayed beside its name.



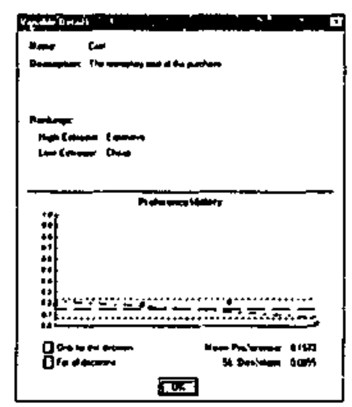
To change the score of a variable, (for a given alternative) click on the up and down symbols of the score indicator associated with the variable. As you change score, a coloured bar indicates the relative value on the measurement scale. This acts as a quick, visual guide to the score you have assigned. A numeric scale value between 0 and 9 is also displayed.

NOTE It is assumed that the scores of the variables are independent of each other.

As explained in the previous section, the weight for a variable is derived using all the variable comparisons you have performed. How you have compared variables to each other (when defining the decision) can be viewed by selecting the *Variable Preferences* menu tab. This is further explained in *the examining your preferences* section of this guide.

To change the weight of a variable, you have to review the pair-wise comparisons between variables. A change that you make to a single variable is also reflected in other variables as the weights are normalised. To review the comparisons that relate to a given variable, double-click on the weight displayed besides the variable name.

To get details of a variable, double click on the variable name. A window with variable details will be displayed. This window contains basic variable details such as the name, description and the domain that it belongs. In addition it may also contain a graph showing the history of weights given to this variable. This graph can be changed to either display the weight history of the variable on all occasions that it has been used, or just the occasions on which it has been used for the current decision. The mean weight and standard deviation are also displayed. A trend line of the weights on the graph



allows you to learn how your preference to this variable has changed over time.

To **delete a variable**, drag it to the trash can on the control panel. You can achieve this by depressing the left mouse button over the variable name and then moving the mouse pointer over the trash can. Release the mouse button to drop the variable. Notice how the trash can opens when the mouse pointer is correctly over it.

To **reuse a deleted variable**, double-click on the variable name in the control panel. You can also achieve the same result by selecting the variable and then clicking the *Select Variable* button. Newly selected variable appears as a new row in the matrix.

To **add a new variable**, click the New Variable button. A dialogue box prompting details of the new variable will appear. Please read the *defining a new variable* section of this guide for details.

To **add a new alternative**, click the *New Alternative* button. A dialogue box requiring the decision name and the description will be detailed. Provide these details and select the OK button or select the Cancel button to exit without creating an alternative. If a new alternative is added a column is appended to the matrix.

To **delete an alternative**, simply drag it to the trash can on the control panel. You can achieve this by depressing the left mouse button over the alternative name and then moving the mouse pointer over the trash can. Release the mouse button to drop the alternative. Notice how the trash can opens when the mouse pointer is correctly over it.

NOTE This version of ADAPTOR has limit of a maximum of five alternatives and twelve variables.

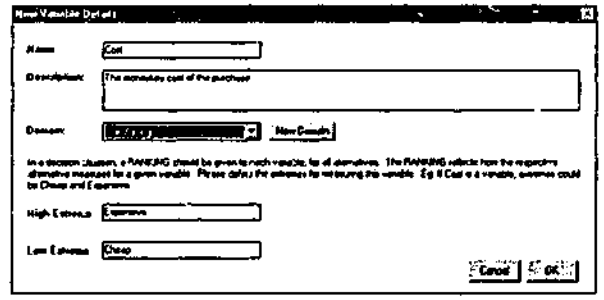
When you manipulate the elements on the screen, flashing icons may be visible on the control panel. This is ADAPTOR's active support component indicating various anomalies it has found in your decision making. Click on the flashing icon or the *Inquire* button on the control panel to get details. These messages are further explained in *active support with* ADAPTOR section of this guide.

After you are satisfied with the decision, save it by selecting the *Save Decision* menu tab.

NOTE Save the decision only after you are satisfied that the current formation of the model is your preferred decision.

Defining a new variable

Factors that influence your decision making are called variables. The term variable is used because by changing the value of them the decision outcome can be manipulated. ADAPTOR learns about you and your personality type from the weights that you attach to variables. Hence defining and manipulating variables is a major component in ADAPTOR.



To define a variable. you should select the *New Variable* button on the control panel of the *Explore Decision* screen. When this button is pressed a dialogue box with a number of entry fields is displayed. Two of these fields are mandatory: the name of the variable, and the domain that it belongs. However, you attempt to provide all the details whenever possible.

Variable name: Provide a short name to identify the variable. Always make variable names meaningful. This is a mandatory field.

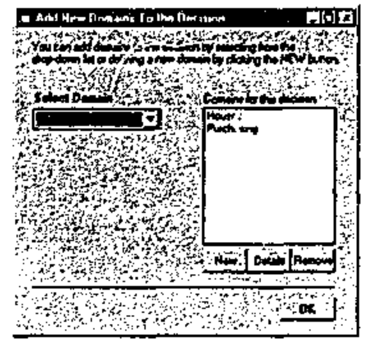
Description: The description of the variable. You should explicitly state the context in which variable is used and the meaning attached to it. The description is very important as variables in ADAPTOR can be used repeatedly by the person who created it as well as others. The variable can be validly re-used only if the context is applicable to a new situation.

Domain: Domains are subject areas to which the decision belongs. In addition to defining the domains that a decision belongs, you should also attach variables to domains. This is required because even though the decision may belong to many domains, a variable can belong to only one domain. This variable-domain link is useful when ADAPTOR learns about decisions. It is also used to provide you with useful lists of variables. This entry field is mandatory.

You can select a domain from the drop-down list. This list contains domains to which you attached the decision when the decision was defined.

If you cannot find a suitable domain, it is necessary to attach the decision to a new domain.

To attach to a new domain, select the *New Domain* button. A dialogue box is displayed. You are now able to pick from all the domains that are recorded in ADAPTOR. Select from the drop-down list, if a suitable domain exists. If you are unable to find a suitable domain in the list, create a new domain.



To create a new domain click the *New* button. Now you are able. Another dialogue box will prompt you for a domain name and a description.

Note that the name is mandatory and the description is optional. However, providing a good description is a good practice. You may either select the *OK* or the *Cancel* button to exit the domain creation dialogue box.

To get details of a domain, select the variable from the list and then click the Details button.

To remove a domain that you have just attached, select the domain name and click the *Remove* button. Note that domains that have been previously linked cannot be deleted.

When you have finished defining new domains, click the *OK* button to return to the variable creation window.

