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Users' individual differences and their impact on selection and endorsement of competing computer decision aids

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USERS' INDIVIDUAL DIFFERENCES AND THEIR IMPACT ON SELECTION AND ENDORSEMENT OF COMPETING COMPUTER DECISION AIDS

by

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ABSTRACT

USERS' INDIVIDUAL DIFFERENCES AND THEIR IMPACT ON SELECTION AND ENDORSEMENT OF COMPETING COMPUTER DECISION AIDS

by

David T. Cadden

Advisor: Professor Moshe Banai

A large literature exists concerning the implementation and use of computer decision aids such as management information systems and decision support systems. However, a very limited literature is available about what factors lead to the perception of usefulness and satisfaction with the latest form of computer decision aids - expert systems.

This research describes, explains and proposes a new theory of interaction between competing computer decision aids and individuals. A model is presented that shows how individual characteristics moderate the user's satisfaction and the user's perception of the usefulness of the information generated by alternative computer decision aids. The experimental study is exploratory in nature. The research design required the participants to evaluate both type of systems over an eight week period.

A major finding of this exploratory study is that the user's cognitive style plays a critical role in determining how an individual responds to either an expert system or a decision support system. Individuals whose cognitive style is classified as Feeling-oriented and Intuitive-oriented express greater satisfaction and perceive greater usefulness of information when using an expert system while those classified as Sensing-oriented and Sensing/Thinking oriented express greater satisfaction and perceive greater usefulness of information when using a decision support system. The findings also indicate that those individuals who are "experts" for a particular decision domain, express less satisfaction with an expert system than with a decision support system. Individual's tolerance for ambiguity or locus of control had no relationship to his/her satisfaction or perception of usefulness of information for either the expert system or the decision support system.

DEDICATION:

This work is dedicated to Helen C. Lane, who I cherish and without whose love, warmth, wit and wisdom I would never have been able to come this far. All my love - Nell.

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No piece of research is truly the product of one individual and that is certainly true of this dissertation. First and foremost I would like to express my deepest thanks and graditude to Dr. Moshe Banai, my advisor and friend. Dr. Banai provide critical moral and intellectual support during all stages of this work. He worked, unceasingly, to teach me the importance of properly doing research. In addition to being a superlative teacher and the perfect advisor, his care and concern was an expression of humanity that is too seldom seen. I cannot begin to estimate all that I owe Moshe and I know that I can never fully repay his kindness.

I wish to thank all the members of my reading committee. Dr. Lawrence Harris is a man whose intelligence, enthusiasm, and commitment to students exemplifies the true scholar. His support will never be forgotten. Dr. Louis Stern extended his support for this work during its most difficult period. For this I thank him. I also wish to thank him for the opportunity to realize that great teachers bring wit as well as wisdom into their classrooms. Dr. Michael Chanin will always be a standard against which I wish to measure myself. He has been a friend and a cogent critic of my work. Dr. George Schneller was always there when I needed his comments and inputs. No one could ask for a more rigorous eye in an editor and I thank him.

Family members often play a crucial role in supporting work on a dissertation. I must thank, Dorothy Cadden, my beloved mother, for a lifetime of moral support. She set me on the road to a career in academia and was a diligent editor on this work. I also wish to apologize for using her as a sounding board on far too many occasions. Last but not least, I want to thank my adored wife Sandy for all her support and understanding. She knew how to gently keep me on track and encouraged me at all times. Someday I hope to repay the favor.

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CHAPTER 1

INTRODUCTION

The purpose of this dissertation is to describe, analyze, and propose a new theory of interaction between computer technology and computer users. During the last quarter century, computer technology has provided managers with a veritable alphabet soup of decision aids: MIS (Management Information Systems); DSS (Decision Support Systems); CIM (Computer Integrated Manufacturing); CAD (Computer Aided Design); AHP (Analytical Hierarchy Process); AI (Artificial Intelligence): and ES (Expert Systems).

Although there is a rich literature concerning the use of certain computer decision aids (i.e., management information systems), precious little material exists on the critical questions of what factors lead to successful implementation of the latest form of computer decision aids - expert systems (Benbasat, 1984).

This research focuses on two specific types of computer decision aids - expert systems and decision support systems - and how individual differences of users affect their perception of usefulness and their decision to use these systems. Henderson (1987) has argued for research programs that examine the similarities and differences between expert systems and decision support systems:

".... the greatest potential benefit to be gained from this current debate likely will be a better understanding of how research contributions of each field might influence, and be leveraged effectively by, an interrelated research program" (pg. 333).

An expert system has been defined by Edward Feigenbaum, of Stanford University, as

" ... an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution... The knowledge of the expert system consists of facts and heuristics. The "facts" constitute a body of information that is widely shared, publicly available, and generally agreed upon by experts in the field. The "heuristics" are mostly private, little discussed rules of good judgment (rules of plausible reasoning, rules of good guessing) that characterize expert-level decision making in the field" (Harmon and King, 1985, pg. 5).

[For a more detailed discussion of the structure of expert systems and the methodologies used by expert systems, the reader is advised to review Appendix A, pages 124-128.]

During the last few years, expert systems were transformed from a research curiosity into the basis of a multimillion dollar business. Industry is beginning to apply expert system methodologies to areas as diverse as aggregate production planning (Duchessi, 1986); accounting (O'Leary, 1987a); medical diagnosis (Buchanan and Shortliffe, 1983); configuring computer systems (Kraft, 1984); mining (Duda and Reboh, 1984); machine scheduling (Descotte and Latcombe, 1981); and job shop scheduling (Bourne and Fox, 1984).

Expert systems can be further distinquished from standard computer decision aids by the fact that they can provide to the user a detailed description of the logic and reasoning that was employed to arrive at a specific solution.

Expert systems is a field that has so expanded during the last several years that one is forced into the sense that a true revolution is being witnessed. The literature describing this "revolution" seems to be categorized by texts that are technically specific - i.e., they detail how such systems are developed - or "gee-whiz" tomes praising the promise of this emerging technology.

One of the areas where expert systems will have a great impact is in those domains where expertise is at a premium (Harmon and King, 1985). In such situations, expert systems can function as a training device for those individuals who lack a broad and deep knowledge base for a particular field. They will also act as supplemental support tools for experts. No work has been done on the possible differential response (with respect to usage and satisfaction) by these two distinct groups to expert systems' advice. In addition, little, if any, research has been conducted on how individual differences might impact on the user's perception of the expert system's effectiveness. In many domains expert systems will operate in conjunction with other decision tools such as decision support systems and management science tools. However, situations will arise, as in large scale job-shop scheduling (Ow and Smith, 1987), where expert systems will "compete" with other approaches and techniques such as management science models. Again, we found no research on users' preference for advice from expert systems or other types of decision tools. This study should be seen as an exploratory one and therefore is designed to address some of the aforementioned questions.

Decision support systems have been defined by Leigh and Doherty (1986) as *"a set of computer-based tools used by a manager in connection with his or her problem solving and decision-making duties"* (pg. 3). It is useful to elaborate on the meaning of a DSS. Alavi and Henderson (1981) point out that a DSS is not designed, primarily, to collect and distribute information, but it is a system linked to the process of decision-making. The difference between decision support systems and other computerized management tools is, at best, imprecise. Keen and Scott-Morton (1981) have attempted to make the decision support system overlap with MIS and management science techniques. These two latter approaches are specifically geared to operate in structured decision environments, that is, with "given" data base manipulation and with particular decision solution methodologies. In contrast, a DSS should be able to function in less structured situations since they cannot be modelled apriori.

Rather than singularly functioning as a strong normative guide, as is the case with management science models, a DSS is designed to support rather than replace managerial judgement. Wedley and Field (1984) point out that DSS is a term inclusive enough to incorporate programs as diverse as DECAID (Power, 1982) which covers the entire decision making process; the Analytical Hierarchy Process (Saaty, 1977) which facilitates the ranking of outcomes in a multiattribute environment; and LOTUS 1-2-3.

Alter (1980) discussed how decision support systems improve a manager's effectiveness by increasing personal effectiveness, reducing time for problem solution, expanding the manager's insights into the problem, improving communications, and facilitating learning and training. Several studies that have been conducted attempt to determine the factors that lead to the successful (or unsuccessful) implementation of DSS (Alavi and Henderson, 1981; Aldag and Power, 1986; Bean, Radnor, Neal, and Tansik, 1975; Goslar, Green and Hughes, 1986; Harvey, 1970; Watkins, 1984).

Prior research in the fields of management information systems and decision support systems has generated theoretical schemes for relating a system's use to both the user's satisfaction and individual differences. No comparable theoretical schemes currently exist to guide research on expert systems.

These two (expert systems and decision support systems) computer decision aids do not necessarily stand in direct counterpoint to each other, although there are important differences, namely: (1.) expert systems can process symbolic information while decision support systems are currently limited to numerical information processing; (2.) expert systems rely heavily upon heuristic methods while DSS generally rely upon analytical and management science techniques; and (3.) expert systems implicitly contain an emphasis on performance while "the performance impact of a DSS is defined in terms of relatively vague concepts such as 'learning' or 'better understanding'" (Henderson, 1987). There are similarities that exist between these two approaches: (1.) expert systems were initially seen as being able to stand in total isolation, that is, as a "replacement" for an expert whereas now they are envisioned as having a supportive role in the decision- making process, a role which is quite similar to that envisioned for a DSS; and (2.) another key similarity articulated by Henderson (1987) is the emphasis that both methodologies place upon the interface with the user.

In examining the similarities and differences that exist between expert systems and decision support systems, one begins to appreciate the synergistic benefits that could be derived from a research project that investigates the users' perceptions and the performance of two such systems in a particular decision domain.

1.1 RESEARCH QUESTIONS

Given the points of similarities and differences of expert systems and decision support systems, a number of research questions have been identified.

(1.) Do individuals, for a particular decision-making domain, derive greater satisfaction from an expert system or a decision support system?

(2.) What specific differences between individuals determine the difference in the level of satisfaction with using expert systems or decision support systems?

(3.) Do individuals, for a particular decision-making domain, perceive that there is a difference in the usefulness of the information provided by an expert system or a decision support system?

(4.) What specific differences between individuals determine the difference in the perceived usefulness of information derived from an expert system or a decision support system?

(5.) How does an individual's "expertise" with regard to a particular decision domain affect his/her satisfaction with using either system?

(6.) How does an individual's "expertise" with regard to a particular decision domain affect his/her perception of the usefulness of the information provided by an expert system or a decision support system?

(7.) What specific differences between individuals will affect their selection to use either an expert system or a decision support system?

1.2 IMPORTANCE OF THIS STUDY

The answers to these research questions will provide significant information to develop a new theory of expert system usage. Hayes-Roth, Waterman, and Lenat (1983) have concluded that the literature on expert systems is lacking a formal system of evaluating programs: "*Evaluations pervade the system-building process and are crucial for improving systems design and performance... Another reason for conducting evaluations of expert systems is that controlled experiments, producing hard data, will contribute to AI's (Artificial Intelligence) scientific respectability*" (pg. 242).

The key to their guidelines for evaluating expert systems is the human-system interaction. Bell (1984) examined the sources of expert system failure. One crucial source of system failure is associated with user acceptance. These authors illustrate the importance of user acceptance and satisfaction; however, their work contains standard bromides and fails to specify a theory or research design for the study of user satisfaction.

Currently, a literature survey has not revealed such a theory. The theory presented in this dissertation is built upon prior work done in the allied fields of management information systems and decision support systems. The development and testing of such a theoretical model represents a significant contribution to the field. It extends research that has been conducted in the fields of management information systems and decision support systems - thus, it adds to the body of knowledge. Expert systems' parent field - artificial intelligence - has always placed great emphasis on the issue of interfacing a system with the user. However, this concern has not yet been transmitted to the study of expert systems. One can find research on validating expert systems (O'Leary, 1987b; Ngyuen, Perkins, Laffey and Percora, 1987), on design principles (Goul and Tonge, 1987), and knowledge acquisition (Pereau, 1987) but no work on users' response to expert system information.

From a practical standpoint, the issue of how "experts" and "non-experts" respond to expert systems is of considerable importance. Fuerst and Cheney (1982) have pointed out that in some cases millions of dollars have been spent on decision support systems that were never used. Among the reasons identified for such failures are the characteristics of the decision makers and the characteristics of the system. There is no reason not to assume that many expert systems will suffer the same fate. The design of such systems must recognize how different individuals will respond to these expert systems. In addition, it is of great importance to identify the users' preference for alternative computer decision aids - in this case, the choice between a decision support system approach and an expert system approach. The reason for this importance is that as organizations acquire both types of systems their members will interact with these systems. It is crucial to identify who prefers what type of system and why, with the hope to gain a better match between individuals' characteristics and their computer systems.

This study must be seen as being exploratory in nature. The reason for this is twofold. First, as it has been mentioned, there currently exists no theoretical scheme that addresses the issue of what factors affect a user's response to an expert system. Lacking such a theoretical scheme to build upon, a researcher is forced to draw upon work done in allied fields (i.e., management information systems and decision support systems). This means that any model, theory, or hypothesis that are formulated should be seen as being tentative and the associated research as being exploratory. Second, the exploratory nature of this research is also a product of the research design (See Chapter 3.) which required an extensive commitment of time and effort on the part of each research subject. This drastically limited the number of available subjects. With a limited research population the results must be seen as the preliminary effort to define a theoretical scheme to understand the relationships between a user and the user's response to an expert system.

1.3 PROPOSED MODEL

The model proposed in this dissertation has three sets of variables: a dependent variables set, an independent variable, and an intervening variables set. They are presented as follows:

1.3.1 DEPENDENT VARIABLES

The dependent variables set are the user's satisfaction with the computer system and the user's perception that the information generated by the computer system is useful. In the field of management information systems and decision support systems, the user's satisfaction with the system has been identified as crucial to the ultimate success of a computer decision aid (Lucas, 1973; Lucas, 1975a; Lucas, 1975b; Lucas, 1978a; Powers and Dickson, 1973). Some researchers (Powers and Dickson, 1973 and; Swanson, 1974) have argued that user satisfaction is the most critical criterion in measuring a computer system's success or failure. Evans (1976) suggested that those developing computer decision aids should consider that users may have a lower limit to satisfaction below which a user may cease to employ the computer system.

Swanson (1974) has defined satisfaction with a computer decision aid as the beliefs, held by the user, about the relative value of the system as a means of inquiry. Debons, Ramage, and Orien (1978) argued that user satisfaction should be seen as a multifaceted construct. They identified ten items affecting satisfaction: accuracy, reliability, timeliness, assistance, adequacy, accommodation, communication, access, cost and environment (Bailey and Pearson, 1983). Neumann and Segev (1980) used four factors -accuracy, content, frequency, and recency - to evaluate a user's satisfaction. Since there is no generally accepted consensus on how to measure user satisfaction, this research employed two measures of user satisfaction - Aldag and Power's Attitudes-toward-Decision-Aid Questionnaire (Aldag and Power, 1986) and Sander's Questionnaire (Sanders and Courtney, 1985). Aldag and Powers Attitude-Toward-Decision-Aid Questionnaire is present in Appendix E on pages 176-178 and is listed as questions 1-13. Sander's Questionnaire is also presented in Appendix E, listed on pages 178-180 as questions 14-26. Aldag and Power's Questionnaire examines three elements of a user's satisfaction with a computer decision aid: challenge and accomplishment; warmth of interaction; and positive effect. The internal reliability score for these three factors were .83, .79, and .69, respectively. Sander's questionnaire examines two factors - overall satisfaction and satisfaction with decision-making. The internal reliability values for the individual items in Sander's questionnaire varied from .62 to .76.

The second dependent variable used in this research was perceived usefulness of information. Some authors (Larcker and Lessig, 1980; and Zmud, 1978) make a careful distinction between the user's satisfaction with the computer system and the user's perception of the quality of the system's output. Whereas, satisfaction can be seen as being related to the totality of the user's response to the system; perceived usefulness of the information is related to whether the information is seen by the user as relevant, informative, and meaningful. Larcker and Lessig (1980) have argued that perceived information usefulness is a measure of information quality. They also argue that a user of a computer system evaluates its perceived usefulness of information on the basis that the information generated can be used as a direct input to the task of problem solving. Zmud (1978) stated that the degree to which the user perceived the information as being useful was a key element in the determination of the success or failure of a computer information system. He defined perceived usefulness of information as the extent to which the user sees information as relevant, accurate, reliable, and complete. There is an overlap between some of the dimensions of perceived usefulness of information and user satisfaction depending upon the definitions of some authors - Zmud (1978) and Debons, Ramage, and Orien (1978). The four instruments that were used, in this study, to measure the two dependent variables were drawn from theoretical models that did not suffer from such an overlap of constituate dimensions.