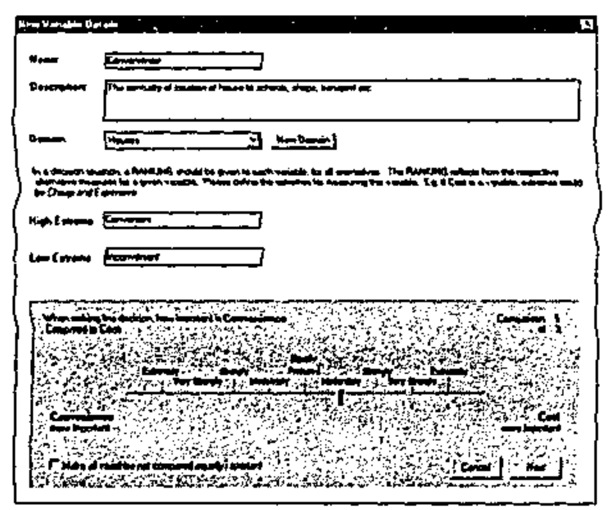
Variable scale extremes (high extreme and low extreme): These are based on the perceived high and lower ends of the measurement scale when alternatives are assessed on this variable.

For example, if *Cost* is a variable in a decision to purchase a house, each house that we evaluate can rate between *Expensive* and *Cheap* on this factor. Thus, we define *Expensive* as the low extreme and *Cheap* as the high extreme for this variable. In this situation, the high extreme can be perceived as 'good' and the low extreme as 'bad'. These labels should be understood in the context of the decision situation.

Having these two values make variable assessment easier.

After all the fields (at least the mandatory fields) have been filled, select the *OK* button. Select the *Cancel* button to exit without creating a new variable.

If you have already got other variables in your decision definition, you have to indicate your preferences between the newly created variable and all the variables already in the model. If such comparisons have to be done, ADAPTOR provides you the opportunity after you press the *OK* button.



The dialogue box is extended with an area to perform these comparisons. The comparisons are presented to you one at a time. The comparisons are done on nine-point scale and indicate your preference between the two variables.

When performing the comparison, always relate it to the current decision. These comparisons are used to derive the weight of the variable. Read the section on *examining your preferences* to see details on how this is done.

To change the comparison for given two variables, click on the desired position on the scale. You can achieve the same result by dragging the indicator to the desired position. To drag, depress the left mouse button on the indicator, move pointer to the new location and release the button. Notice that the default is equal importance of both variables.

When you have finished the comparison, click the either the *Next* or the *Done* button. If there are more comparisons to be done, the *Next* button is visible. If the current comparison is the last, the *Done* button is visible.

You have the option of **giving all the variables equal importance**. If you desire to do this, click on the small white square at the bottom left of the window.

You also can **postpone comparisons** by selecting the cancel button at any time.

The number of comparisons that relate to the newly created variable is displayed in the top-right corner of the in-set area of the window.

NOTE You can change the comparisons given here at anytime. Please read the section on *examining your preferences* for details.

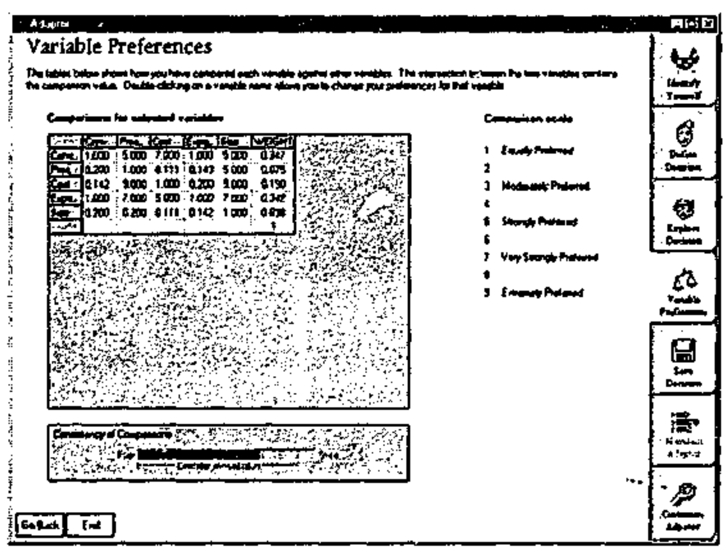
Examining your preferences

The multi-criteria decision model used in ADAPTOR uses scores and weights of variables to decide between decision alternatives. The weight is a measure of the importance of a variable when making a decision.

ADAPTOR uses a method of pair-wise comparison of variables to generate weights. This method entails you having to compare each variable with all the other variables on a semantic scale. You are asked to evaluate the importance of a given variable against the others when making the decision. This results in you expressing your preferences in relation to the variables in the decision situation.

The comparisons are done on a nine-point scale. The semantic labels used are internally converted to a numeric scale. Using this scale, a matrix of comparisons is built. Final weights for variables are calculated using this matrix.

To look at your comparison matrix, select the *Variable Preferences* menu tab. The matrix also contains the derived weights for all the variables used in the current decision.

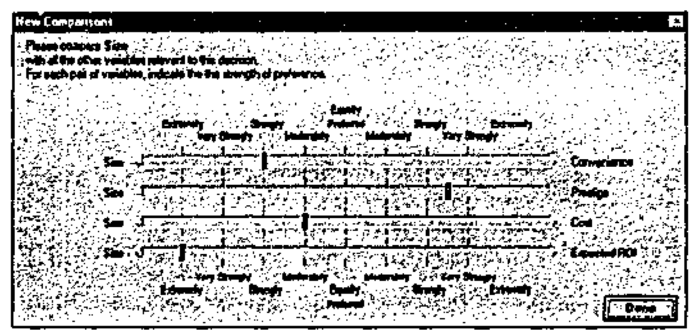


Besides the matrix of comparisons, this screen contains a consistency indicator. This is an extremely sensitive indicator of consistency of your comparisons. This indicator is colour coded for quick visualisation.

- A green status bar indicates a highly consistent matrix.
- Amber: acceptable consistency
- Red: comparisons are not very consistent. Should consider re-evaluation.

NOTE It is common for decision makers to perform inconsistent comparisons, although consistency is sometimes desirable. The consistency indicator should therefore be used with care. Re-evaluate your comparisons according to the indicator if you consider consistency an important factor in your comparisons.

To **re-evaluate comparisons**, double-click on the variable name in the matrix. A window with comparison scales for the selected variable is displayed. The indicators point to the current comparison values. Change any comparisons as you desire, always thinking how it would impact the current decision. Click the *Done* button when finished.



To **change the comparison** for given two variables, click on the desired position on the scale. You can achieve the same result by dragging the indicator to the desired position. To drag, depress the left mouse button on the indicator, move pointer to the new location and release the button.

Repeat the process of re-evaluation for all the variables. Notice how you have to compare only one half of the matrix.

To change you preferences while in the *Explore* screen, double-click on the weight of the variable. A window similar to the one above is displayed. The manipulations are identical to the description above.

Active support with ADAPTOR

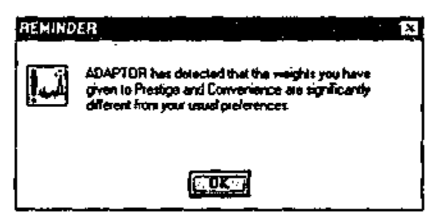
The major advantage of ADAPTOR over other decision support tools is its ability to learn about an individual's decision making preferences and through that learning provide 'active' decision support. Active decision support is compared with 'passive' support. In passive support, the system simply acts as a tool that you can use in any desired manner to support your decision making. Active support on the other hand is when the system has the ability to get more involved in the decision process.

Sometimes, active support entails the system behaving as a 'devil's advocate' by providing suggestions. ADAPTOR also has this capability. However because of ADAPTOR's learning ability, active support is taken a step further. It is capable of learning your typical behaviour giving it the advantage of being able to observe deviances from typical behaviour.

Every time you make a change to the decision model, ADAPTOR analyses all the components looking for anomalies and deviances from typical behaviour. When such behaviour is observed you are notified using flashing icons on the *explore control panel* on the explore screen.

There are two types of warnings that ADAPTOR provides:

- **Inconsistent weights warning**: this is generated when the weights that you have given to a single variable or a set of variables is significantly different from your usual preferences. Click on the flashing icon or the *Inquire* button on the control panel to get the details. The details are displayed in a message box.

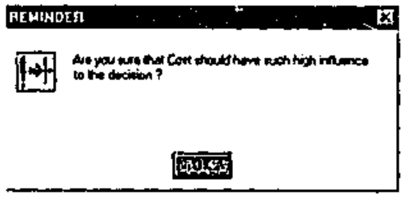


If you wish to change weights that you have given to the variables because of this, double-click on the weight associated with the variable in question. See *exploring the decision* section for details. Note that you are not required to make any changes.

To look at how weights for a particular variable has changed over time, double-click on the variable name. A window with variable details and a graph depicting weight history will be displayed. See *exploring the decision* section for details.

This warning is generated when a predefined threshold is exceeded from your mean weight for a given variable. The threshold is defined in terms of standard deviations. To change the warning threshold, select the Customise ADAPTOR menu tab, and change the appropriate value. See the customise ADAPTOR section of this guide for details.

- **Inconsistent forces warning:** This occurs when the forces contributed by the variables in a binary decision are uneven, ie. There is a large difference between the contribution of some variables and others. This is caused by large weights or scores attached to some variables. As the large values given may be deliberate, you are not compelled to make any changes. To get the details of the specific anomaly, click on the flashing icon or the *Inquire* button on the control panel. The details are displayed in a message box.



If you wish to change weights that you have given to the variables because of this warning, double-click on the weight associated with the variable in question. See *exploring the decision* section for details.

To change the score of a variable, click on the up and down arrow symbols on the score indicator relevant to the variable. See *exploring the decision* section for details.

This warning is generated when the difference between the contributions of sets of variables exceed a predefined threshold. The threshold is defined in terms of percentage contributions to the force-field. To change the warning threshold, select the Customise ADAPTOR menu tab, and change the appropriate value. See the customise ADAPTOR section of this guide for details.

NOTE As the active support component is based on the learning capability, the usefulness of warnings will increase with use (as ADAPTOR knows more about your decision making).

You are not compelled to change your decision model because of these warnings. They simply act as guides to help your decision making. Some deliberate strategies adopted by you may seem as anomalies to ADAPTOR.

If you wish, all active support components can be switched off. Please see customising ADAPTOR for details.

Saving the decision

Saving the decision in ADAPTOR is not limited to writing decision details to the disk for later retrieval. As previously discussed, ADAPTOR learns from every instance of its use. This learning process is carried out at the time you save the decision.

It is important that you save the decision only when satisfied with the way in which the decision model is organised and willing to commit to the decision suggestion finalised with ADAPTOR. This is because you only want ADAPTOR to learn about your actual decision.

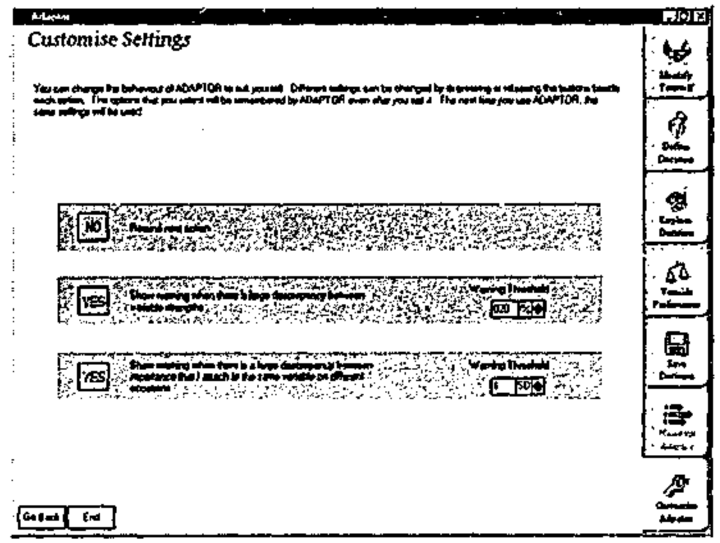
Another reason for saving only at the conclusion of the decision process is that saving/learning process can take a long time. The time is mostly determined by the number of items ADAPTOR learns from and the complexity of the already learnt facts.

To save the decision, select the *Save Decision* menu tab. Press the *Save Details* button. You can observe the progress of the process through the status bar on the button. Once the saving process is complete, the button will be disabled. This button will only be activated again if you make further changes to the decision.

Notice how Microsoft Excel® and Neuralyst™ software are momentarily activated after you selected the button. This is because ADAPTOR uses neural network technology for learning. Neural networks try to match human neurone learning. The way ADAPTOR is set up, it does not independently learn from each instance, but incrementally learns from all the decision instances by retaining previous learning. Hence the learnt facts become increasingly accurate with more use.

Customising ADAPTOR

ADAPTOR can be customised to suit your specific requirements. There are three possible options that can be selected in this version of ADAPTOR. These settings can be accessed on the by selecting the Customise ADAPTOR menu tab.