Perceived usefulness of information was measured by two scales - Franz and Robey's Perceived Usefulness of System

Questionnaire and Larcker and Lessig's Questionnaire. Both questionnaires are presented in Appendix E on pages 180-183 - Franz and Robey's Perceived Usefulness of System Questionnaire is listed as questions 33-43; while Larcker and Lessig's Questionnaire is listed as questions 27-32. Franz and Robey (1986) report that their Perceived Usefulness of System Information Questionnaire had a Cronbach alpha score (for the scale) of .84.

Since this research centers on the user's possible differential response to a decision support system and an expert system, it is critical that both satisfaction and perceived usefulness of information be used as the dependent variable set. A user might find one of the two systems easier to use, quicker in its response and that it generates information in a more comprehensible manner, and yet, finds that the other system produces what is perceived as more accurate and useful information.

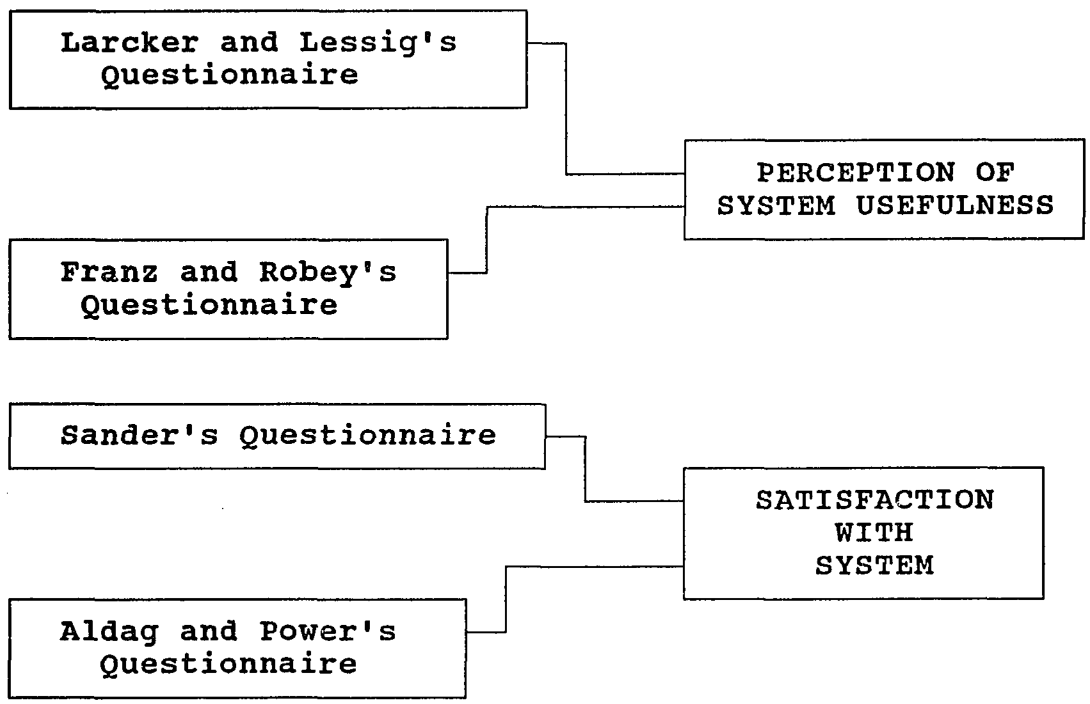
To clarify the exact relationship between the dependent variables and their measurement instruments a schematic is presented in Figure 1.1.

1.3.2 INDEPENDENT VARIABLE

The independent variable in this study is the type of computer decision aid - a decision support system and an expert system. Both of these systems, for the purpose of

FIGURE 1.1

DEPENDENT VARIABLES' INSTRUMENTS



comparability, must be geared to the same decision environment. The decision-making domain for this study is that of production/operations management. It employs a simulation game - DECIDE/POM. [The game is detailed in Appendix B on pages 129-135] The game is sufficiently complex to warrant the use of several types of decision-making techniques.

A decision support system was built by the author for the DECIDE/POM game environment. It was designed for the personal computer environment and uses two available packages: STORM and LOTUS 1-2-3. STORM is a package of programs that is directly associated with production/ operations techniques. It includes a forecasting module, linear programming, assembly line balancing, assignment algorithm, regression routines and other allied programs. The decision support system utilizes the regression and linear programming modules. During the course of the introductory play of the game, the users are provided with data with which they can build regression models to forecast future demand. The users employ STORM's regression module to determine to what extent past demand levels were dependent on factors such as past prices, market indices, and economic indices. The results of these analyses are then "transferred" to the user's LOTUS template. (A detailed discussion of this decision support system is provided in Appendix C, pages 125-141. The reader will also find a flow chart for the use of the decision support system and a sample output from the various elements of this template.)

The DECIDE/POM game supplies a linear programming model which is given in Appendix C. For any particular period, the user simply altered the desired level of production for each product and the total labor capacities. The program then computed the optimal scheduling of each type of labor for each work center.

The LOTUS template section of the decision support system takes the set of values generated by the STORM modules and the decisions of the users to generate an income statement, a cash flow statement, and a balance sheet. This enables the users to evaluate the consequences of their decisions. All three statements can be updated after the decision set has been executed.

Several expert systems were written and available for use by the participants. Before describing the nature of the respective expert systems, it is important to discuss the language in which they were developed.

All expert systems used in this work were written using the shell program EXSYS. This is a commercially available package geared for the development of rule-based expert systems. It is written in the C language for speed of execution. It is a powerful language with the capacity to handle a 5,000 rule system on a PC/XT type machine. It also allows for probabilistic conditions on any rule. Given the constraints of available computer facilities for the participants and financing, the EXSYS package was ideal.

Four expert systems were made available to the participants. The first system, a rather simple expert system, was designed to aid the user in forecasting for the demand of the products. Another system was a diagnostic system into which the user inputted values from the prior decision period such as the income statement, balance sheet, and cash flow statement. It scanned these systems and highlighted decision areas where improvements could be made. As an example, it could recognize that spending for raw materials is "too high" for anticipated demand or specify that allocation of funds to machine maintenance is insufficient given the level of machine downtime. The third expert system was a labor scheduling program developed by the author with Mr. Robert Fox and Ms. Sue Burgess of CREATIVE OUTPUT to see if OPT scheduling rules could be applied to the context of the DECIDE-P/OM game. The author also contacted Dr. Pray, the developer of the DECIDE-P/OM game, to ascertain what scheduling rules could be incorporated into the expert system. Several members of APICS also provided suggestions and advice on the development of the three expert systems. Unlike the linear programming formulation, there was no assurance that this expert system would generate an "optimal" decision; however, it may have generated results that were conceptually "more" acceptable to some participants.

The last expert system dealt with maintenance investment issues. It examined the user's current machine utilization and downtime and provided suggested values for investment.

As with the development of any expert system, one faces the issue of who is an expert and what constitutes expertise. There is universal consensus as to how one identifies, in a clear and unambiguous manner, such expertise; however, in this case the system tapped several sources including those associated with the development of the game. A listing of the heuristics used in the two most complex expert systems and a specification of some of their rules is given in Appendix D, pages 142-154.

1.3.3 INTERVENING VARIABLES

The model presented in this dissertation possesses four intervening variables that affect individual response to competing computer decision aids. The four moderating variables are cognitive style, expertise, tolerance for ambiguity, and locus of control.

Cognitive research centers on the argument that the way individuals process information is dependent upon their cognitive style. Simon (1960) defined cognitive style as *"the characteristic, self-consistent mode of functioning which individuals show in their perception and intellectual activities"* (pg. 72). Although such perceptions might change for a given task at hand, many individuals demonstrate a consistent preference for particular cognitive styles (Chervany and Dickson, 1978). In his review of individual differences and MIS success, Zmud (1979) presented the following definition: *"...cognitive style represents characteristic modes of functioning shown by individuals in their perceptual and thinking behavior"* (pg. 967). These approaches to delineating cognitive style represent a shift in study from personality oriented concepts, such as traits, to a "sturdier" process measure. Pratt (1980) argues that *"there is a clear distinction between <u>what</u> an individual thinks (personality) and <u>the way</u> an individual thinks (cognitive style)"* (pg. 502).

Vannoy (1965) argued that cognitive style is a multifaceted construct rather than a unitary trait. This notion is generally accepted (Bariff and Lusk, 1977). However, the specific number of the dimensions and their exact relationships to each other have not been clearly identified (Zmud, 1979). Several dimensions are consistently referred to in the MIS and DSS literature (Benbasat and Taylor, 1978). Schroeder, Driver and Streufert (1967) identify a "simple/complex" dimension which relates to the structural characteristics of thinking. A second dimension used in cognitive style research is "field dependence/field independence". This concept is tied to the context of perception - whether an individual's cognition is determined by external or internal referents. The third dimension is referred to as "systematic/heuristic." Its central theme is whether an individual approaches issues from an analytical and systematic viewpoint or whether they utilize an experiential and common sense viewpoint in problem solving (Huysmans, 1970).

Not surprisingly, these multiple perspectives of the cognitive style construct have led to numerous measurement instruments. This, in turn, has become the basis of a critique of the entire field (Huber, 1983; and Schweiger, 1983). Bariff and Lusk (1977) have advised researchers to select more than one instrument to operationalize the construct. One of the most frequently used measurement instruments in cognitive style studies is the Myer-Briggs Type Indicator (MBTI). It is predicated upon Jung's work on psychological types. Jung's theory perceives individuals as differing in their perceptions and judgments. This reflects a bi-polar perspective that categorizes individuals as being oriented, in their information processing, to either an analytical mode or process mode. The Myers-Briggs Type Indicator envisions perception as being either intuitive or sensing, and judgment is done either through thinking or feeling. Intuitive individuals are concerned with potentialities rather than specifics. Their mental orientation is toward an "holistic" understanding of the situation. Sensing individuals seek the concrete; they are facts- and data-oriented. Thinkers' mental processes may be described as being linear-logical. They seek out cause-effect relationships and process material in an impersonal manner. Those classified as being feeling-oriented respond to situations on an emotional basis. These dimensions are combined to form four categories: ST - Sensing plus Thinking; SF - Sensing plus Feeling; NT - Intuition plus Thinking; and NF - Intuition plus Feeling.[1] This, of course, is an idealized classification system. Individuals, in any real world environment, utilize an admixture of these

[1] The Myers-Briggs Type Indicator produces a sixteen category classification. The instrument itself, when used for vocational preferences, limits its discussion to the four aforementioned categories. Further, the computer systems research studies that employed the Myers-Briggs Type Indicator (Alavi and Henderson, 1981) only used the ST, SF, NT, AND NF categories.

approaches; however, the concept of cognitive styles argues that people rely consistently upon a dominant mode.

Robey and Taggart (1981) point out that the Myers-Briggs Type Indicator is an instrument whose reliability and validity measures are well documented and do not pose a major problem to researchers.

Other instruments exist in the cognitive style research literature. Keen (1975) developed a test which used 12 verbal and visual subtests to measure different cognitive styles. Two styles are associated with the processing of information, and two other styles are associated with the evaluation of information. Schweiger (1983) argues that Keen's test is more a measure of cognitive ability than cognitive style.

The Embedded Figures Test (EFT) is described by Robey and Taggart (1981) as an ability test since it is scored on the basis of the number of questions answered "correctly". Guilford (1980), Knudson and Rorer (1980), and Scott (1975) have all questioned whether the EFT accurately measures cognitive style.

Huysmans (1970) developed an instrument in which the processing of information is evaluated, by judges, based on the direct observation of behavior. Schweiger (1983) reviewed the Huysmans' study and pointed out that the observations were not of direct behavior. Rather, the observations were taken from post problem-solving questionnaires. An instrument developed by Benbasat (1974) - the Analytical/Heuristic

Questionnaire (AHQ) - was used extensively in a body of research in the field of MIS that eventually became known as "the Minnesota Experiments" (Zmud, 1978). It was used as a measure of cognitive style. The questionnaire has a reported internal reliability of 0.85 (Benbasat, 1974).

A review of the literature indicates that the Myers-Briggs Type Indicator is one of the most commonly used measures for evaluating cognitive style, and it poses the least difficulty with respect to the issue of a valid psychometric instrument.

In a personal conversation between the author and Dr. Victor Vroom (November 20, 1987) of Yale University, Dr. Vroom commented that the critical aspect of cognitive style for this research centers on decision style which can be seen as an element of cognitive style. Rowe and Boulgarides (citation mentioned in Rowe, Mason, and Dickel (1985) pg. 238) developed a twenty-question Decision Style Inventory (DSI). Their instrument recognizes that individuals utilize various constructs to evaluate information; on the other hand, the low-cognitive complex individual tends to perceive the environment in terms of a few rigid rules. They also found that individuals with high-cognitive complexity can more easily tolerate ambiguity in information. The Decision Style Inventory is predicated upon two prime components: cognitive complexity and values orientation. Bifurcating each of these components yields four decision styles: directive, analytical, conceptual, and behavioral. The following description of the four decision styles comes from Rowe, Mason and Dickel (1985) and a schematic representation of their system is given in Figure 1.2.

FIGURE 1.2

COGNITIVE-CONTINGENCY MODEL

COGNITIVE COMPLEXITY	Task/technical	People/social
Tolerance for Ambiguity	**ANALYTICAL** Enjoys problem solving. Wants best answer. Wants control. Uses considerable data. Enjoys variety. Is innovative. Uses careful analysis.	**CONCEPTUAL** Is achievement oriented. Has broad outlook. Wants independence. Is humanistic. Initiates new ideas. Is future oriented.
Need for Structure	**DIRECTIVE** Expects results. Is aggressive. Acts rapidly. Uses rules. Needs power/status. Uses intuition. Is verbal.	**BEHAVIORAL** Is supportive. Uses persuasion. Needs affiliations. Is empathetic. Commmunicates easily Prefers meetings. Uses limited data.

VALUES ORIENTATION

The directive style implies that an individual has a low tolerance for ambiguity and tends to focus on the technical side of issues. He/she tends to use little information and examines few alternatives.

The analytical style has a higher tolerance for ambiguity than the directive style, preferring more information and more alternatives.

The conceptual style requires high data usage, and values many alternatives so as to improve the chance of arriving at the best possible solution.

The behavioral style is low on the cognitive complexity scale, more comfortable with verbal communication and does not seek high levels of data input. The DSI does not categorize individuals as being exclusively a member of one of these four groups. Individuals receive a score on each style and one can thus determine which style is that individual's dominant decision style. This research used the Decision Style Inventory and the Myers-Briggs Type Indicator as measures of the construct of cognitive style. A copy of the Myers-Briggs Instrument instruments was administered to all participants. The Decision Style Inventory Questionnaire is also given in Appendix E on pages 168-172, and it is listed as questions 112-131.

General intellectual ability and specific content knowledge have been seen as determinants of MIS and DSS usage. Individuals with more education and longer tenure have tended to be less satisfied with MIS (Lucas, 1975a; Lucas, 1975b; Lucas, 1978b; Werner, 1974). Those who possessed greater task knowledge exhibited greater MIS usage (Werner, 1974).

Since this research argues that "experts" respond differently to an expert system than a "non-expert", some way of determining expertise is required. One obvious way of making this distinction is to "segment" the sample into those with little experience in the given decision-domain (the decision-domain in this research is production) and those with demonstrated "expertise." This latter group is comprised of certified APICS (American Production and Inventory Control Society) members, certification in APICS being equivalent to a CPA in accounting. Another method of determining degree of knowledge in the decision-domain is to test. The author has developed two instruments that "determine" the extent of knowledge that a participant has about required bodies of knowledge in the field of production/operations management and management science techniques. These instruments were applied to a pilot group of undergraduate students and APICS members during the summer of 1987. The production/operations management questionnaire had a coefficient of reproducibility of .89 and a coefficient of scalability of .76 for this pilot study. The management science questionnaire had a coefficient of reproducibility of .91 and a coefficient of scalability of .85. Both questionnaires are presented in Appendix E on pages 184-289. The production/operations management questionnaire is listed as questions 1-20, and the management science questionnaire is also listed as questions 1-20.

Externality of locus of control - the degree to which an individual attributes outcomes to external factors such as fate and luck, as opposed to internal factors such as ability - was assessed by a scale developed by Rotter (1966) which is presented in Appendix E on pages 165-168, and it is listed as questions 83-111. Those with an externally oriented locus of control should express less satisfaction with computer decision aids (Taylor and Dunnette, 1975). The logic of this is predicated on the fact that they will perceive the tool as a "replacement" for their own decision-making capabilities.

Tolerance for ambiguity is defined as *"the tendency to perceive ambiguous situations as sources of threat"* (Robinson and Shaver, 1973, pg. 221). Ambiguity arises in situations characterized by novelty or complexity. It is assumed that participants with a low tolerance for ambiguity will be satisfied with a more structured approach to decision-making (Lanzetta and Driscoll, 1966). Therefore, those individuals should express a greater level of satisfaction with the more structured (in terms of output) decision support system than with the advisory output generated by expert systems. Tolerance for ambiguity was measured by Budner's (1960) instrument. This instrument is presented in Appendix E on pages 172-175, and it is listed as questions 132-147.

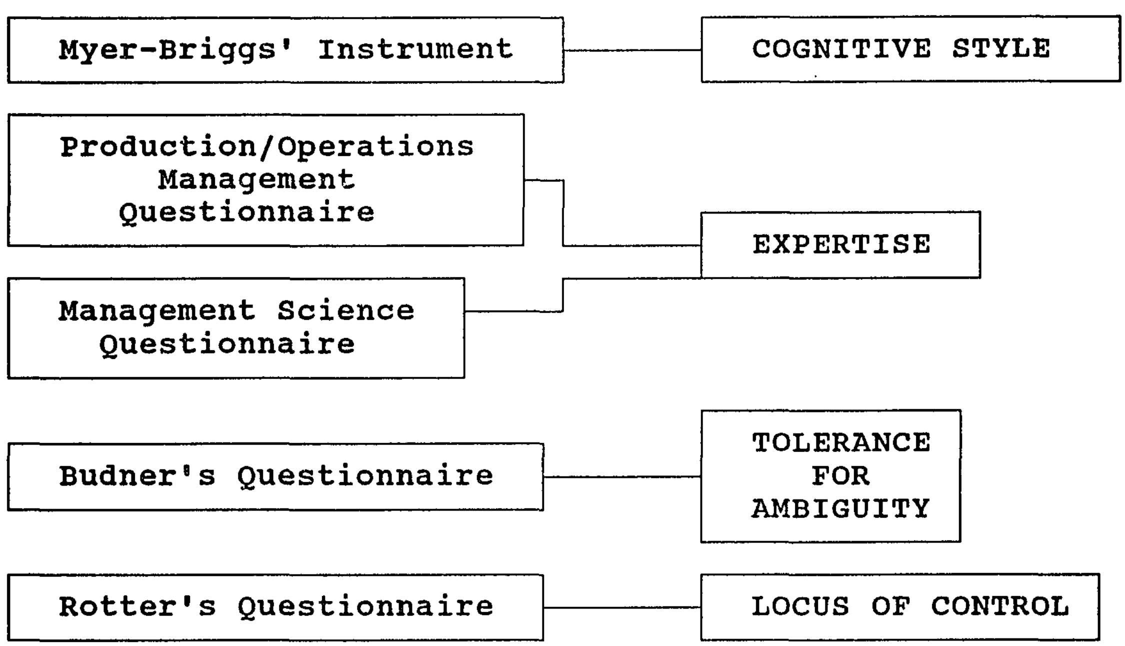
To clarify the exact relationship amongst the dependent intervening variables and their measurement instruments a schematic is presented in Figure 1.3.

1.4 SPECIFICATION OF MODEL

Lucas' (1975a) work is the starting point for the model proposed in this work. It presents a clear set of relationships amongst the variables and has a strong behavioral component. Ives, Hamilton, and Davis (1980) point out that most of the research on this model was conducted by Lucas himself, and that no dissertation has stemmed from this work.

FIGURE 1.3

INTERVENING VARIABLES' INSTRUMENTS

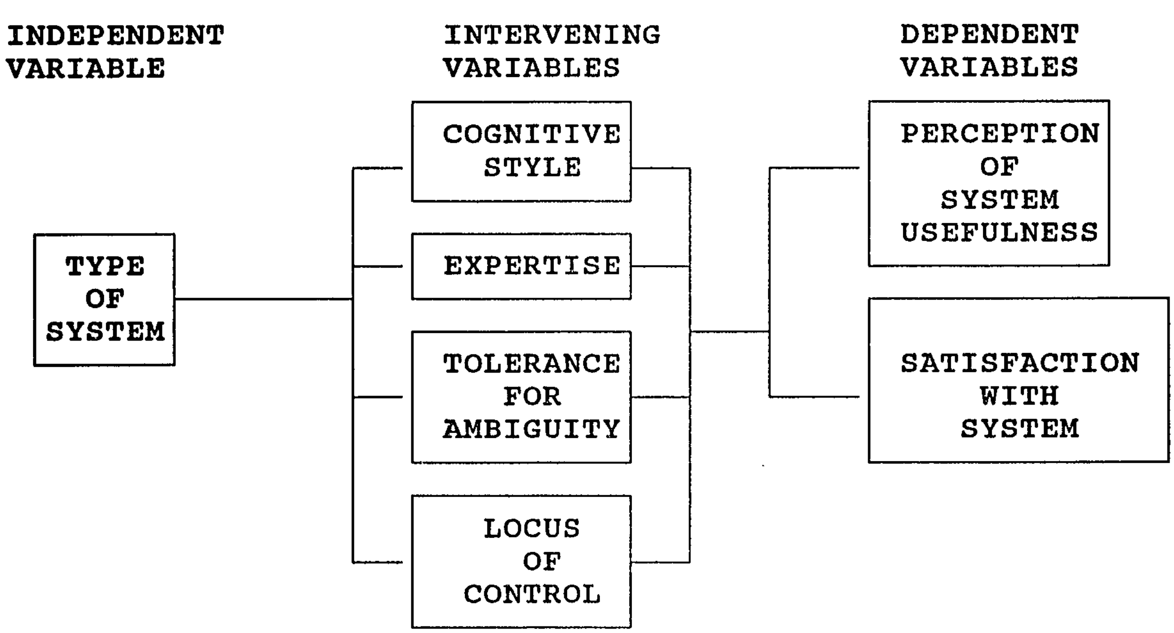


Lucas' work offers the most attractive formulation upon which to build a theory of expert system usage. It provides the most explicit set of relationships amongst the variables. Lucas (1975a) points out that the usage of the system will affect performance and that performance will affect usage, while both performance and usage will be affected by personal and situational factors. In addition, several of the constructs in his theory - Quality of the System, Analysis and Action - are difficult to operationalize.

The model proposed in this dissertation is based on Lucas' (1975a) work which is presented in detail in the next chapter. In this proposed model, satisfaction with the system and perception of the usefulness of the system's information are the dependent variables; type of system is the independent variable; and the intervening variables are cognitive style, level of expertise, locus of control and tolerance for ambiguity. The model is presented in Figure 1.4.

FIGURE 1.4

SCHEMATIC OF PROPOSED MODEL



This model differs from others (Chervany, Dickson, and Kosar, 1971; Gorry and Scott-Morton, 1971; Lucas, 1973; Mason and Mitroff, 1973; and Mock, 1973) in that it explicitly considers alternative types of computer decision aids being available to the user. In the next chapter the relationships amongst these variables are discussed.

CHAPTER 2.

THEORETICAL BACKROUND

2.1 CURRENT MODELS AND THEORIES

In order to be able to answer the proposed research questions we must be able to articulate a theory of computer decision aid usage; one that would be able to make specific predictions about the usage of a variety of different types (decision support systems vs. expert systems) of these aids.

There are five major models for management information systems research (Ives, Hamilton, and Davies, 1980). Several of these models have been used to guide research of decision support systems (Fuerst and Cheney, 1982) and therefore are described here. The description of the five models will be followed by a review of the literature that includes theories of MIS or DSS usage and those empirical studies that cast light on the issues involved in this dissertation.

Gorry and Scott-Morton (1971) provide one of the earliest models of information systems. The authors center their model on the information that a system provides to management. Drawing upon Simon's work (1960) they argue that the characteristics of the requisite information will vary depending on the degree of structure required by the particular decision. In this context, structured decisions can be handled by a "generic" information system. Unstructured decisions require a decision support system that is specifically tailored to the task and the individuals. In examining the outcome variables for any information system, they argue that the focus should be upon the attributes of information. These attributes would include accuracy, timeliness, and frequency of use.

Gorry and Scott-Morton indicate that the design process for an information system should focus upon the task at hand, the structure of the organization, and individual differences. This model is important for this research since it can be argued that it was the basis for Grochow's (1973) investigation of cognitive style's impact upon the use of decision support systems.

Mason and Mitroff (1973) take an approach to management information systems that places a heavy emphasis upon behavioral considerations. They present the argument that prior research assumed that there was *"one underlying psychological type, one class of problem, one or two methods of generating evidence, and, finally, one mode of presentation"* (pg. 480). Their model breaks down into several key elements. The first centers on the psychological classification of the user. The second element in the model examines the type of problem that is to be "solved." They bifurcate problems into the now familiar scheme of structured versus unstructured. Structured problems are further classified into decisions under certainty, decisions under risk, and decisions under uncertainty. The third element represents Mason and Mitroff's most unique contribution to MIS studies - a typology of inquiry systems based on methodology. Their inquiry systems are predicated upon the methodologies to gather knowledge as specified by major philosophers. Mason and Mitroff's model also includes the organizational context in which the MIS is to be employed and the various modes in which information can be presented to the user. Although conceptually fascinating, it fails to adequately address the critical issue of how one evaluates the performance of an MIS once it is in place.

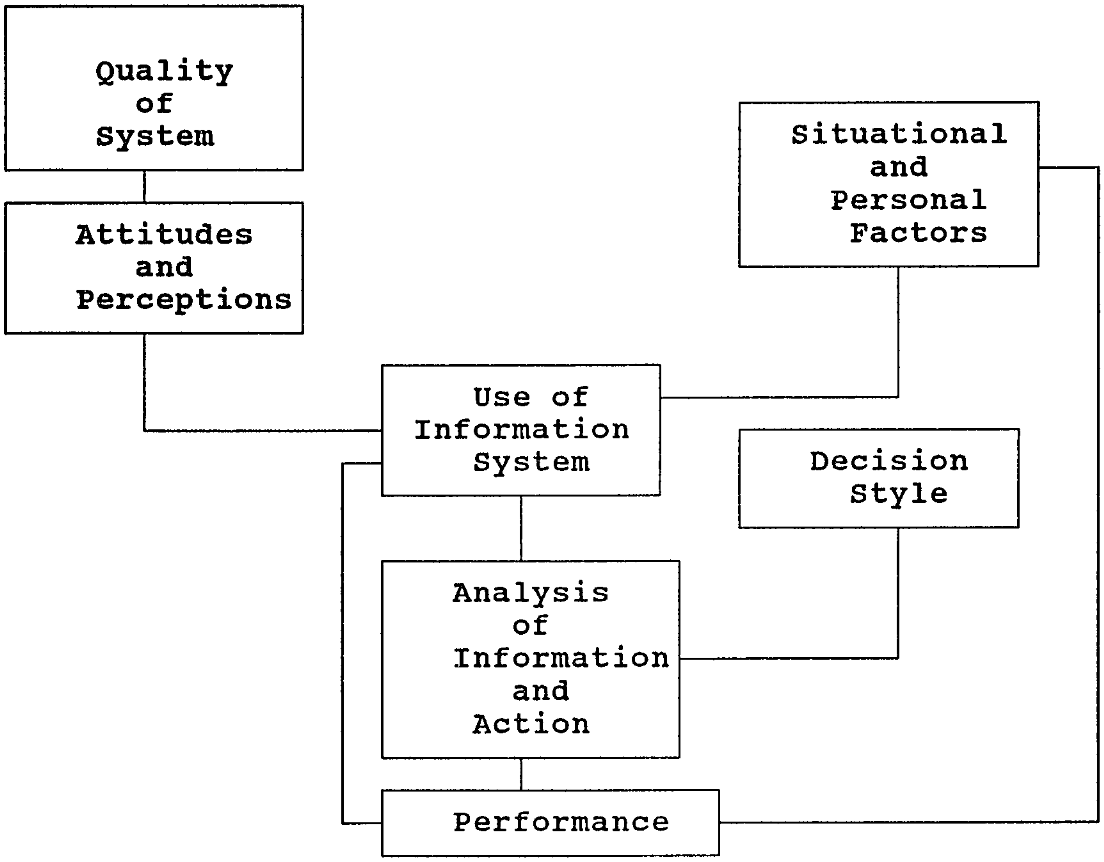
A third major model for MIS research is by Lucas (1973). This model is summarized in Figure 2.1 - [This schematic is taken from Ives, Hamilton, and Davis (1980), pg. 913].

Key to this model is its emphasis that performance of a system is affected by the user's attitudes. Lucas (1975a) offered a theory based on this model by specifying the interrelationships amongst the variables. This theory is comprehensive in its integration of the behavioral elements with outcome variables (performance and use).

The fourth model was formulated by Mock (1973) who argued that decision makers operate in constrained en-

FIGURE 2.1

LUCAS'S MODEL



vironments. They are limited by their own specific psychological characteristics, by the organizational situation, and by the information requirements. His work placed little emphasis on the technical end of management information systems, but, rather, centered on the behavioral issues associated with the use of an on-going system.

Several studies can be said to emanate from Mock's suggested research model. King (1973) examined how various accounting information models are influenced by psychological variables. Vasarhelyi (1973) used the notion of individual cognitive style's impact on the processing and utilization of information. These studies provide us with several important concepts. First, they place great emphasis on the premise that any successful study of MIS must include the psychological characteristics of the user. Second, they incorporate the issue of what type of decision MIS will be called upon for support. Third, they discuss the variety of measures that can be used to evaluate MIS performance. These same research issues are carried over to the study of decision support systems, but, as of yet, they have not been incorporated into any systematic study of expert systems and their use.

The fifth model is of Chervany, Dickson, and Kosar (1971). This model attempted to identify the key determinants of the effectiveness of information systems. This research model has been the basis of the "Minnesota Experiments" (Dickson, Senn and Chervany, 1977). It is distinquished from the other models in that it provides a clear identification of operational independent and dependent variables. A listing of their variables is given in Table 2.1.

In reviewing the appropriate literature for this study we must also examine the field of management information systems. This will enable us to see those factors that prior researchers saw as having an effect on a user's preference for system use.

Ackoff (1960) and Argyris (1971) have written on the discrepancy between technology and its use by line managers.

TABLE 2.1

VARIABLES USED BY CHERVANY, DICKSON, AND KOSAR

INDEPENDENT VARIABLES			DEPENDENT VARIABLES
DECISION MAKER	**DECISION ENVIRONMENT**	**NATURE OF SYSTEM**	**DECISION EFFECTIVENESS**
INDIRECTLY ACQUIRED ATTRIBUTES Aptitudes Attitudes	FUNCTION Finance Production Marketing R&D	FORMAT Content Form Media Presentation	QUALITY Cost Profit Time
DIRECTLY ACQUIRED ATTRIBUTES Training Experience	LEVEL Strategic Tactical	TIME Availability	
	ENVIRONMENTAL STABILITY Competitive-ness Time Pressure	DECISION AID	

A number of studies (DeWaele 1978; Ginzberg, 1974, 1978; Powers and Dickson, 1973; and Zand and Sorensen, 1975) have discussed what factors facilitate the successful implementation of management information systems. Several key factors have been identified.

One factor that has received wide attention is user involvement in the development of the MIS (Edstrom, 1977; Garrity, 1963; Higginson, 1965; Orlicky, 1969; Powers, 1971; Seward, 1973; Swanson, 1974; and Thurston, 1959).

Communication between the system developer and the user plays an important role in system success. Edstrom (1977) illustrated that indicators of dysfunctional communication are positively related to user dissatisfaction. DeBrabander and Edstrom (1977), in their study of successful MIS implementation, make effective communication a critical intervening variable. DeBrabander and Thiers (1984) attempt to operationalise "effective" communication by examining the outcome between developer of a system and its user in terms of their interactions. These interactions include two critical elements: (1.) the mutual agreement to end interactions after all available information has been exchanged; and (2.) the agreement to implement a specific information system after all available information has been exchanged. The important notion presented here is that the dialogue between user and developer must have some "clear" point of termination. The importance of these findings to this study is that users of computer decision aids must have some clear idea of their needs and transmit those needs to the system's developers. In the case of this research, both the decision support system and the expert system packages were modified from their original form, after test group use, so as to meet the needs of the research subjects.

User expectation has also been seen in the literature as an important determinant of the system's implementation success. Evan and Black (1967), Ginzberg (1978), and Schultz and Slevin (1975) have presented evidence that expectation during the development process is directly tied to user satisfaction - and satisfaction is often (Ginzberg 1978, 1981) used as a measure of MIS success. Unrealistic expectations concerning the capacity of systems are perceived as leading to higher rates of dissatisfaction. Zand and Sorensen (1975) showed that in unsuccessful systems users perceived the system's overall design as being too "large" to implement. Keen's (1975) paper argued that MIS and Operations Research implementation failures stem from improper management of users expectations.

Given the technology and nature of expert systems, any comprehensive model of system success should explicitly examine this question of user expectation.

Like management information systems, the field of decision support systems has generated an extensive literature.