To switch any option on or off, click the button relevant to the option.

To change a threshold value, click on the up and down arrow symbols.

The available options are:

- Activate or de-activate the next action pointer. This is the small red arrow which indicates the next operation to perform.

- Enable or disable the inconsistent forces warning. The threshold is expressed as a percentage of the forces in the force-field for a binary decision. Enabling this active decision support component provides you with warnings when there are large discrepancies between the forces contributed by variables. See *active support with* ADAPTOR for details.

- Enable or disable the inconsistent weights warning. The threshold is expressed as standard deviations from the mean of weights given to a variable. Enabling this active decision support component provides you with warnings when the weight attached to a variable is significantly different from your usual preferences. See *active support with* ADAPTOR for details.

Maintaining ADAPTOR

The maintaining capability is reserved to be used by an administrator of the system. This option remains disabled for other users.

GLOSSARY

Active decision support: Active decision support is compared with 'passive' support. In passive support, the system simply acts as a tool that you can use in any desired manner to support your decision making. Active support on the other hand is when the system has the ability to get more involved in the decision process. Behaving as a 'devil's advocate' is one example of active support.

Binary decision situations: Binary situations often are an important part of a larger decision process. It is common to decide between two alternative solutions or to decide whether to implement an alternative that has been decided through a multiple-alternative process. Hence, they take the form of *yes* or *no* decisions.

Decision domains: Decision domains are various subject areas for decision making. For example, a decision to purchase a house may belong to *purchasing* and *houses* domains.

Decision variables: Factors that influence a decision are called variables. The term variable is used because by changing the value of them, the decision outcome can be manipulated. *Criteria* and *factors* are other terms that are used for variables.

Force of a variable (contribution): In the linear weighted sum approach to decision making, the product of the weight and score of a variable is considered as the contribution of that variable. In this user's guide this is referred as the force of the variable. The forces contributed by all variables are summed to derive the value of an alternative.

Linear-weighted sum approach: This is a useful and easily understood way of modelling decisions. This kind of model is used in multiple-criteria decision situations. With this kind of model, decision outcomes are derived using *weights* and *scores* of all the factors in the situation.

Multiple-alternative decision situations: Situations where many possible solutions can be identified for the problem.

Multi-criteria decision situations: When a number of factors have to be considered in making a decision, it is called multi-criteria decision situation. Final decisions are arrived at by evaluating possible solutions against the factors to be considered.

Pair-wise comparison: This is when you compare two variables with each other to evaluate which has greater importance when making a decision. This process can be repeated until all the variables in a given situation are compared with each other. This mechanism is used in ADAPTOR to derive weights for variables.

Score of a variable: The score of a variable is a measure of how a given alternative fares on the variable. For example, if you were considering buying a house, the cost can be cheap to expensive on a scale that you define. The position of this house on the scale is its score for the cost variable.

Value of a decision: To arrive at the final value for the decision, we add the forces contributed by all the variables. The alternative with the highest value is taken to be the most appropriate decision. The usefulness of decision aids such as ADAPTOR is that you can interactively manipulate each element that contributes to the final value.

Weight of a variable: The weight is a representation of the importance of this variable to the final decision. In ADAPTOR, the weight of a variable is derived using the preferences that you indicate when comparing the sets of variables.

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Appendix F: Experimental Results (Stage 3)