Fuerst and Cheney (1982) delineate three multi-dimensional factors that influence preference of DSS usage. The first factor details the characteristics of the decision-maker. These consist of the age, educational background, experience, and cognitive style of the potential user. The second factor identifies the characteristics of the implementation process - which consist of user involvement, user training, and top management support. The last factor concerns the characteristics of the decision support system - which are measured by the system's response time, accuracy, relevancy, format, and mode of input/output.

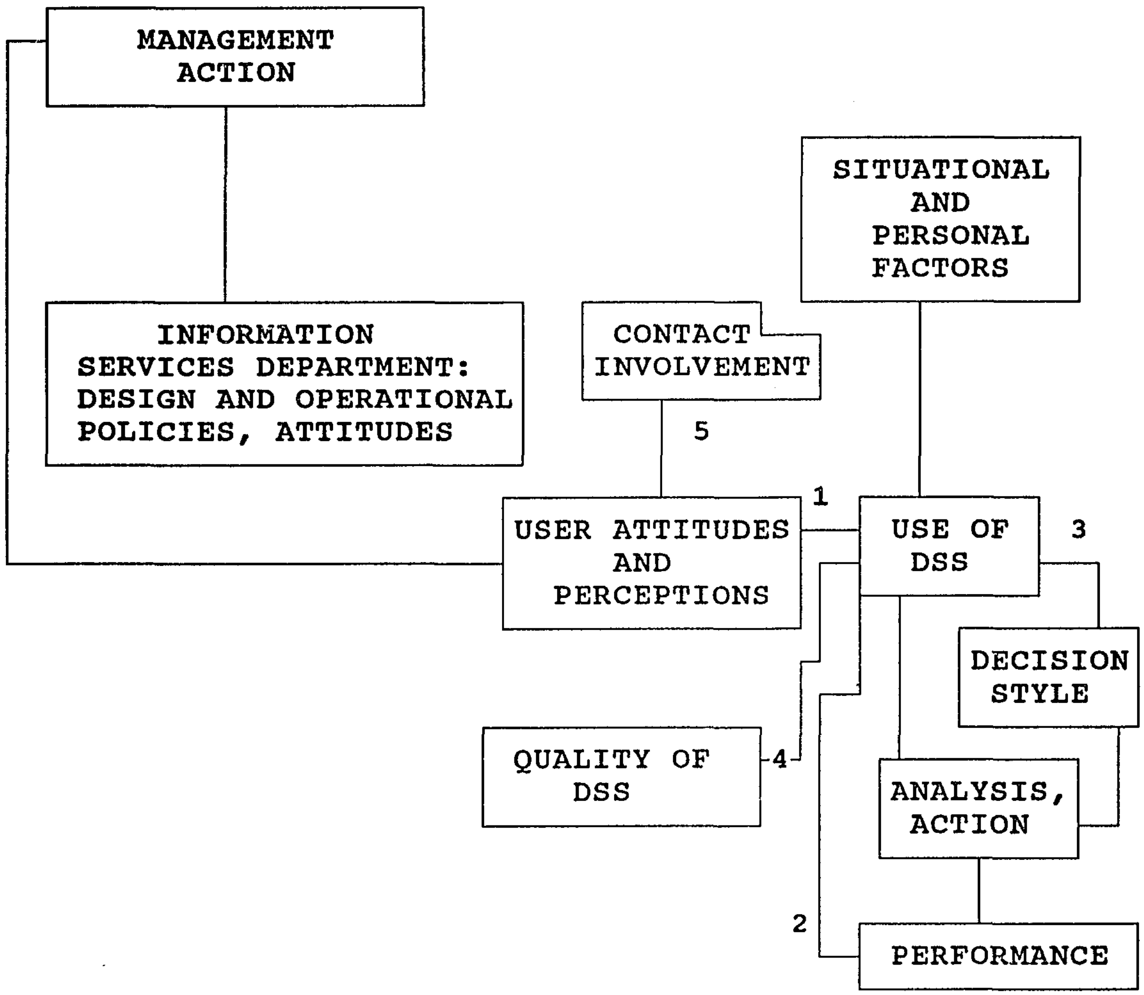
A schematic of Fuerst and Cheney's theoretical model is presented in Figure 2.2. Only the numbered relationships were tested in their research. The dependent variable used in this study was preference of system usage. They supported their approach by referring to the works of Gingras (1975), Lucas (1975a), Schroeder and Benbasat (1975), Swanson (1974), and Vasarhelyi (1977). The participants were eight major oil companies. The decision support systems were all mainframe oriented. Sixty-four users of these systems were involved in this experiment.

The results indicated that general use of the system was affected by the accuracy of the information received from the DSS and user training of the DSS during the implementation process. Four factors were found to impact on specific DSS preference of use: experience of the user; user training during the implementation process; accuracy of output; and relevancy of output. An important point made by the authors was that, unlike many MIS studies, user involvement during the implementation process did not appear to be critical.

Goslar, Green, and Hughes (1986) examined a broad range of response variables for a decision support system used in a laboratory setting. The response variables included the number of options considered, time expended, amount of information considered, decision confidence, and performance level.

FIGURE 2.2

FUERST AND CHENEY'S MODEL



Watkins (1984) examined the way in which perceived information structure could be used in the context of a decision support system. This research sought to examine two major questions: (1.) *"What are the perceived dimensions of decision information cues as indicated by similarity judgements of top decision-makers?"* and (2.) *"Can relatively homogeneous groups of top-level decision-makers be formed on* *the basis of commonality of perceptual space?"* (pg. 98)

The subjects of this study consisted of chief executive officers. The findings indicated that the group dimensions of decision information cues for these officers were: (1.) firm/product; (2.) environmental; (3.) financial; and (4.) mode-of-presentation. The author also found that relatively homogeneous groups could be formed based upon commonality of perceptual space. The importance of this study for the research discussed in this dissertation is that it points to the importance of the cognitive structure of individual decision-makers, and it reinforces the notion that decision-makers can be categorized on that basis.

Lanzetta and Driscoll (1966) have indicated that the user's response to uncertainty can influence the use and acceptance of computer decision aids. The propensity for risk-taking and the need for achievement are critical factors in the works of Benbasat and Taylor (1981), and Taylor and Dunnette (1974, 1975) . Cognitive complexity and its impact on computer usage is mentioned by both Vannoy (1965) and Watkins (1984). An individual's dogmatism and how it affects decision-making is covered in the works of Taylor and Dunnette (1974, 1975).

The concept of cognitive style has been previously mentioned. In the earlier section of this paper, the focus was on the concept of that construct. Here the emphasis is on the application of that concept in studies of management information systems and decision support systems.

A number of papers (Bariff and Lusk, 1977; Benbasat and Taylor, 1978; Dickson, Senn, and Chervany, 1977; Driver and Mock, 1975; and Mason and Mitroff, 1973) have examined how cognitive style impacts on a decision-maker's processing of information or the individual's use of a management information system. Doktor and Hamilton (1973) and Huysmans (1970) illustrated that the acceptance of operations research models is related to the individual's cognitive style. McKenney and Keen (1974) demonstrated that cognitive style can affect both the implementation process of an MIS and the use of the system.

Two major reviews (Libby and Lewis, 1977; and Zmud, 1979) point out that there are also some major inconsistencies in this field of study. Barkin and Dickson (1977) obtained results that individuals who are "systematic" in their cognitive style prefer information presented to them in an aggregated form. Rittenberg (1973) found, in his study, that those who are systematic preferred raw data. Grochow's (1973) and Mock's (1973) research indicated that those who are "systematic" desired more information from management information systems while the opposite result was obtained by Rittenberg (1973). Blaylock and Rees (1984) used the MBTI to evaluate if cognitive style affected the perception of the usefulness of information. Their study used MBA students as subjects and differed from others by allowing for *"an* *iterative succession of information gathering, evaluation and feedback"* (pg. 87). Their findings indicated that cognitive style does affect a decision-maker's evaluation of a strategic planning problem, and that differences in preference for information sets can be explained by the Jungian typology of psychological types. A third finding was that information preferences varied dynamically as additional feedback was provided. This last point will be shown to be important for the research outlined in this dissertation.

In reviewing the decision support system literature, one finds several articles which specifically incorporate the concept of cognitive style. Others expand on that concept and build an even richer picture of how specific cognitive activity influences the use of decision support systems.

Alavi and Henderson (1981) carried out an interesting study involving cognitive style and decision support systems. Their central focus was on the implementation of a DSS as a social change process. They argue that under traditional procedures there is a minimum of user input with the system analyst being responsible for the development of DSS, defining the model, and the solution methodology. The authors refer to this as a "traditional" approach. This approach runs counter to the prevailing research literature which specifically calls for the user to play a highly active role during the system's development. This implementation approach is designated as an evolutionary strategy.

The experiment conducted by Alavi and Henderson was designed to see how cognitive style and implementation strategy influence a system's usage and the users' satisfaction with the system. The experiment was conducted in a controlled laboratory experiment. The subjects were graduate students at Ohio State University. (A similar use of students in laboratory studies can also be found in the work of Chanin (1980, 1983); Chanin and Shapiro (1980, 1982); and Chanin, Wulwick, and Shapiro (1984)). The subjects assumed the responsibility of a production manager in a simulated factory. They were expected to set work force size, production schedules, and inventory levels over a 12 week horizon. The decision-making process used in this assignment could be either intuitive or analytical.

The DSS element of this experiment consisted of the linear decision rule (LDR) model of Holt, Modigliani, Muth and Simon (1955). This model determines values for the work force size and production rates so as to minimize cost over the planning horizon. In addition to this model, the research incorporated a series of regression models. These regressions "were used to estimate the relative importance of information (independent variables) used by the decision-maker" (Alavi and Henderson, 1981, pg. 1315). These regressions can make the decision- maker aware of the cost implications of their actual decisions. The logic of this approach can be found in the works of Bowman (1963) and Moskowitz and Miller (1975).

After administering the Myers-Briggs Type Indicator (MBTI), the subjects were divided into three groups. The first group, classified as using the traditional approach, only used the LDR model. The second group, classified as using the evolutionary approach, had access to the LDR and regression models. The last group, classified as using a "bootstrapping" approach, had access only to the regression models. Bootstrapping refers to a learning program in which decision-makers are first given descriptive models and then are provided with normative (regression) models.

The experiment was conducted in three phases. The preliminary stage was geared to familiarize the participants with the experiment. After two decision periods, both the experimental and traditional groups were required to use the LDR model. At the end of the third decision period, the participants were questioned regarding the simulation, the decision aid, and the task. User satisfaction with the decision aid was measured by the use of a seven point Likert scale. The second phase of the study consisted of three decision periods in which the use of decision aids were optional. The third phase of the study consisted of a debriefing session.

The findings of this research indicated that decision support system utilization was significantly affected by the implementation strategy. User satisfaction was affected by an interaction of implementation strategy and cognitive style. In addition, Sensing-Thinking (ST) types were more satisfied with the LDR model than the "bootstrapping" model. This finding was reversed for the Intuitive-Feeling (NF) type, although this was not statistically significant. The lack of statistical significance for the NF types was attributed to the fact that the bootstrapping model was essentially an analytical approach designed to cover a broad range of situations. This was perceived as not being very characteristic of Intuitive-Feeling types.

This study is important for the research being presented in this dissertation because: (1.) it advocates a multi-stage research design; (2.) it stresses that cognitive style should not be seen as the single causal agent; and (3.) it uses a laboratory simulation whose focus is on production.

2.2 PROPOSED THEORY

In an effort to integrate the various models described earlier, a theory is being proposed here that links the cognitive style, expertise, tolerance for ambiguity, and locus of control of the user to preference to use a particular computer decision aid.

2.2.1 COGNITIVE STYLE

The proposed theory recognizes that cognitive style research sees individuals as differing in perceptions and judgements. With respect to their perceptions individuals are dichotomized as being either intuitive or sensing. Those classified as being intuitive-oriented tend to perceive situations in generalized terms, that is, they pay less attention to facts and pay more attention to a "gestalt mode of information intake" (Alavi and Henderson, 1981, pg. 1310). Those classified as sensing-oriented tend to prefer specific data - data that is provided in detail. On the basis of this perception classification scheme the two groups would be expected to have differential responses to data presented in different formats. Data that provides explicit and detailed outputs would be more appealing to those who are classified as being sensing, while data that provides an overview would be more appealing to those classified as intuitive.

The second element of the Jungian typology of cognitive style is judgement. Again, individuals are segmented into two modes - thinking and feeling. The thinking mode prefers to process data in a logical and systematic manner. Feeling-oriented individuals prefer to process data on the basis of the unique aspects of the situation. Given a predilection to judge information in a particular way (i.e., thinking or feeling) individuals would be expected to express different levels of satisfaction with data depending upon the manner in which that data was presented.

Decision support systems are generally built upon the interactive use of management science models. Although geared for flexibility, they require data that is detailed and specific. They also require that the user possess some familiarity with the modeling techniques. Decision support systems generate specific, normative solutions for the user. Expert systems rely upon heuristic solution methodologies. By employing heuristic methodologies these systems can approach problems that are broader in perspective. They, too, provide normative solutions but they require less specific knowledge on the part of the user. In addition, expert systems provide the user with descriptions and rationales for the solutions. There is a clear difference between the systems in terms of the type and form of information that is given to the user. This theory proposes that the differences between the two computer decision aids will yield differential levels of satisfaction between intuitive and sensing individuals and between thinking and feeling individuals. In addition to the issue of satisfaction, one should also examine the user's perception of the usefulness of the information generated by each decision aid. Cognitive style taxonomy is clearly related to how an individual processes and evaluates information. The manner in which an individual conducts these activities will bear directly on how useful they will perceive information that is presented.

In addition to the Jungian classification scheme for cognitive style, we can classify individuals on the basis of how they use various constructs to evaluate information (Rowe, Mason and Dickel, 1985). This taxonomy contains two classifications - conceptual and behavioral - that should yield differential responses on the part of users who employ decision support systems and expert systems. Conceptual types, by definition, require high data usage and also require the opportunity to examine many alternatives in order to determine the best possible solution. Therefore, they would be attracted to decision support systems which possess "what-if" capabilities and optimizing management science models. Behavioral types are more comfortable with information conveyed in a verbal format. They would prefer expert systems since they provide rationales and explanations for their decisions.

2.2.2 EXPERTISE

The proposed theory also argues that other "intervening" variables will affect the user's perception of the usefulness of a particular system's information and the user's satisfaction with that system. The theory argues that an individual's "expertise" (that is, exposure to or knowledge of production/operations management concepts and management science techniques), will affect the user's satisfaction with a particular decision aid and the user's perception of the usefulness of the information provided by a particular system.

The rationale behind this argument is as follows: decision support systems provide the user with the option of employing a number of management science techniques. Users who are unfamiliar with such techniques will derive less information and thus experience less satisfaction and see less usefulness in the provided information. Expert systems, on the other hand, are structured to provide rationales for their decisions. Thus, users who have less familiarity with modeling techniques would "feel" more comfortable with such a system. Likewise, the user's "expertise" with the decision domain would impact on his/her satisfaction and perception of information usefulness.

2.2.3 LOCUS OF CONTROL

Locus of control, the third intervening variable, is seen as having an impact on the satisfaction with and perceived usefulness of information generated by a given computer decision system. The greater the locus of control for individuals the more they perceive themselves in control of events. Since the use of all elements of a decision support system is dictated by individual choice to a greater extent than using an expert system, the theory holds that the greater the individual's locus of control the more likely that s/he will express a preference to use the decision support system than the expert system.

2.2.4 TOLERANCE FOR AMBIGUITY

The last intervening variable is tolerance for ambiguity. The proposed theory argues that individuals with a lower tolerance for ambiguity will express a greater level of satisfaction with results that are explicit and unambiguous. They will perceive that information is more useful if it is viewed as being more exact and explicit. Such users will see the optimizing techniques used by decision support systems as being more rigorous and exact than the heuristic methodologies employed by expert systems. The proposed theory enters relatively uncharted realms.

Although prior research has used the aforementioned variables, no research, model or theory specifically compares a user's response to both an expert system and a decision support system. Such a theory is needed. Currently, there is a question about whether expert systems will provide advice that is equal to or superior to management science models. Supporters of expert systems argue that although their models do not seek optimal solutions, they provide solutions which have a higher probability of being implemented by users. (This argument, in a very real sense, is similar to that of Bowman's (1963) management coefficient model.) These supporters would be correct only if users derive greater satisfaction (and perceive more useful information) by employing expert systems. It is therefore critical to determine what factors would contribute to differential satisfaction between competing decision support systems and expert system.

2.3 HYPOTHESES

In this section, there are two sets of hypotheses. The first set of hypotheses examines the issue of how individuals' cognitive style impacts on their preference for system use.

HA1. Individuals classified as Sensing-oriented will express less satisfaction with the expert system than those classified as Intuitive oriented.

HA2. Individuals classified as Sensing-oriented will express greater satisfaction with the decision support system than those classified as Intuitive oriented.

HA3. Individuals classified as Feeling-oriented will express greater satisfaction with the expert system than those classified as Thinking-oriented.

HA4. Individuals classified as Feeling-oriented will express less satisfaction with the decision support system than those classified as Thinking-oriented.

HA5. Those classified as Sensing/Thinking-oriented will express less satisfaction with the expert system than those classified as Feeling/Intuitive-oriented.

HA6. Those classified as Sensing/Thinking-oriented will express greater satisfaction with the decision support system than those classified as Feeling/ Intuitive-oriented.

HA7. Those classified as Sensing-oriented will have a greater level of perceived usefulness of the information generated by the decision support system than those classified as Intuitive-oriented.

HA8. Those classified as Sensing-oriented will perceive less usefulness of the information generated by the expert system than those classified as Intuitive-oriented.

HA9. Those classified as Feeling-oriented will have a greater level of perceived usefulness of information generated by the expert system than those classified as Thinking-oriented.

HA10. Those classified as Feeling-oriented will perceive less usefulness of the information generated by the decision support system than those classified as Thinking-oriented.

HA11. Those classified as Sensing/Thinking-oriented will have a greater level of perceived usefulness of the information generated by the decision support system than those classified as Feeling/Intuitive-oriented.

HA12. Those classified as Sensing/Thinking-oriented will perceive less usefulness of the information generated by the expert system than those classified as Feeling/Intuitive-oriented.

HA13. The greater the user's Conceptual orientation the more likely the user will be more satisfied with the decision support system than with the expert system.

HA14. The greater the user's Behavioral orientation the more likely the user will be more satisfied with the expert system than with the decision support system.

HA15. Given the opportunity to use either the expert system or the decision support system those classified as Sensing will be more likely to select the decision support system.

HA16. Given the opportunity to use either the expert system or the decision support system those classified as Intuitive will be more likely to select the expert system.

HA17. Given the opportunity to use either the expert system or the decision support system those classified as Thinking will be more likely to select the decision support system.

HA18. Given the opportunity to use either the expert system or the decision support system those classified as Feeling will be more likely to select the expert system.

The logic of these hypotheses stems from the fact that the Thinking-oriented, by definition, are linear-logical in their mental processes; Sensing-oriented individuals are data oriented, tending to prefer numerically oriented results. Intuitive types are less concerned with specifics, more concerned with possibilities. Feeling-oriented individuals are driven predominantly by their emotions placing much less importance on detailed analysis.

Evidence from Grochow (1973), Huysmans (1970), Mock (1973), and Vasarhelyi (1977) would support the logic of these hypotheses.

The second set of hypotheses examines the influence of the role of personal factors (expertise, tolerance for ambiguity, and locus of control) on the user's satisfaction with the system and the user's perception of the usefulness of the information generated by the system.

HB1. The greater the user's familiarity with mathematical modeling (management science) the more likely the user will be more satisfied with the decision support system than with the expert system.

HB2. The greater the user's familiarity with mathematical modeling (management science) the more likely the user will have a perception that the usefulness of information provided by the decision support system is greater than that of the expert system.

HB3. The greater the user's familiarity with production/operations management concepts the more likely the user will be more satisfied with the decision support system than with the expert system.

HB4. The greater the user's familiarity with production/operations management concepts the more likely the user will have a perception that the usefulness of information provided by the decision support system is greater than that of the expert system.

HB5. The lower the user's tolerance for ambiguity the more likely the user will be more satisfied with the decision support system than with the expert system.

HB6. The lower the user's tolerance for ambiguity the more likely the user will perceive that the usefulness of the information generated by the decision support system is greater than that generated by the expert system.

HB7. The greater the locus of control of individuals the more they will express satisfaction with the decision support system than with the expert system.

HB8. The greater the locus of control of individuals the more they will perceive the usefulness of the information generated by the decision support system as greater than that generated by the expert system.

CHAPTER 3

METHODOLOGY

This chapter looks at the respondents that were used in this study, the instruments that were employed, the research design, and the statistical tests that were carried out.

3.1 RESPONDENTS

In order to test both the model and hypotheses, the author has developed a decision support system and expert systems geared to operate in the environment of the DECIDE-P/OM game. This game is normally played by teams of three to five individuals. However, to avoid problems of group dynamics and confounding interactions, all decisions for the game were made on an individual basis.

This study's subjects came from three groups - an undergraduate class in production/operations management (20 subjects); a graduate class in production/operations management (36 subjects); and certified members of the

American Production and Inventory Society (10 subjects).

Of this total of sixty-six (66) subjects, forty-three (43) were male and twenty-three (23) were female. All of the certified members of the American Production and Inventory Control Society were male. The graduate class consisted of fifteen (15) females and twenty-one (21) males. The undergraduate class consisted of eight (8) females and twelve (12) males.

The average length of employment for the total sample was 9.03 years. The average length of employment for the undergraduate class was 2.75 years (this included part-time employment) and the average length for the graduate class was 10.41 years (the median was 6.8 years). The APICS members had an average length of employment of 16.62 years.

3.2 INSTRUMENTS

The Myer-Briggs Type Indicator has probably been the most commonly used instrument to measure an individual's cognitive style in computer decision aid research. The instrument is not included, as it is proprietary, but copies of all the other questionnaires used are included. The Myer-Briggs Type Indicator has eight scales: extraversion, introversion, sensing, intuitive, thinking, feeling, judging, and perception. This research uses four of these scales: sensing, intuitive, thinking, and feeling. Lake, Miles and Earle (1973) report that the internal-consistency reliability scores (Cronbach's alpha coefficient) for the scales ranged from .64 to .84. For the sample used in this study, the alpha scores for the four scales are given in Table 3.1

TABLE 3.1

CRONBACH ALPHA SCORES FOR MYER-BRIGGS SCALES

SCALE	CRONBACH ALPHA SCORE
SENSING	.72
INTUITIVE	.65
THINKING	.82
FEELING	.73

The Decision Style Inventory consists of twenty questions, each of which has four possible responses. Each of the four possible responses corresponds to one of the decision styles. The subject selects the responses in the order of their appropriateness to the subject's beliefs. The most appropriate response is coded as eight (8). The next most appropriate response is coded as four (4), the next is coded as two (2), and the least appropriate is coded as one (1). The scores for each of the four responses are totaled for the twenty questions.

Tolerance for ambiguity was measured by Budner's (1960) instrument. This instrument has sixteen items which are scored on a seven point scale ranging from "strongly disagree" (coded as a 1) to "strongly agree" (coded as 7). Half of the items were reverse coded. The higher the overall score on this instrument the less tolerant the individual is to ambiguous situations. The Cronbach alpha score for this instrument was .56.

Rotter's (1966) locus of control instrument consists of twenty-nine paired items. The respondent is asked to select the one element of the pair that best describes his/her belief system. Of the twenty-nine paired items twenty-three are actually scored and the other six are seen as dummy items. To evaluate the reliability of this instrument we used Guttman scaling. The coefficient of reproducibility was .92 and the coefficient of scalability was .81.

Key to this research are the notions of user satisfaction with a particular computer decision aid and the user's perception of the usefulness of the information generated by a computer decision aid. Two instruments, Sanders' Questionnaire (Sanders and Courtney, 1985) and Aldag and Power's (1986) Attitude-toward-Decision Aid were used to measure the users' satisfaction with both the decision support system and the expert systems. Two instruments, Larcker and Lessig's (1980) Questionnaire and Franz and Robey's Questionnaire (1986) were used to measure the users' perception of the information generated by the two computer decision aids. Each instrument was administered to the participants after they had had the opportunity to use each computer decision aid. That is, all instruments were administered twice - once after the use of the decision support system and the second time after the use of the expert systems.

Sanders' Questionnaire consists of thirteen items. Each item is scored on the basis of a seven point scale ranging from "completely disagree" (given a value of 1) to "completely agree" (given a value of 7). The higher the score on this questionnaire the greater the measured satisfaction with the computer decision aid. The alpha score for the Sander's Questionnaire was .95 for both the decision support system and the expert system.

The Aldag and Power's Attitude-toward-Decision Aid Questionnaire also consists of thirteen items scored on the basis of the same seven point scale. Four of the thirteen items are negatively worded and are reverse coded. The alpha score for this questionnaire was .89 when administered for the decision support system, and .95 when administered for the expert systems.

The questionnaire developed by Larker and Lessig to measure the perceived usefulness of information consists of six items. All six items are measured on a seven point scale. The greater the score on this questionnaire, the more positive is the user's perception of the usefulness of the information generated by the particular computer decision aid. The alpha score was .76 when administered for the decision support system, and .79 when administered for the expert system.

The Franz and Robey Questionnaire consists of eleven items. Each item is scored on the basis of a six point scale ranging from a response of "Not at all" (given a value of 1) to "Very much" (given a value of 6). Four items are reverse coded so that the higher the score on this questionnaire the greater the user's perception of the usefulness of the information generated by the particular computer decision aid. The alpha score was .78 when administered for the decision support system and .61 when administered for the expert systems.

To measure an individual's understanding of production/ operations management and management science concepts the author of this dissertation developed two questionnaires. Each consisted of twenty questions. Each question's response is scored as being either right or wrong. Guttman scaling techniques were employed on both instruments. The production operations management questionnaire had a coefficient of reproducibility of .89 and a coefficient of scalability of .80. For the management science questionnaire the coefficient of reproducibility was .87 and the coefficient of scalability was .75.

3.3 DESIGN

The sample size was dictated by the nature of the research design. The subjects were required to make eight sets of decisions for the P/OM DECIDE game. For the two student groups (graduates and undergraduates) this meant that decisions were made on a weekly basis. This did not pose much of a problem for the undergraduates; however, in many cases some of the graduate students "missed" one of the weekly classes. This meant that the author had to go to their homes or place of employment in order to pick-up the diskettes that contained their decisions so that the weekly schedule would be maintained. The APICS members devoted time on Saturdays or after work to submit their decisions.

The research subjects made two set periods' worth of decisions for the P/OM DECIDE game without the benefit of either a decision support system or an expert system. This provided participants with an opportunity to become familiar with the game. For the third and fourth periods, half of the individuals had access to the decision support system while the other half had access to the expert systems. This split design was used so that the participants were not biased into thinking that there might be an implied evolution of computer decision aids. By that we mean, that if all participants used the decision support system before they used the expert systems (or vice versa) then they might believe that expert systems (or the decision support system) represent(s) a level of greater sophistication and therefore rate them more favorably. For periods five and six the participants were required to use the other tool, that is, if one used the DSS in periods three and four s/he was to use the expert systems in the next two periods. During the last two periods, participants were free to choose either tool. This option was used to determine user preference of the two systems.

The DECIDE-P/OM game required participants to utilize some of the following techniques: forecasting, materials requirement planning, inventory control, quality control, maintenance, and scheduling.

Each period's decisions were entered on a computer diskette and then submitted to the instructor. Results were returned to the participants either in the next class or by mail.

The participants were informed that their performance would be evaluated on the basis of profits, cost of inventory, and stockouts. The graduate and undergraduate students were also informed that their performance in this game would have no impact on their grades. This was done because of the high level of anxiety on their part; if this had not been addressed many students would have dropped the course and reduced the sample size. It should be pointed out that students had their own copy of the STORM programs; therefore, they could use the decision support system on any IBM compatible computer. The expert system program (EXSYS), however, required a hard disk and was placed on a computer in the author's office.

3.3.1 STATISTICAL ANALYSES

All statistical analyses conducted for this dissertation were done using the SPSS-PC computer package. In the last chapter a total of twenty-four hypotheses were presented. If we review Hypotheses HA1 to HA12, we see that we are comparing the response of two groups on some measure of satisfaction or perceived usefulness for either computer decision aid. These hypotheses can be tested by examining the difference in the means of the measure (satisfaction or perceived usefulness) for the two groups, i.e., a t-test. The t-test executed by the SPSS-PC package computes the mean, standard deviation, and standard error for both groups. It computes two t values: one that employs a separate variance estimate and one with a pooled variance estimate. This latter test is based on the assumption that the population variances in the two groups are equal and can be obtained using a pooled estimate of that common variance (Norusis, 1988). In addition, the SPSS-PC output provides an observed significance level for both variations of the t-test.

Hypotheses HA13, HA14, and HB1 to HB6 compare the relationship between some characteristic of the research subject (locus of control, tolerance for ambiguity, etc.) and the subject's attitudes (satisfaction and perceived usefulness of information) with respect to both computer decision aids. To test these hypotheses we used two

techniques. For the first technique, the correlation between the subject's characteristic and the subject's attitude was determined for both types of computer decision aids. We then examined if there was a statistically significant difference between these two correlations. In order to test this, we used the z-transformation (Richmond, 1964). This analysis requires that each correlation be transformed from r to z,
where z is given by:

$$Z = \frac{1}{2} \log_e \frac{1+r}{1-r}$$

After transforming both correlations, we then must compute Z which is given by:

$$Z = \frac{z_1 - z_2}{\sigma_{z_1 - z_2}}$$

where:

$$\sigma_{z_1 - z_2} = \sqrt{\frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}}$$

and n_1 is the sample size for group 1

n_2 is the sample size for group 2

After performing these calculations Z is then compared with z values for the level of significance for a normal distribution.

In the second technique, the measure of the subject's characteristic (i.e., score for tolerance for ambiguity, etc.) was regressed on the score for the subject's attitude toward the computer decision aids. This was done for both types of decision aids. The purpose was to determine if there was a significant difference between the regression coefficients.

To test if there was a difference in the values for the slope of the regression lines, we compute the following statistic:

$$T = \frac{B_1 - B_2}{S_{B1-B2}}$$

where: B_1 is the least squares estimate of the slope of group 1.

B_2 is the least squares estimate of the slope of group 2.

S_{B1-B2} is the estimate of the standard deviation of the estimated difference between the slopes.

S_{B1-B2} is the square root of the following variance:

$$S^2_{B1-B2} = S^2_p \left\{ \frac{1}{(n_1 - 1) S^2_1} + \frac{1}{(n_2 - 1) S^2_2} \right\}$$

where:

$$S_P^2 = \left\{ \frac{(n_1 - 1) S_{Y1}^2 + (n_2 - 1) S_{Y2}^2}{n_1 + n_2 - 4} \right\}$$

and

S_{y1}^2 is the residual mean square error for the group 1 data.

S_{y2}^2 is the residual mean square error for the group 2 data.

S_1^2 is the variance for the independent variable.

S_2^2 is the variance for the dependent variable.

n_1 is the sample size for group 1.

n_2 is the sample size for group 2.

The computed T value can then be compared to the critical values for a Student's t distribution.

Hypotheses HA15 to HA18 were tested by means of a Chi-square test.

CHAPTER 4.

FINDINGS

In the last chapter, several sets of hypotheses were delineated together with the methods by which they would be tested. The results of those tests are presented in this chapter which is organized so that each of the findings for each group of hypotheses is presented separately. A general summary of the findings is given at the end of the chapter.

4.1 THE IMPACT OF COGNITIVE STYLE

Here we present the findings on how cognitive style impacts on user satisfaction with a system, on the perception of the usefulness of the information generated by each system, and on the user's preference (in terms of actual selection) for each system. Each hypothesis is re-stated and the statistical results are presented.

HA1. Individuals classified as Sensing-oriented will express less satisfaction with the expert system than those classified as Intuitive-oriented.

Two measures of user satisfaction (Sander's Questionnaire and Aldag and Power's Attitude-toward-Decision-Aid Questionnaire) were used. The t-test results are presented only for the Sander's Questionnaire in this chapter. The results for the Aldag and Power's Attitude-toward-Decision-Aid Questionnaire are presented in Appendix F. This is done because this second questionnaire's results for almost all tests are identical to the results obtained with the Sander's Questionnaire.

TABLE 4.1

T-TEST BETWEEN SENSING AND INTUITIVE GROUPS' SATISFACTION WITH THE EXPERT SYSTEM AS MEASURED BY SANDER'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
SENSING	36	51.86	15.85	2.65		
INTUITIVE	30	66.67	11.53	2.10	-4.26	.001

Table 4.1 shows that the mean score on the Sander's Questionnaire, with respect to the expert system, for the Intuitive group (66.67) is significantly greater ($p < .001$) than the Sensing group (51.86). For the Sander's Questionnaire the greater the score the greater the measured satisfaction. Hence, HA1 is corroborated.

HA2. Individuals classified as Sensing-oriented will express greater satisfaction with the decision support system than those classified as Intuitive-oriented.

The t-test results for the Sander's Questionnaire are presented in Table 4.2.

TABLE 4.2.