Table 1: Histograms of preference values for Profile 1

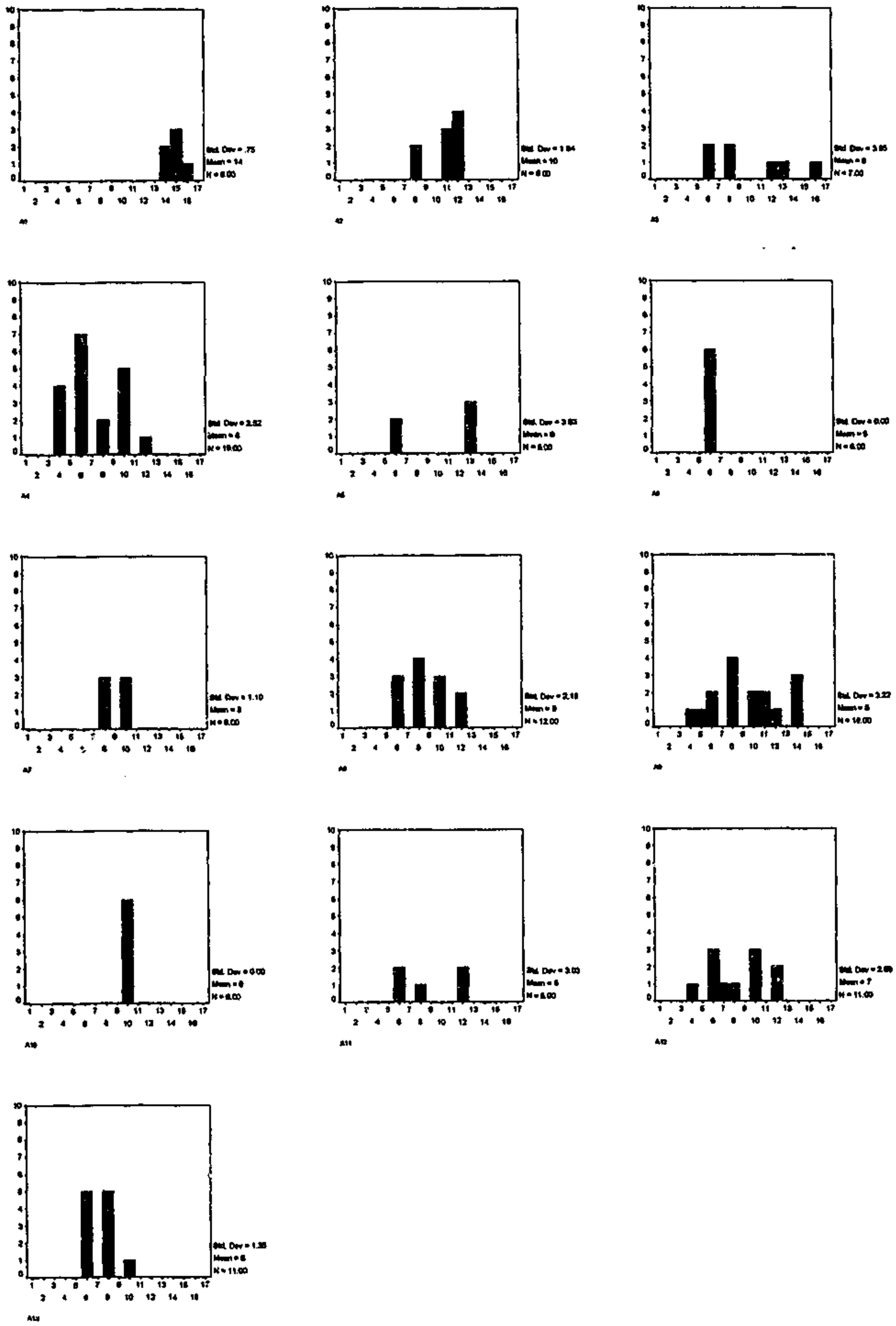


Table 2: Histograms of preference values for Profile 2

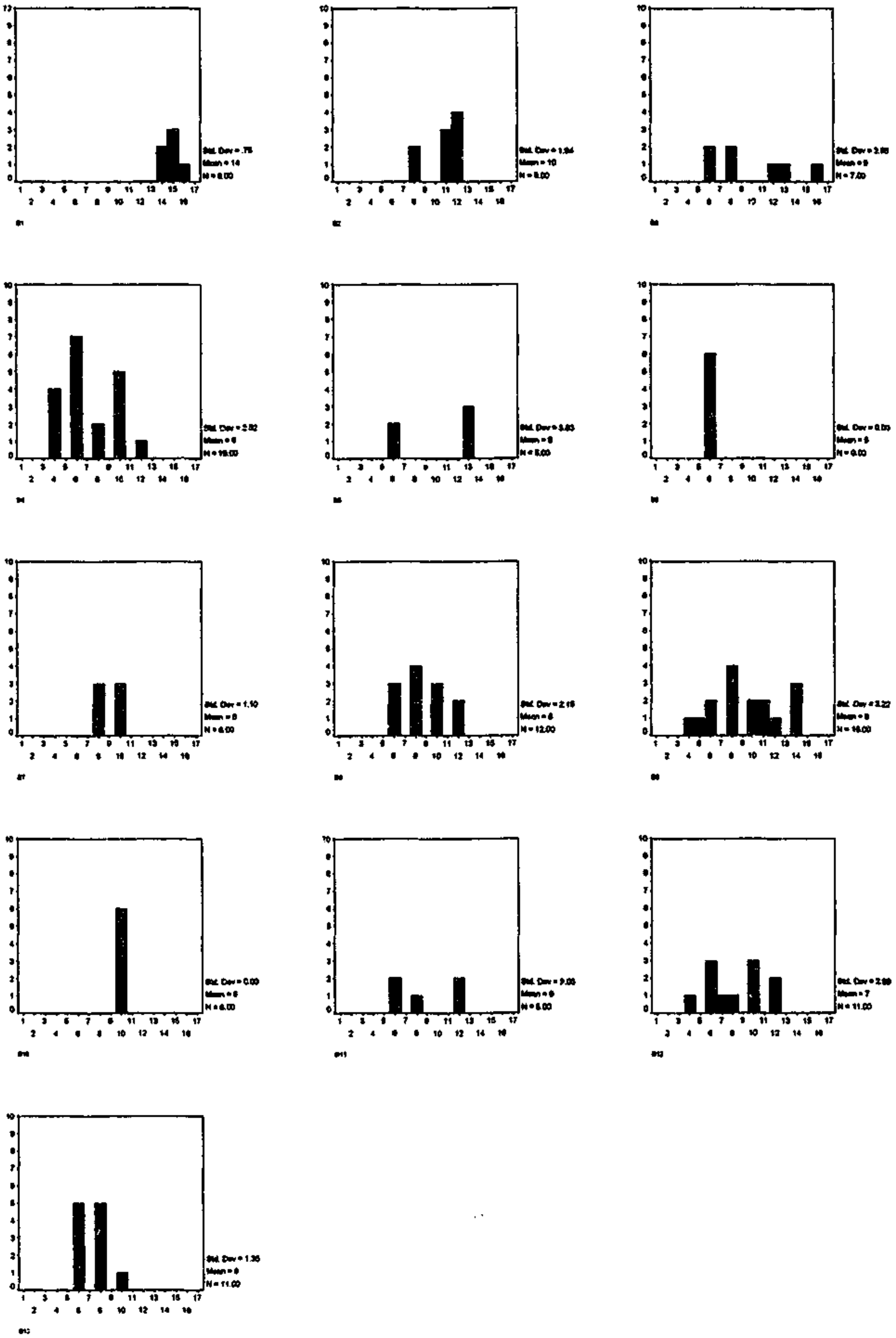


Table 3: Histograms of preference values for Profile 5

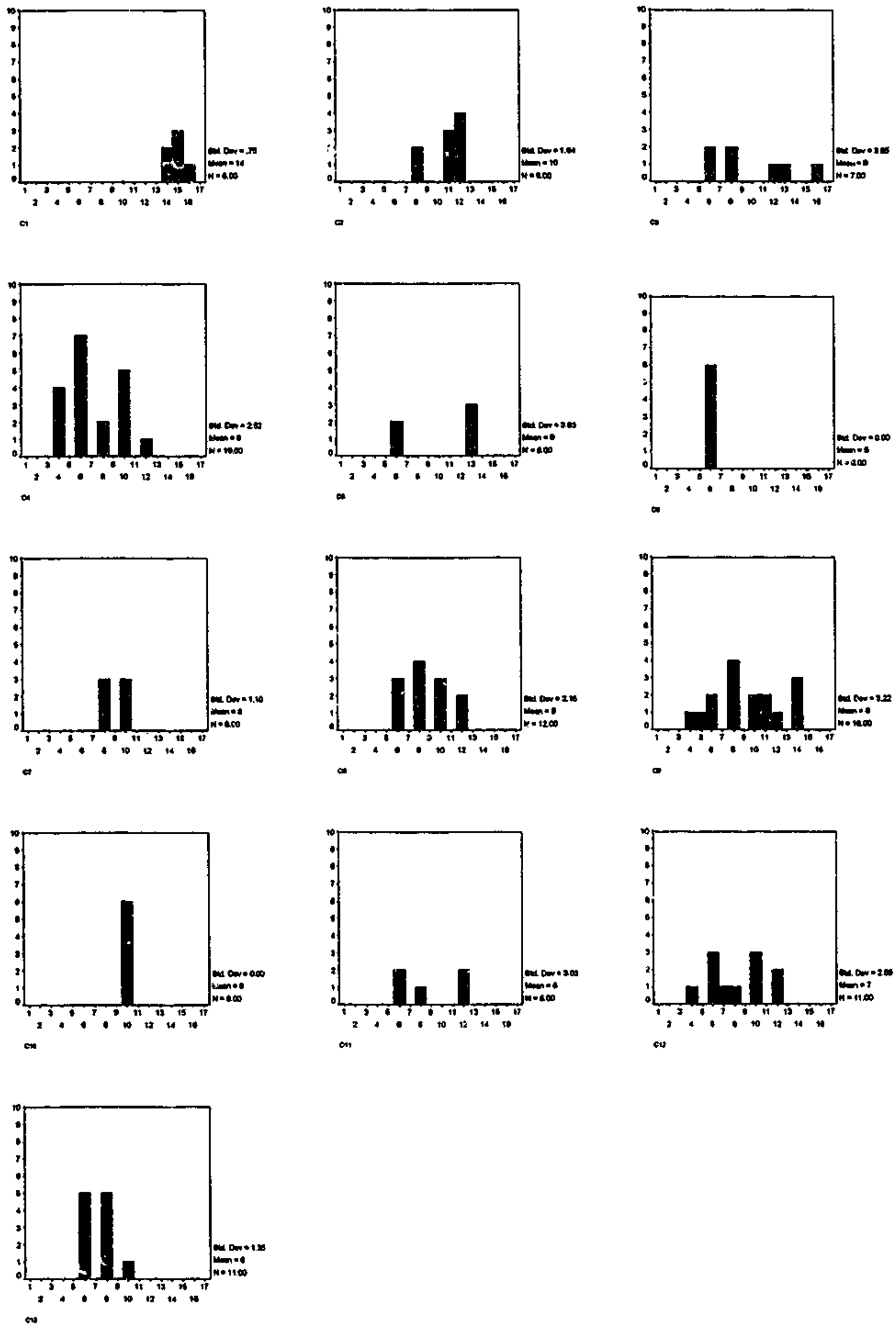