T-TEST BETWEEN SENSING AND INTUITIVE GROUPS' SATISFACTION WITH THE DECISION SUPPORT SYSTEMS AS MEASURED BY SANDER'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
SENSING	36	56.64	12.27	2.04		
INTUITIVE	30	50.03	12.93	2.36	2.13	.037

Table 4.2 shows that the mean score on the Sander's Questionnaire, with respect to the decision support system, for the Sensing group (56.64) is significantly greater ($p < .05$) than the mean for the Intuitive group (50.03). Hence, HA2 is corroborated.

HA3. Individuals classified as Feeling-oriented will express greater satisfaction with the expert system than those classified as Thinking-oriented.

In Table 4.3 we present the t-test results for the Sander's Questionnaire.

TABLE 4.3

T-TEST BETWEEN THINKING AND FEELING GROUPS' SATISFACTION WITH THE EXPERT SYSTEMS AS MEASURED BY SANDER'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
THINKING	49	54.47	15.24	2.18		
FEELING	17	70.47	10.83	2.63	-3.98	.001

Table 4.3 shows that the mean score for the Sander's Questionnaire, with respect to the expert system, for the Feeling-oriented group (70.47) is significantly greater ($p < .001$) than the mean for the Thinking-oriented group (54.47). <u>HA3 is, therefore, corroborated</u>.

HA4. Individuals classified as Feeling-oriented will express less satisfaction with the decision support system than those classified as Thinking-oriented.

In Table 4.4 we present the t-test results for the Sander's Questionnaire.

TABLE 4.4

T-TEST BETWEEN FEELING AND THINKING GROUPS' SATISFACTION WITH THE DECISION SUPPORT SYSTEMS AS MEASURED BY SANDER'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
THINKING	49	54.96	12.74	1.82		
FEELING	17	49.82	13.01	3.15	1.42	.159

Table 4.4 shows that the mean score for the Sander's Questionnaire, with respect to the decision support system, for the Feeling-oriented group (49.82) is not significantly smaller than the mean score for the Thinking-oriented group (54.96). Therefore, HA4 is rejected.

HA5. Those classified as Sensing/Thinking-oriented will express less satisfaction with the expert system than those classified as Feeling/Intuitive oriented.

In Table 4.5 we present the t-test results for the Sander's Questionnaire.

TABLE 4.5

T-TEST BETWEEN SENSING/THINKING (S/T) AND FEELING/INTUITIVE (F/I) GROUPS' SATISFACTION WITH THE EXPERT SYSTEMS AS MEASURED BY SANDER'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
S/T	31	48.03	13.26	2.38		
F/I	12	68.33	11.35	3.28	-4.67	.001

Table 4.5 shows that the mean score on the Sander's Questionnaire, with respect to the expert systems, for the Sensing/Thinking group (48.03) is significantly smaller ($p < .001$) than the mean score for the Feeling/Intuitive group (68.33). Hence, HA5 is supported.

HA6. Those classified as Sensing/Thinking-oriented (S/T) will express greater satisfaction with the decision support system than those classified as Feeling/Intuitive-oriented (F/I).

In Table 4.6 we present the t-test results for the Sander's Questionnaire.

TABLE 4.6

T-TEST BETWEEN SENSING/THINKING (S/T) AND FEELING/INTUITIVE (F/I) GROUPS' SATISFACTION WITH THE DECISION SUPPORT SYSTEMS AS MEASURED BY SANDER'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
S/T	31	57.29	11.02	1.98		
F/I	12	48.67	10.09	2.91	2.35	.023

Table 4.6 shows that the mean score on the Sander's Questionnaire, with respect to the decision support system, for the Sensing/Thinking group (57.29) was significantly greater ($p < .05$) than the mean score for the Feeling/Intuitive group (48.67). Hence, HA6 is supported.

HA7. Those classified as Sensing-oriented will have a greater level of perceived usefulness of the information generated by the decision support system than those classified as Intuitive-oriented.

Two instruments - Larcker and Lessig's Questionnaire and Franz and Robey's Questionnaire - were used to measure the perceived usefulness of information. Again because of the similarity in the results achieved with both questionnaires only the results for Larcker and Lessig's Questionnaire are presented in this Chapter. The results for Franz and Robey's Questionnaire are given in Appendix F., pages 202-207.

In Table 4.7 we present the t-test results for Larcker and Lessig's Questionnaire.

TABLE 4.7

T-TEST BETWEEN SENSING AND INTUITIVE GROUPS' PERCEIVED USEFULNESS OF THE DECISION SUPPORT SYSTEMS AS MEASURED BY LARCKER AND LESSIG'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
SENSING	36	26.31	4.33	.72		
INTUITIVE	30	22.87	4.81	.88	3.05	.003

Table 4.7 shows that the mean score on the Larcker and Lessig Questionnaire, with respect to the decision support system, for the Sensing group (26.31) is significantly greater ($p < .01$) than the mean for the Intuitive group (22.87). The greater the score on the Larcker and Lessig Questionnaire the greater the measured usefulness of the information. Therefore, HA7 is supported.

HA8. Those classified as Sensing-oriented will perceive less usefulness of the information generated by the expert system than those classified as Intuitive-oriented.

In Table 4.8 we present the t-test results for the

Larcker and Lessig Questionnaire.

TABLE 4.8

T-TEST BETWEEN SENSING AND INTUITIVE GROUPS' PERCEIVED USEFULNESS OF THE EXPERT SYSTEMS AS MEASURED BY LARCKER AND LESSIG'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
SENSING	36	23.22	6.14	1.02		
INTUITIVE	30	28.57	5.01	.91	-3.82	.001

Table 4.8 shows that the mean score on the Larcker and Lessig's Questionnaire, with respect to the expert system, for the Sensing group (23.22) is significantly smaller ($p < .001$) than the mean for the Intuitive group (28.57). Therefore, HA8 is corroborated.

HA9. Those classified as Feeling-oriented will have a greater level of perceived usefulness of information generated by the expert system than those classified as Thinking-oriented.

In Table 4.9 we present the t-test results for the Larcker and Lessig Questionnaire.

TABLE 4.9

T-TEST BETWEEN THINKING AND FEELING GROUPS' PERCEIVED USEFULNESS OF EXPERT SYSTEMS AS MEASURED BY LARCKER AND LESSIG'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
THINKING	49	24.08	6.33	.90		
FEELING	17	30.18	2.79	.68	-3.83	.001

Table 4.9 shows that the mean score on the Larcker and Lessig Questionnaire, with respect to the expert system, for the Feeling-oriented group (30.18) is significantly greater ($p < .001$) than the mean score for the Thinking-oriented group (24.08). <u>Hence, HA9 is supported</u>.

HA10. Those classified as Feeling-oriented will perceive less usefulness of the information generated by the decision support system than those classified as Thinking-oriented.

In Table 4.10 we present the t-test results for the Larcker and Lessig Questionnaire.

TABLE 4.10

T-TEST BETWEEN FEELING AND THINKING GROUPS' PERCEIVED USEFULNESS OF DECISION SUPPORT SYSTEMS AS MEASURED BY LARCKER AND LESSIG'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
THINKING	49	25.27	4.89	.70		
FEELING	17	23.24	4.48	1.09	1.51	.137

Table 4.10 shows that the mean score on the Larcker and Lessig Questionnaire, with respect to the decision support system, for the Feeling-oriented group (23.24) is not significantly smaller ($p > .1$) than the mean score for Thinking-oriented group (25.27). Therefore, HA10 is rejected.

HA11. Those classified as Sensing/Thinking-oriented (S/T) will have a greater level of perceived usefulness of the information generated by the decision support system than those classified as Feeling/Intuitive-oriented (F/I).

In Table 4.11 we present the t-test results for the Larcker and Lessig Questionnaire.

TABLE 4.11

T-TEST BETWEEN SENSING/THINKING (S/T) AND FEELING/INTUITIVE (F/I) GROUPS' PERCEIVED USEFULNESS OF DECISION SUPPORT SYSTEMS AS MEASURED BY LARCKER AND LESSIG'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
S/T	31	26.42	4.32	.78		
F/I	12	22.25	4.14	1.19	2.87	.006

Table 4.11 shows that the mean score on the Larcker and Lessig Questionnaire, with respect to the decision support system, for the Sensing/Thinking group (26.42) is significantly greater ($p < .01$) than the mean score for the Feeling/Intuitive group (22.25). Therefore, HA11 is

supported.

HA12. Those classified as Sensing/Thinking-oriented will perceive less usefulness of the information generated by the expert system than those classified as Feeling/Intuitive-oriented (F/I).

In Table 4.12 we present the t-test results for the Larcker and Lessig Questionnaire.

TABLE 4.12

T-TEST BETWEEN SENSING/THINKING (S/T) AND FEELING/INTUITIVE (F/I) GROUPS' PERCEIVED USEFULNESS OF EXPERT SYSTEM AS MEASURED BY LARCKER AND LESSIG'S QUESTIONNAIRE

	NUMBER OF CASES	MEAN	STANDARD DEVIATION	STANDARD ERROR	t Value	2-Tail Prob.
S/T	31	22.03	5.75	1.03		
F/I	12	30.00	3.16	.91	-4.52	.001

Table 4.12 shows that the mean score on the Larcker and Lessig Questionnaire, with respect to the expert systems, for the Sensing/Thinking group (22.03) is significantly smaller than the mean score for the Feeling/Intuitive group (30.0). HA12 is, therefore, corroborated.

4.1.1 SUMMARY OF COGNITIVE STYLE FINDINGS

It may be useful at this point to provide (in Table 4.13) a summary of the results for the first set of hypotheses.

TABLE 4.13

SUMMARY OF FIRST SET OF HYPOTHESES

HYPOTHESIS	VARIABLE	SYSTEM	GROUPS	RESULTS
HA1	SATISFACTION	EXPERT	SENSING < INTUITIVE	s
HA2	SATISFACTION	DSS	SENSING > INUITIVE	s
HA3	SATISFACTION	EXPERT	THINKING < FEELING	s
HA4	SATISFACTION	DSS	THINKING > FEELING	ns
HA5	SATISFACTION	EXPERT	(S/T)* < (F/I)**	s
HA6	SATISFACTION	DSS	(S/T) > (F/I)	s
HA7	PERCEIVED USEFULNESS	DSS	SENSING > INTUITIVE	s
HA8	PERCEIVED USEFULNESS	EXPERT	SENSING < INTUITIVE	s
HA9	PERCEIVED USEFULNESS	EXPERT	THINKING < FEELING	s
HA10	PERCEIVED USEFULNESS	DSS	THINKING > FEELING	ns
HA11	PERCEIVED USEFULNESS	DSS	(S/T) > (F/I)	s
HA12	PERCEIVED USEFULNESS	EXPERT	(S/T) < (F/I)	s

* Sensing/Thinking ** Feeling/Intuitive

s Signifies that hypothesis was supported
ns Signifies that hypothesis was not supported

A summary of the preceding results and the results for the Aldag and Power Questionnaire and the Franz and Robey Questionnaire is given in Appendix F on pages 202-207.

It should be noticed that the results for the hypotheses associated with satisfaction (HA1 to HA6) are identical with the results for the hypotheses associated with perceived usefulness (HA7 to HA12). This might indicate that the construct of perceived usefulness of information is similar to the construct of satisfaction. The author examined the correlations among the four instruments - Aldag and Power's Attitude-toward-Decision-Aid, Sander's Questionnaire, Larcker and Lessig's Questionnaire, and Robey's Questionnaire. All four were statistically significantly correlated. This means that we should be very cautious in viewing satisfaction and perceived usefulness of information as distinct constructs. The data that was required to compute the z-transformation and the T statistic, to test hypotheses HA13, HA14, and HB1 to HB8, is presented in Table F.2 of Appendix F.

For Hypotheses HA13, HA14, HB1, HB2, HB3, HB4, HB5, HB6, HB7, and HB8 the results for both pairs of questionnaires will be presented.

HA13. **The greater the user's Conceptual orientation the more likely the user will be more satisfied with the decision support system than with the expert system.**

In Table 4.14 we present the values for the z-transformation and the T statistic.

TABLE 4.14

Z-TRANSFORMATION SCORE AND T STATISTIC FOR COMPARISON OF SATISFACTION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM MODERATED BY USER'S CONCEPTUAL ORIENTATION

INSTRUMENT	z-transformation	T statistic
ALDAG AND POWER	.406	.168
SANDER	-.318	-.115

* p < .05; ** p < .01; *** p < .001

Both the z-transformation and the T-statistic's values are compared to critical values for statistical significance for the normal distribution and the Student's t distribution. For a one-tail test at a 5% level of significance the critical value for the normal distribution is 1.65. For a one-tail test at a 5% level of significance and 130 degrees of freedom the critical value is 1.66. The results, on both tests, for both instruments were therefore not statistically significant. Hence, HA13 is rejected.

HA14. The greater the user's Behavioral orientation the more likely the user will be more satisfied with the expert system than with the decision support system.

In Table 4.15 the z-transformation and the T statistic are presented.

TABLE 4.15

Z-TRANSFORMATION SCORE AND T STATISTIC FOR COMPARISON OF SATISFACTION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM MODERATED BY USER'S BEHAVIORAL ORIENTATION

INSTRUMENT	z-transformation	T statistic
ALDAG AND POWER	-1.48	-.461
SANDER	-1.08	-.332

* P < .05;   ** P < .01;   *** P < .001

None of the results for the test of Hypothesis HA14 were statistically significant. Therefore, HA14 is rejected.

Hypotheses HA15 to HA18 focus on the question of use of competing computer decision aids by individual's different cognitive styles. The research design of this experiment allowed each individual to choose the decision support system or the expert system for each period of the game's play. This option could lead to four possible outcomes:

OPTION	PERIOD 7	PERIOD 8
1	DECISION SUPPORT	DECISION SUPPORT
2	DECISION SUPPORT	EXPERT SYSTEM
3	EXPERT SYSTEM	DECISION SUPPORT
4	EXPERT SYSTEM	EXPERT SYSTEM

Options 1 and 4 represent the greatest commitment to one particular computer decision aid.

HA15. Given the opportunity to use either the expert system or the decision support system those classified as Sensing-oriented will tend to select the decision support system.

HA16. Given the opportunity to use either the expert system or the decision support system those classified as Intuitive-oriented will tend to select the expert system.

Table 4.16 presents a crosstabulation of the four options with the Sensing and Intuitive groups.

TABLE 4.16

CROSSTABULATION RESULTS - OPTIONS 1 TO 4 FOR SENSING AND INTUITIVE GROUPS

(FREQUENCIES)

OPTION	1	2	3	4
SENSING	(20)	(14)	(1)	(1)
INTUITIVE	(1)	(4)	(10)	(15)

CHI-SQUARE	D.F.	SIGNIFICANCE
42.16	3	.0001

The results in Table 4.16 show that there is a significant ($p < .0001$) difference in how the Sensing and Intuitive groups opted to use the computer decision aids. It should be noted that the use of the chi-square distribution requires that certain conditions must be met. One of these conditions is that the expected frequencies, in each cell, should be at least 5. This condition was met in Table 4.16.

Options 2 and 3 represent cases where the user employed both systems - this implies a lack of conviction that either system is clearly superior. Options 1 and 4 represent those cases where individuals employed the same computer system in both periods. In Table 4.17 we present a crosstabulation of options 1 and 4 with the Sensing and Intuitive group.

TABLE 4.17

CROSSTABULATION RESULTS FOR OPTION 1 AND 4 FOR SENSING AND INTUITIVE GROUPS

(FREQUENCIES)

OPTION	1	4
SENSING	(20)	(1)
INTUITIVE	(1)	(15)

CHI-SQUARE	D.F.	SIGNIFICANCE
25.79	1	.0001

Table 4.17 shows that there is a significant ($p < .001$) difference in the way these two groups opted to use the computer decision aids. Hence, HA15 and HA16 are supported. Again, the expected frequencies for the four cells were greater than 5.

HA17. Given the opportunity to use either the expert system or the decision support system those classified as Thinking-oriented will tend to select the decision support system.

HA18. Given the opportunity to use either the expert system or the decision support system those classified as Feeling-oriented will tend to select the expert system.

In Table 4.18 we present a crosstabulation for the four options and the Thinking-oriented and Feeling-oriented groups.

TABLE 4.18

CROSSTABULATION RESULTS FOR OPTIONS 1 TO 4 FOR THINKING AND FEELING GROUPS

(FREQUENCIES)

OPTION	1	2	3	4
THINKING	(20)	(16)	(7)	(6)
FEELING	(1)	(2)	(4)	(10)

CHI-SQUARE	D.F.	SIGNIFICANCE
18.80	3	.0003

In Table 4.18, one of the cells had expected frequencies that were less than 5. There have been studies (Everitt, 1977) that indicate that this value is too stringent. However, Richmond (1964) indicated that in a 2 by 4 table, one cell with an expected frequency less than 5 does not destroy the usefulness of the test. In this case we see that there is a significant ($p < .001$) difference in the way the two groups opted to use the decision tools. Table 4.19 presents the cross-tabulation for options 1 and 4 and the Thinking-oriented and Feeling-oriented groups.

Table 4.19 shows that there was a significant ($p < .001$) difference in the way the two groups opted for use of the computer decision aids. One cell had an expected value less than 5. Since this was a 2 by 2 table, Yates correction

TABLE 4.19

CROSSTABULATION RESULTS FOR OPTIONS 1 AND 4 FOR THINKING AND FEELING GROUPS

(FREQUENCIES)

OPTION	1	4
THINKING	(20)	(6)
FEELING	(1)	(10)

CHI-SQUARE	D.F.	SIGNIFICANCE
11.86	1	.0006

for continuity was employed yielding a chi-square of 11.86. Hence, HA17 and HA18 are supported. A summary of the results for Hypotheses HA13 to HA18 is presented in Table 4.20.

4.2 FINDINGS WITH RESPECT TO PERSONAL CHARCTERISTICS

The second set of findings focuses on the influence of the role of personal characteristics on the user's satisfaction with the system and the user's perception of the usefulness of the information generated by the system.

TABLE 4.20

SUMMARY OF RESULTS FOR HYPOTHESES HA13 TO HA18

HYPOTHESES	GROUP	VARIABLE	SYSTEM PREFERENCE	RESULTS
HA13	CONCEPTUAL ORIENTATION	SATISFACTION	DSS>EXPERT	ns
HA14	BEHAVIORAL ORIENTATION	SATISFACTION	EXPERT>DSS	ns
HA15	SENSING ORIENTATION	USE	DSS>EXPERT	s
HA16	INTUITIVE ORIENTATION	USE	EXPERT>DSS	s
HA17	THINKING ORIENTATION	USE	DSS>EXPERT	s
HA18	FEELING ORIENTATION	USE	EXPERT>DSS	s

s Signifies that hypothesis was supported.
ns Signifies that hypothesis was not supported.

4.2.1 EXPERTISE HYPOTHESES

HB1. The greater the user's familiarity with mathematical modeling (management science) the more likely the user will be more satisfied with the decision support system than with the expert system.

In Table 4.21 we present the results of the z-transformation and the T statistic.

The results show that there was a significant ($p<.05$) difference between the regression coefficients of the two

TABLE 4.21

Z-TRANSFORMATION AND T STATISTIC FOR COMPARISON OF SATISFACTION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM AS MODERATED BY USER'S FAMILIARITY WITH MATHEMATICAL MODELING

INSTRUMENT	z-transformation	T statistic
ALDAG AND POWER	1.29	1.95*
SANDER	1.67*	1.74*

* p < .05; ** p < .01; *** p < .001

instruments. The difference in the correlation coefficients was significant (p<.05) for one of the two instruments. The hypothesis HB1 is therefore partially corroborated.

HB2. The greater the user's familiarity with mathematical modeling (management science) the more likely the user will have a perception that the usefulness of information provided by the decision support system is greater than that of the expert system.

In Table 4.22 we present the values for the z-transformation and the T statistic.

The results were significant for the Franz and Robey instrument at the 1% level. The results for the Larker and Lessig instrument were not significant. Therefore, hypothesis HB2 was partially supported.

TABLE 4.22

Z-TRANSFORMATION AND T STATISTIC FOR COMPARISON OF PERCEIVED USEFULNESS OF INFORMATION PROVIDED BY EXPERT SYSTEM AND DECISION SUPPORT SYSTEM AS MODERATED BY USER'S FAMILIARITY WITH MATHEMATICAL MODELING (MANAGEMENT SCIENCE) CONCEPTS

INSTRUMENT	z-transformation	T statistic
LARKER AND LESSIG	.88	1.05
FRANZ AND ROBEY	2.69**	2.56**

* $p < .05$; ** $p < .01$; *** $p < .001$

HB3. The greater the user's familiarity with production/operations management concepts the more likely the user will be more satisfied with the decision support system than with the expert system.

In Table 4.23 we present the values for the z-transformation and the T statistic.

TABLE 4.23

Z-TRANSFORMATION SCORE AND T STATISTIC FOR COMPARISON OF SATISFACTION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM MODERATED BY USER'S FAMILIARITY WITH PRODUCTION/OPERATIONS MANAGEMENT CONCEPTS

INSTRUMENT	z-transformation	T statistic
ALDAG AND POWER	1.95*	2.98**
SANDER	2.81**	2.90**

* $p < .05$; ** $p < .01$; *** $p < .001$

Table 4.23 shows that there were significant differences for both the regression coefficients and the correlation coefficients. Hence, HB3 is supported.

HB4. The greater the user's familiarity with production/operations management concepts the more likely the user will have a perception that the usefulness of information provided by the decision support system is greater than that of the expert system.

In Table 4.24 we present the results for the z-transformation and the T statistic.

TABLE 4.24

Z-TRANSFORMATION AND T STATISTIC FOR COMPARISON OF PERCEIVED USEFULNESS OF INFORMATION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM AS MODERATED BY USER'S FAMILIARITY WITH PRODUCTION/ OPERATION MANAGEMENT CONCEPTS

INSTRUMENT	z-transformation	T statistic
LARKER AND LESSIG	2.84**	2.98**
FRANZ AND ROBEY	2.37*	2.40*

* $p < .05$; ** $p < .01$; *** $p < .001$

For both instruments the differences in the regression coefficients and the correlation coefficients were significant. Hence, HB4 is supported.

4.2.2 TOLERANCE FOR AMBIGUITY HYPOTHESES

HB5. The lower the user's tolerance for ambiguity the more likely the user will be more satisfied with the decision support system than with the expert system.

In Table 4.25 we present the results for the z-transformation and the T statistic.

TABLE 4.25

Z-TRANSFORMATION AND T STATISTIC FOR COMPARISON OF SATISFACTION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM AS MODERATED BY USER'S TOLERANCE FOR AMBIGUITY

INSTRUMENT	z-transformation	T statistic
ALDAG AND POWER	.388	.371
SANDER	.254	.140

* $p < .05$; ** $p < .01$; *** $p < .001$

None of the tests for differences in the correlation coefficients or regression slopes yielded significant results. Hence, HB5 was not supported.

HB6. The lower the user's tolerance for ambiguity the more likely the user will perceive that the usefulness of the information generated by the decision support system is greater than that generated by the expert system.

In Table 4.26 we present the results for the z-transformation and the T statistic.

None of the tests for differences in the correlation coefficients or the regression slopes yielded significant results. Hence, HB6 was not supported.

TABLE 4.26

Z-TRANSFORMATION AND T STATISTIC
FOR COMPARISON OF PERCEIVED USEFULNESS OF
INFORMATION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT
SYSTEM AS MODERATED BY USER'S TOLERANCE FOR AMBIGUITY

INSTRUMENT	z-transformation	T statistic
LARKER AND LESSIG	1.16	.95
FRANZ AND ROBEY	.95	.13

* $p < .05$; ** $p < .01$; *** $p < .001$

4.2.3 LOCUS OF CONTROL HYPOTHESES

HB7. The greater the locus of control of individuals the more they will express satisfaction with the decision support system than with the expert system.

In Table 4.27 we present the results for the z-transformation and the T statistic.

TABLE 4.27

Z-TRANSFORMATION AND T STATISTIC
FOR COMPARISON OF SATISFACTION BETWEEN
EXPERT SYSTEM AND DECISION SUPPORT SYSTEM
AS MODERATED BY USER'S LOCUS OF CONTROL

INSTRUMENT	z-transformation	T statistic
ALDAG AND POWER	1.37	1.97^{*}
SANDER	1.19	1.25

* $p < .05$; ** $p < .01$; *** $p < .001$

The difference in the regression slopes was significant at the 5% level for the results on the Aldag and Power's Questionnaire. None of the other tests proved to be significant. Therefore, HB7 was weakly supported.

HB8. The greater the locus of control of individuals the more they will perceive the usefulness of the information generated by the decision support system as greater than that of the expert system.

In Table 4.28 we present the results for the z-transformation and the T statistic.

TABLE 4.28

Z-TRANSFORMATION AND T STATISTIC FOR COMPARISON OF PERCEIVED USEFULNESS OF INFORMATION BETWEEN EXPERT SYSTEM AND DECISION SUPPORT SYSTEM AS MODERATED BY USER'S LOCUS OF CONTROL

INSTRUMENT	z-transformation	T statistic
LARKER AND LESSIG	1.06	1.22
FRANZ AND ROBEY	1.54	1.56

* $p < .05$; ** $p < .01$; *** $p < .001$

None of the tests for differences in the correlation coefficients or the regression slopes yielded significant results. Hence, HB8 was not supported.

4.2.4 SUMMARY OF THE SECOND SET OF HYPOTHESES

Again, it is useful to summarize the findings of the second set of hypotheses in Table 4.29.

TABLE 4.29

RESULTS FOR HYPOTHESES HB1 TO HB8

HYPOTHESES	VARIABLES	SYSTEM PREFERENCE	RESULTS
HB1	SATISFACTION AND MATHEMATICAL MODELS	DSS > EXPERT	ps
HB2	PERCEIVED USEFULNESS AND MATHEMATICAL MODELS	DSS > EXPERT	ps
HB3	SATISFACTION AND PRODUCTION/ OPERATIONS CONCEPTS	DSS > EXPERT	s
HB4	PERCEIVED USEFULNESS AND PRODUCTION/ OPERATIONS CONCEPTS	DSS > EXPERT	ps
HB5	SATISFACTION AND TOLERANCE FOR AMBIGUITY	DSS > EXPERT	n

ps Signifies that hypothesis was partially supported.
s Signifies that hypothesis was supported.
ns Signifies that hypothesis needed to be redefined.

TABLE 4.29 (CONTINUED)

RESULTS FOR HYPOTHESES HB1 TO HB2

HYPOTHESES	VARIABLES	SYSTEM PREFERENCE	RESULTS
HB6	PERCEIVED USEFULNESS AND TOLERANCE FOR AMBIGUITY	DSS > EXPERT	ns
HB7	SATISFACTION AND LOCUS OF CONTROL	DSS > EXPERT	ps
HB8	PERCEIVED USEFULNESS AND LOCUS OF CONTROL	DSS > EXPERT	ns

ps Signifies that hypothesis was partially supported.
s Signifies that hypothesis was supported.
ns Signifies that hypothesis was needed to be redefined.

CHAPTER 5.

DISCUSSION

The aim of the research was to describe, analyze, and propose a new theory of interaction between competing computer technologies and their users. It wished to answer several research questions that were centered on issues such as: what factors affect an individual's satisfaction with different computer decision aids; what factors affect an individual's perception of the usefulness of information generated by different computer decision aids; and what factors affect an individual's decision to use a particular computer decision aid?

Prior research had argued that individuals' cognitive style, expertise, locus of control, and tolerance for ambiguity had a direct impact on their satisfaction with, and use of, management information systems and decision support systems. In the past, models and theories provided no explanation of what factors would affect a user's preference for a particular type of computer decision aid. Additionally, no research had been conducted on what factors relate to the use of expert systems.

This research found very strong evidence that the user's cognitive style has a major impact on how the user "responds" to different computer decision aids. Of sixteen hypotheses related to the user's cognitive style, the research supported fourteen. These findings are summarized in Tables 4.13, 4.20 and 4.29 and are as follows:

(1.) Those classified as Sensing expressed less satisfaction with and perceived less usefulness of information generated by the expert system than those classified as Intuitive.

(2.) Those classified as Sensing expressed greater satisfaction with and perceived greater usefulness of information generated by the decision support system than those classified as Intuitive. Further, those classified as Sensing, given a choice, clearly opted to use the decision support system rather than the expert system.

(3.) Those classified as Feeling-oriented expressed greater satisfaction and perceived greater usefulness of information with the expert system than those classified as Thinking-oriented.

(4.) Those classified as Feeling-oriented, given a choice, clearly opted to use the expert system rather than the decision support system.

(5.) Those classified as Sensing-Thinking expressed less satisfaction and perceived less usefulness of information generated by the expert system than those classified as Feeling-Intuitive.

(6.) Those classified as Sensing-Thinking expressed greater satisfaction and perceived greater usefulness of information generated by the decision support system than those classified as Feeling-Intuitive.

(7.) Those classified as Intuitive, when given a choice, opted to use the expert system rather than the decision support system.

(8.) Those classified as Thinking, when given a choice, opted to use the decision support system rather than the expert system.

The research did not find support for the propositions that Feeling-oriented individuals will express less satisfaction with and perceive less usefulness of information generated by the decision support system than those classified as Thinking-oriented. A possible explanation for this finding might be that Feeling-oriented individuals are emotionally driven and therefore their response to either system may be more a function of their current emotional state rather than a definitive preference. Nor did the findings support the propositions that an individual's decision style (i.e., conceptual vs. behavioral orientation) would affect satisfaction with or perception of information usefulness generated by one of the two computer decision aids. It should be remembered that decision style, unlike cognitive style, does not place an individual in a definite category. It measures an individual's propensity for making decisions with respect to a particular style - conceptual and behavioral. An individual receives a score for both categories and therefore cannot be singularly classified as being either conceptual or behavioral. The lack of findings with respect to decision style might be a result of the fact that the mean scores on the two measures for the sample were nearly identical. This means that for the sample there was no clear preference and distinction in terms of the decision style of the users.

This failure to find that either the conceptual or behavioral style had a significant impact would indicate that the use of decision style as variable, in studies such as this one, should re-examined or eliminated.

Another major question in this dissertation was to see if an individual's "expertise" in the decision-making domain had an impact on user perception of the usefulness of information generated by, and satisfaction with, a particular computer decision aid. Expertise was related to knowledge of management science techniques and knowledge of basic concepts of production/operations management. The findings showed a very strong relationship between knowledge about the production/operations management environment and the level of satisfaction with and the perception of information usefulness generated by a particular system. It was found that the greater one's knowledge of the decision domain (production/operations management) the more likely it is that the user would have a perception that the information generated by the decision support system was more useful than the information generated by the expert system. A similar relationship was found for knowledge in the field of management science; however, the strength of these findings were less significant than those for "expertise" in production/operations management. These findings are presented in Table 4.29.

Recent literature supports these findings. The role of the user's domain expertise has been identified as a important element in expert system design by several authors (Schneider, Wexelblat, and Jende,1979; Schneiderman, 1987; and Wexelblat 1989). These authors treated the importance of expertise as a given; they provided no theoretical models or empirical evidence in support. Wexelblat (1989) has commented that those who develop expert systems must take into consideration the spectrum of users' expertise. He also addressed the issue of how experts might respond to the advice provided by an expert system.

> *"... another aspect is the 'who's in charge around here' phenomenon, the touchy balance between task automation and the user's autonomy. A system that takes charge and controls the interaction might be ideal for one user in one domain but totally unacceptable to a user with another level of expertise"* (Wexelblat, 1989, pg.70).

His comments have particular significance in light of the finding in this study that those with "expertise" preferred the decision support system to the expert system.

In addition to "expertise", the research investigated whether certain psychological characteristics (tolerance for ambiguity and locus of control) had an appreciable impact on the user's attitudes toward competing computer decision aids. The findings did not support any of the hypotheses. In reviewing these negative findings, one could argue that since the locus of control variable has been primarily employed in management information systems and decision support studies which examined the impact of user involvement in the development of such systems, the experimental design used in this research provided no opportunity for the users to be involved in the development of either the expert system or the decision support system. Both systems were presented to the users in a complete form. In a real world environment, the user's role in the creation and/or modification of either a decision support system or an expert system would be of much greater importance than in this research design. This notion - that the user has a critical role in the creation and implementation of a system - has received wide support in the literature (Boland, 1978; Ginzberg, 1978; Keen and Scott-Morton, 1978; Ives and Olson, 1984; Schultz and Slevin, 1975; and Urban and Karash, 1971). The lack of support for the hypothesis about the effects of tolerance for ambiguity could be a result of the fact that the decision domain (a production/operations environment) required that several of the expert systems (the labor scheduler and the maintenance advisor) provide fairly explicit numerical results. The users might have seen little difference between the two competing computer decision aids on the basis of ambiguity with respect to the information provided. Again, in real world environments expert systems would often operate in decision domains (i.e., medical diagnostics) where exact and certain results would not be expected.

In reviewing the findings, it appears that a user's cognitive style and his/her knowledge about the given decision domain have significant effects on how that user will respond to either a decision support system or an expert system. Other factors frequently mentioned in the literature of management information systems, such as tolerance for ambiguity and locus of control, do not seem to have an effect on users' attitudes toward a particular computer decision aid.