Table 4: Histograms of preference values for Profile 6

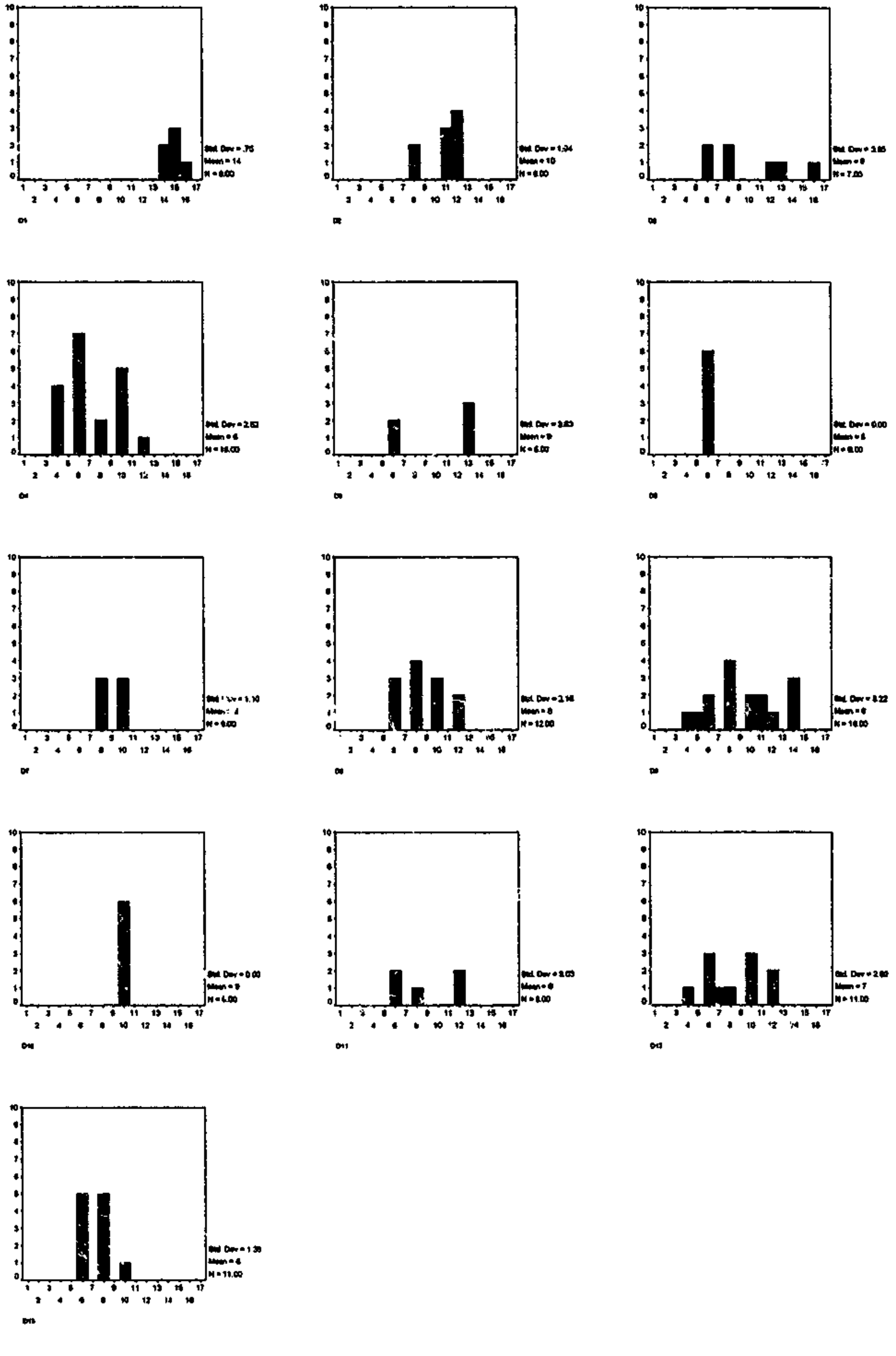
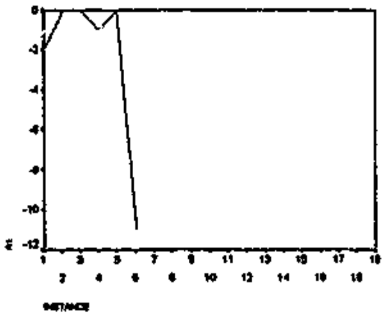
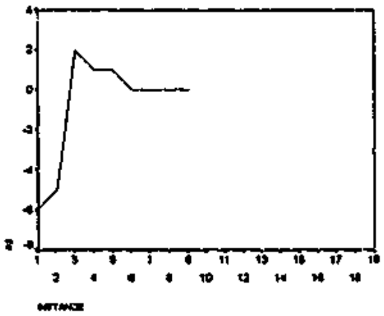
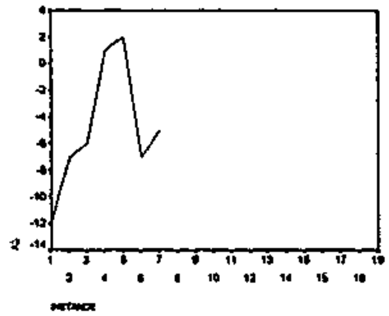
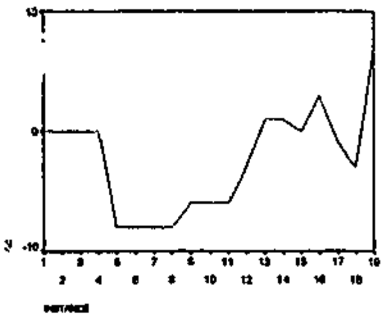


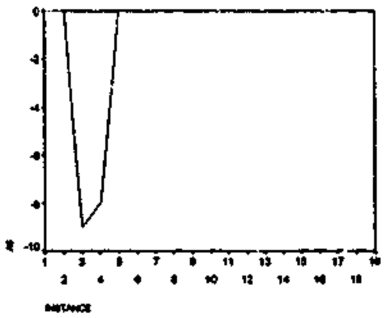
Table 5: Sequence charts for prediction errors in Profile 1





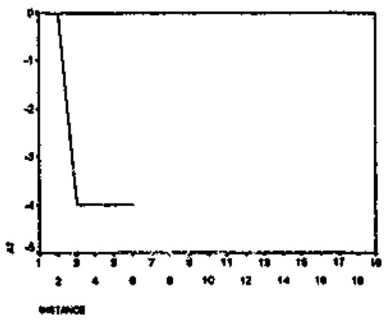


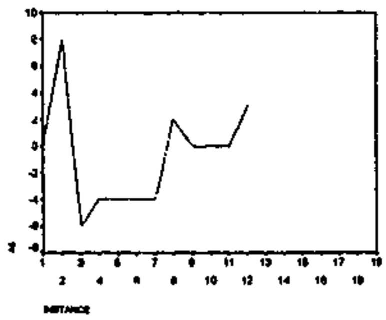


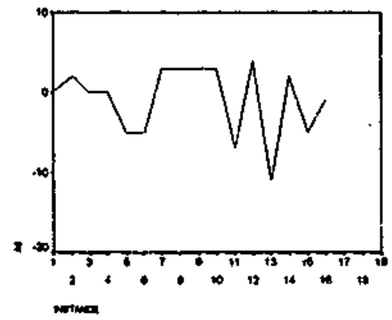


Constantly remains at 0

N = 6

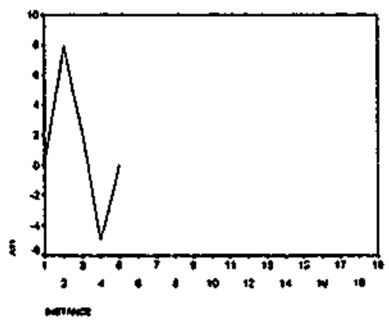


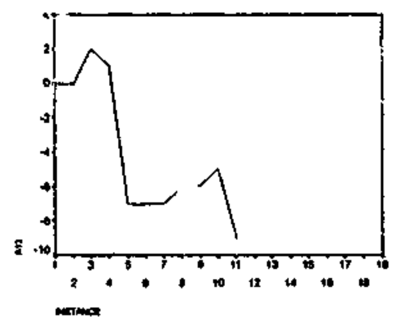




Constantly remains at 0

N = 6





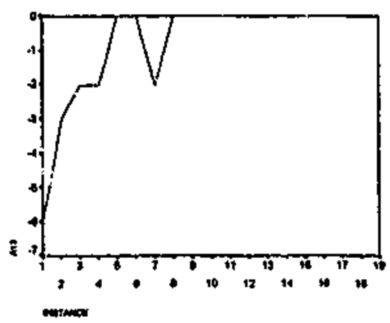
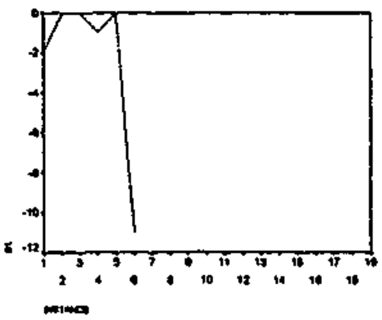
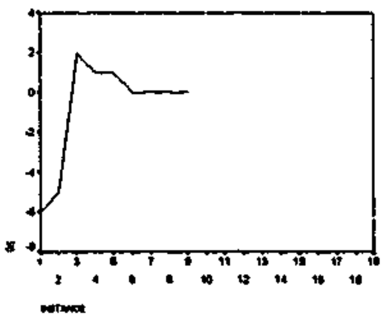
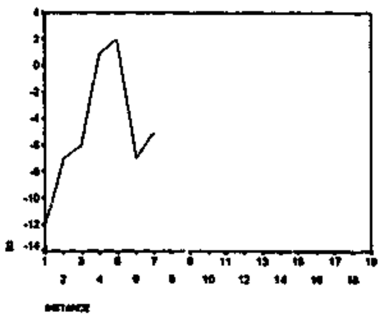
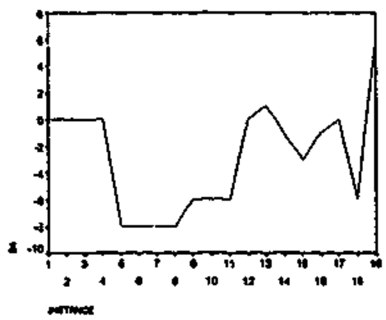


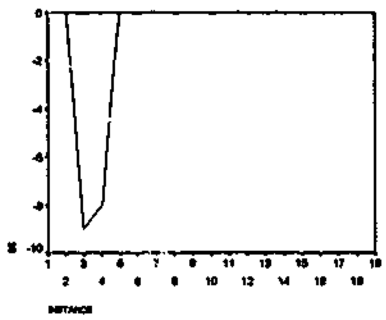
Table 6: Sequence charts for prediction errors in Profile 2





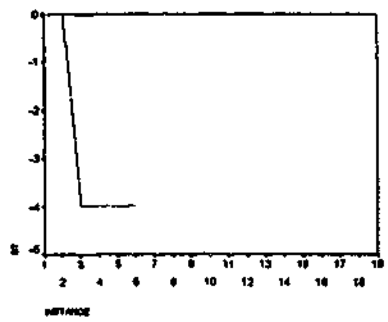


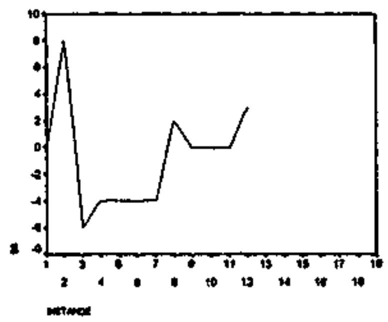


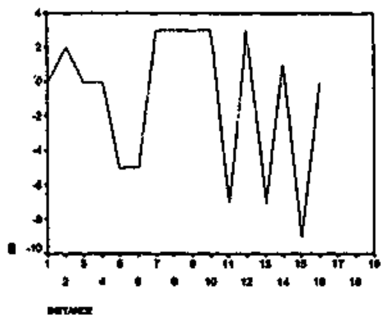


Constantly remains at 0

N = 6

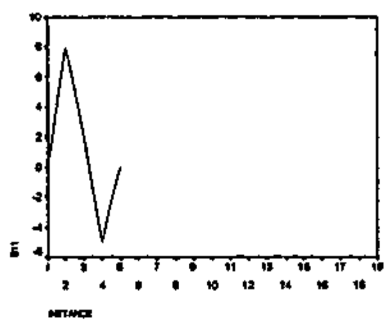


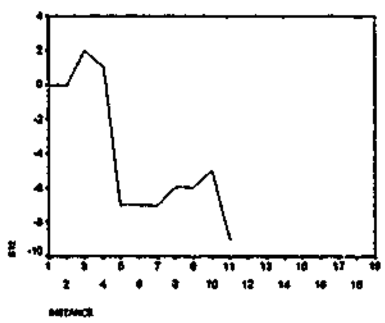




Constantly remains at 0

N = 6





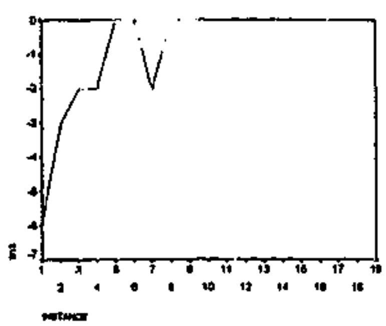
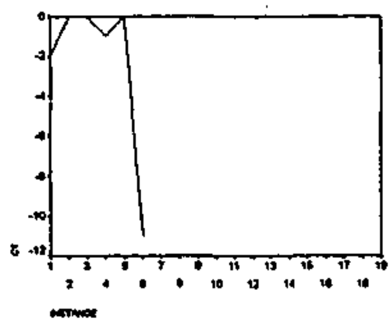
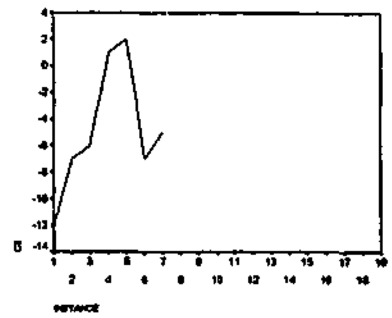
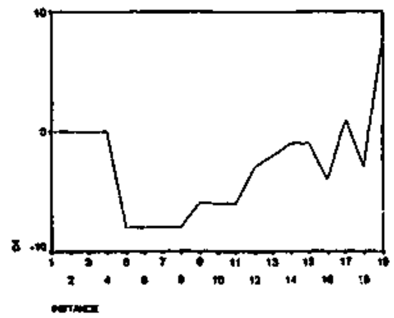
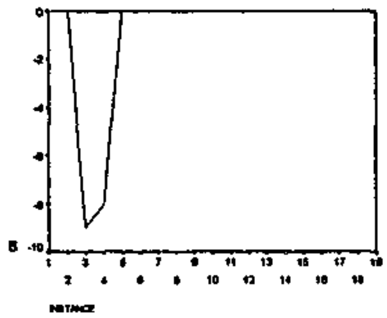


Table 7: Sequence charts for prediction errors in Profile 5



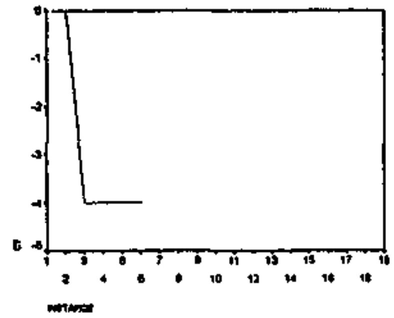


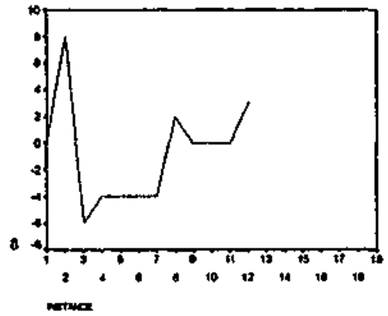


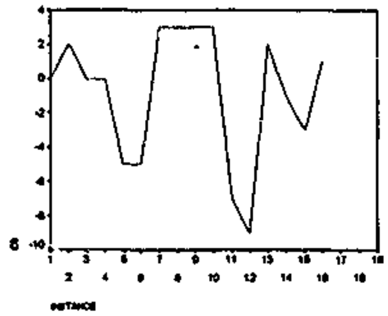


Constantly remains at 0

N = 6

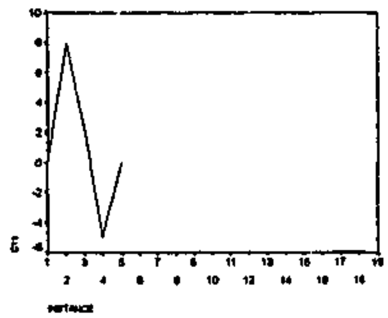


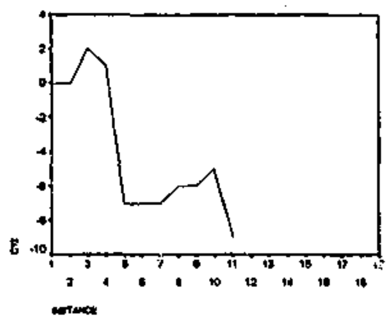




Constantly remains at 0

N = 6





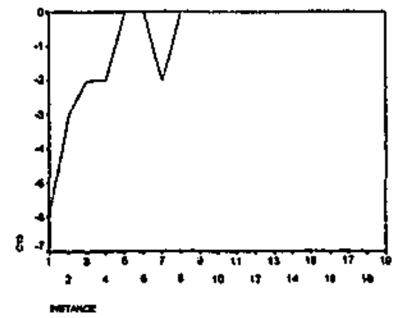


Table 8: Sequence charts for prediction errors in Profile 6