5.1 THEORETICAL IMPLICATIONS

In order to adequately evaluate the contributions of this study with reference to the theoretical understanding of computer systems it would be useful to draw upon the work of Ives, Hamilton and Davis (1980). This model seems to be the most comprehensive of the five models presented earlier and therefore could be used as a good yardstick relative to the contribution of other models, including this paper's model, to the fields of decision support systems and expert systems. They discussed the essential nature of research in the area of computer information systems and identified broad categories of variables that might be incorporated into a totally comprehensive theoretical formulation. These broad categories (environmental, process, and the nature of the information system) were seen as being the key to a "complete" theoretical understanding of computer information systems. Each broad category was seen as being composed of a list of sub-variables. The environmental category included items such as the organizational environment (which reflects the essential characteristics of the work organization), the user environment (which refers to the relationship between primary and secondary users of the system and the characteristics of the users), and the information system's development environment (which refers, primarily, to who was involved in the development of the system). Their notion of process included variables such as the development process (this refers to the conformance of the system to its initial plan), and use process (which relates not only to productivity of the system but also to the satisfaction of primary users). The category "nature of the information system" was seen as having three constituent elements. The first - content - included both the type of data and decision models. The second - presentation form - was seen as focusing on the type of media and the type of presentation format. The last element - time - examined the time required to generate information and reports. Table 5.1, compares the various theoretical models (including this dissertation's work) with respect to these categories and to their structural characteristics. Table 5.1 covers most of the variables mentioned by Ives, Hamilton and Davis (1980) but not all. "Organizational environment" was excluded because it would be inappropriate to compare this study, on that measure, with the other theoretical models. This study assumed the organizational environment to be a given, in contrast to other models that assume it to be a variable. Likewise, the development process was excluded. In this study both computer decision aids were provided to the subjects; they had no opportunity to have an input into their design and consequently no "process" was feasible. "Timing" was also excluded from Table 5.1. Since users, in this study, were working with interactive programs the element of "timing" issue was insignificant.

Table 5.1 illustrates that the theory presented in this dissertation provides for an explicit identification of independent, dependent and intervening variables and their exact relationship, something not done by all other models. Of the other models, only Lucas' attempts to delineate the relationship amongst the variables. This study's theory provided a clear specification of the hypothesized relationships. It allows for a specific comparison between significantly different types of computer systems, while some other models simply examined different types of media formats. This point cannot be overemphasized. Lucas' model, which has been the starting point of this research and the o ne that is most closely linked in Table 5.1 with this

TABLE 5.1

COMPARISON OF VARIOUS MODEL FORMULATIONS

	GORRY & SCOTT-MORTON	MASON & MITROFF	MOCK	CHERVANY, DICKSON & KOSAR	LUCAS	CADDEN
YEAR	(1971)	(1973)	(1973)	(1971)	(1975)	(1990)
IDENTIFIES INDEPENDENT VARIABLES	YES	YES	YES	YES	YES	YES
INTERVENING VARIABLES	NO	NO	NO	NO	YES	YES
DEPENDENT VARIABLES	YES	NO	YES	YES	YES	YES
SPECIFIES EXACT RELATIONSHIPS AMONGST VARIABLES	NO	NO	NO	NO	YES	YES
VARIABLES INCORPORATED DIFFERENT TYPES OF SYSTEMS	NO	NO	NO	NO	NO	YES
COGNITIVE STYLE	NO	YES	NO	NO	YES	YES
EXPERTISE	NO	NO	NO	NO	NO	YES
LOCUS OF CONTROL	NO	NO	NO	YES	NO	YES
TOLERANCE FOR AMBIGUITY	NO	NO	NO	YES	NO	YES
USER SATISFACTION	YES	NO	YES	YES	YES	YES

TABLE 5.1 (CONTINUED)

COMPARISON OF VARIOUS MODEL FORMULATIONS

YEAR	GORRY & SCOTT-MORTON (1971)	MASON & MITROFF (1973)	MOCK (1973)	CHERVANY, DICKSON & KOSAR (1971)	LUCAS (1975)	CADDEN (1990)
VARIABLE USER PREFERENCE	NO	NO	NO	YES	YES	YES
CONTENT	YES	NO	NO	YES	YES	YES
PRESENTATION	YES	YES	NO	YES	NO	YES

study, fails to consider alternative computer decision aids. This puts Lucas' model as well as the other models at a disadvantage since in current organizational life users are presented with the option of choosing from alternative computer decision tools. This theory is unique in that no other model operationally considers the users' expertise as being a variable. This theory also considers the possible effect of the users' tolerance for ambiguity and locus of control. Again, given the exploratory nature of this study (and its experimental design), certain issues, such as organizational environment and the developmental process, could not be approached or adequately addressed.

Although the theoretical formulation was not supported completely, these findings are important for the development of a model and a theory of the implementation of expert systems. It must be remembered that currently no model or theory of expert system implementation and acceptance has been presented in the literature. This research proposes such a theory. It differes from prior theories of management information system and decision support system implementation (Alavi and Henderson, 1981; Bariff and Lusk, 1977; Benbasat and Taylor, 1978; Dickson, Senn and Chervany, 1977; Driver and Mock, 1975; Lucas, 1973, 1975a; and Mason and Mitroff, 1973) in that these do not touch the issue of user's preference for competing computer decision aids. The findings illustrate that research on expert system implementation must consider the user's cognitive style. This represents a change in the direction of the research about computer information systems. Huber (1983) argues that future research should place less emphasis on the cognitive style construct. However, as this disssertation argues, the "moderate" results associated with cognitive style and information systems found in prior studies might be attributable to the fact that both management information systems and decision support systems are quantitatively oriented in their outputs. Expert systems' output and interaction with the user represent a new style of computer tool that appears to be more appropriate for particular cognitive styles. For the development of a theory of expert system usage, the findings associated with the relationship between the user's familiarity with the decision domain and his or her attitude toward an expert system are both novel and critical. The research provides strong evidence that any theory of how users select alternative computer decision aids will have to incorporate both the issue of cognitive style and the user's "knowledge and expertise" with respect to the particular decision-making domain.

Another important theoretical issue that was highlighted by this research was the similar results for the two constructs - user satisfaction and perceived usefulness of information. Consequently, it seems that these two dimensions are nearly identical and they might be interpreted as one dimension. Larker and Lessig (1980) and Zmud (1978) have both argued that these are clear and distinct constructs. The high degree of congruence in the findings for these two constructs in this study casts doubt on the belief that they are in fact independent constructs. It was unfortunate that the statistical package used in this research could not conduct a complete factor analysis (Norusis, 1986) of the instruments to fully test this question. However, the results of this study might suggest to future researchers that perceived usefulness of information could be used as the single dependent variable. It appears to be more distinctive and a more pragmatic choice than using two separate constructs.

5.2 PRACTICAL IMPLICATIONS

From the practitioner's perspective the findings of this research are of great importance. The role of the user in the developmental phase of a computer system has long been seen in the literature as crucial (Bean, Radnor, Neal, and Tansik, 1975; Cheney and Dickerson, 1982; Ginzberg, 1978; and Harvey, 1970; Taylor and Benbasat, 1980a and 1980b). However, we can anticipate the situation in which an "expert" in a field will be called upon to use an expert system that was created by another "expert". The evidence of this research points to the fact that the less expertise an individual has with respect to a particular decision domain, the more favorable his/her attitude toward an expert system. Again let us remember that the decision support system and the expert system used in this study were provided to the users. **They had no input in their development**. Experts in a particular decision domain develop their own heuristic solutions to problems. Systems created by other "experts" might employ other heuristics and thus produce a conflict in the mind of the user. This situation is very different than what one finds in the decision support system environment. There the user can access management science models. The user faces no substantive conflict with regard to the logic of these standard solution techniques. Ironically, the moral of the findings may be that expert systems may be best suited for use by non-experts if the experts are not directly involved in the system's development process.

From a practical standpoint, it is also necessary to recognize the need to "match" the users' cognitive style with the system availability. The term availability may be used here because, with today's explosive growth in hardware and software capability, it becomes economically feasible to provide multiple systems to users. Expert systems and decision support systems can and should evolve concurrently. This means that cognitive style could be used as a screening device to aid in the selection of individuals to be involved in the development process for respective systems.

5.3 CONCLUSIONS

The findings provided very strong evidence to support the hypotheses that users' attitudes toward both expert systems and decision support systems are heavily affected by their cognitive style and their knowledge of the decision domain.

These are important findings since no research has been done on the differential response of users with respect to these two types of computer decision systems. It calls for a re-evaluation of the role of the cognitive style construct in computer system research (Huber, 1983). Further, it provides a strong basis upon which to build a comprehensive theory of expert system implementation.

This dissertation also points to several future research agendas. In terms of the proposed model, research should be done on refining its constructs and determining the relative importance of each variable. Huber (1983), in his criticism of the application of cognitive style research as applied to management information systems and decision support systems, asked if one would be forced to rely upon multivariate statistical models. Earlier researchers in the field of management information systems recognized that this would be the case. Chervany, Dickson, and Kosar (1971); Gorry and Scott-Morton (1971); Lucas (1975a, 1978a); Mason and Mitroff (1973); and Mock (1973) all called for multivariate models for the understanding of the phenomenon. Several models, Lucas (1978a) in particular, are sufficiently detailed to delineate the causal relationships that may exist amongst the hypothesized variables. In addition to the use of multivariate statistical models, the author advocates the use of covariance structure modeling for future research. This mode of analysis would allow for much greater understanding of the relative "strength" of the specified relationships of variables. Covariant structural modeling also allows for the testing of the accuracy of the entire theoretical formulation. It enables the researcher to make comparisons between competing theoretical formulations and then select the one that best "fits" the data.

It would be extremely useful to conduct a similar experiment in other decision domains, domains that had varying reliance upon analytical techniques. Examples might be in the areas of marketing and finance since these two fields have varying reliance upon quantitative methods. The importance of this type of additional research would be the determination of whether expertise in quantitative areas, as opposed to expertise in knowledge domains (non-quantitative areas), is critical to user preference of competing systems.

Another critical question that should be addressed in future research is the role of incorporating the user into the development process of the expert system. Although the findings in this study indicated that "experts" preferred to use the decision support system, it must be recognized that they were not involved in the expert systems' development process. Had they been involved and had they been able to incorporate their own heuristics into the systems, the results might have been significantly different.

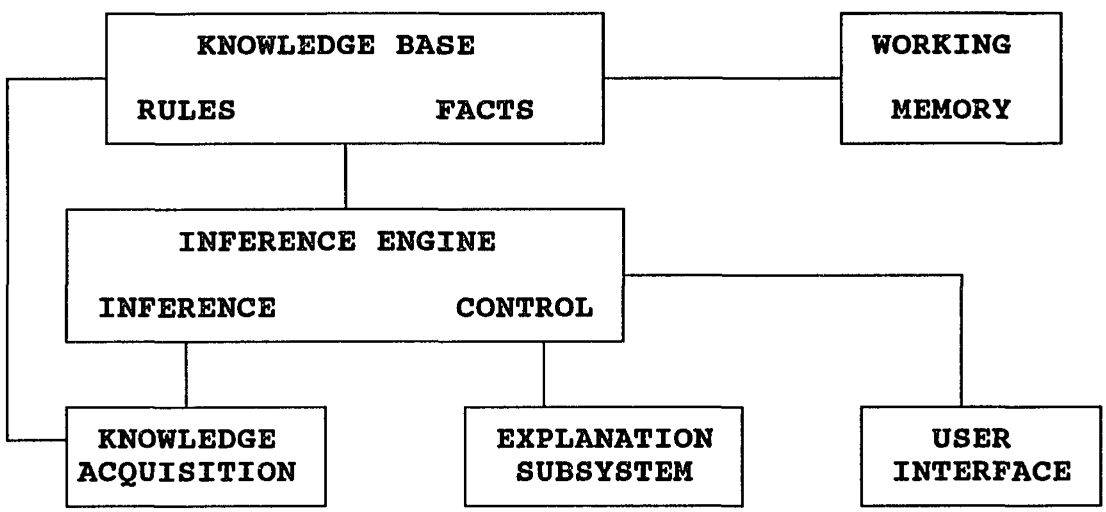
As computer decision aids become even more prevalent and as types of computer decision aids proliferate, we must recognize that unless users are comfortable with these "tools" they will not be used.

APPENDIX A

The basic architecture of an expert system is presented in Figure A.1. This can be divided into two major components. The Knowledge Base and the Working Memory constitute one component.

FIGURE A.1

SCHEMATIC OF AN EXPERT SYSTEM



The second component consists of the Inference Engine, the User Interface, and the various sub-systems.

The Knowledge Base is a system that contains the expert's knowledge in the form of rules and facts. There are a number of ways in which this knowledge can be represented or encoded in the knowledge base. One of the oldest representational methods is semantic networks. In this approach, there are nodes and these nodes are connected by links. Nodes represent objects, which may be conceptual or physical entities, and descriptors, which provide additional information about objects. Links relate objects and descriptors. Another key notion of semantic networks is that of inheritance. This means that one node has the ability to inherit characteristics of another node.

A second method for representing knowledge is the object-attribute-value system. Again, objects may either be physical or conceptual entities. Attributes are general or specific characteristics of objects. If one specifies a particular nature for an attribute under a particular circumstance then that would be defined as a value. This system allows for complex representation of the knowledge base.

The third method is referred to as a frames approach. In this system, objects are allocated to a frame and contained within this frame is all information associated with this object. This system, generally, allows for a richer representation of knowledge than the previously mentioned approaches. The system also permits the linkage of related frames by the two means of declarative and procedural representation. Declarative representation presents facts as simple assertions of truth. Procedural representation presents facts as a series of directions that, when implemented, arrive at the truth.

The last method used in expert systems is a rule-based approach. This is the most commonly used approach in small to medium-sized systems. Rules are used to represent relationships. Rules follow particular formats consisting of a premise and a conclusion. The premise is written in the form of an IF statement, and the conclusion would be presented as the corresponding THEN statement. Rule-based systems can encompass large bodies of knowledge; they can also contain uncertain knowledge. This is done by the inclusion of certainty measures for each rule. As an example, one rule might state that IF the animal is a mammal, THEN it nurses its young--that would be certain; however, another rule might state that IF an animal flies, THEN it is a bird --that might be assigned a certainty value of ninety percent.

Each of these methods of representation has its own strengths and weaknesses. In many systems, these approaches are used in conjunction with each other.

The other major component of an expert system is its inference engine. This mechanism performs several major functions: first, it reviews existing knowledge and facts, and second, it decides how inferences are to be made. Inference engines can use several approaches to the inference process--the most basic being referred to as "modus ponens." This simply means that if we believe a particular rule to be true then we are entitled to believe that the conclusion (of that rule) must also be true. There are several ramifications that come from the use of this inferencing approach. One is that it is conceptually "easy" to understand and to present the logic of the inference to the user of the system. A second ramification of the use of "modus ponens" is that certain valid inferences may not be drawn, thus limiting any expert system that singularly relies on this method.

Experts can sometimes be distinguished by the way they can more effectively deal with decision-making in environments of uncertainty. We have already mentioned that in rule-based systems certainty factors can be incorporated. Inference engines must be able to handle these factors in a consistent and logical manner. Several such approaches exist, such as fuzzy set logic.

Controlling the direction of the inference mechanism is an important question in both the design and operation of an expert system. One must know where to begin with the current knowledge base and what one will do when several alternative lines of reasoning emerge. In most expert systems the direction of the inference mechanism can be classified as either backward or forward chaining.

In backward chaining, one begins with the goal of the system, and then works "backwards" through the knowledge base until one arrives at a solution. For this approach to be effective and efficient the number of possible values for the goal(s) must be well defined and relatively small.

In forward chaining, a system takes the given information and examines the set of rules to determine which are valid. Those that are designated as being valid have their conclusions viewed as being valid. These true conclusions are added to a new list and the rules are reexamined. Dur-ing the inference process the system may "request" additional information from the user. One key factor in determining whether one should employ a backward or forward chaining process is the size of the search space.

One last topic on the mechanisms of expert systems should be discussed, and that concerns search methods. Two prime search mechanisms are used: depth-first and breadth-first. Depth-first searches produce sub-goals at every opportunity looking for greater and greater detail. Breadth-first searches move across all elements of a rule before proceeding for greater detail. Again, there are trade-offs involved in the use of either search mechanisms; however, most "canned" expert system shells tend to use the depth-first mechanism.

EXSYS, the expert system shell used in this dissertation, employed backward chaining. This was done by the author to improve the efficiency, as measured in computer time, of running the programs.

APPENDIX B.

DECIDE-P/OM GAME DESCRIPTION

Although there are many business simulation games currently available, few have had the production function as their central focus. One such specialized game is DECIDE-P/OM (Pray, et. al., 1984). For the purpose of this study, the game is ideal. It is sufficiently complex to warrant the use of a decision support system and can be modeled by an expert system. The game is designed to give the user the experience as an operations manager in the following key areas:

- Productivity
- Quality Control
- Materials Requirement Planning
- Inventory Control
- Forecasting
- Maintenance
- Scheduling
- Capital Investment
- Training

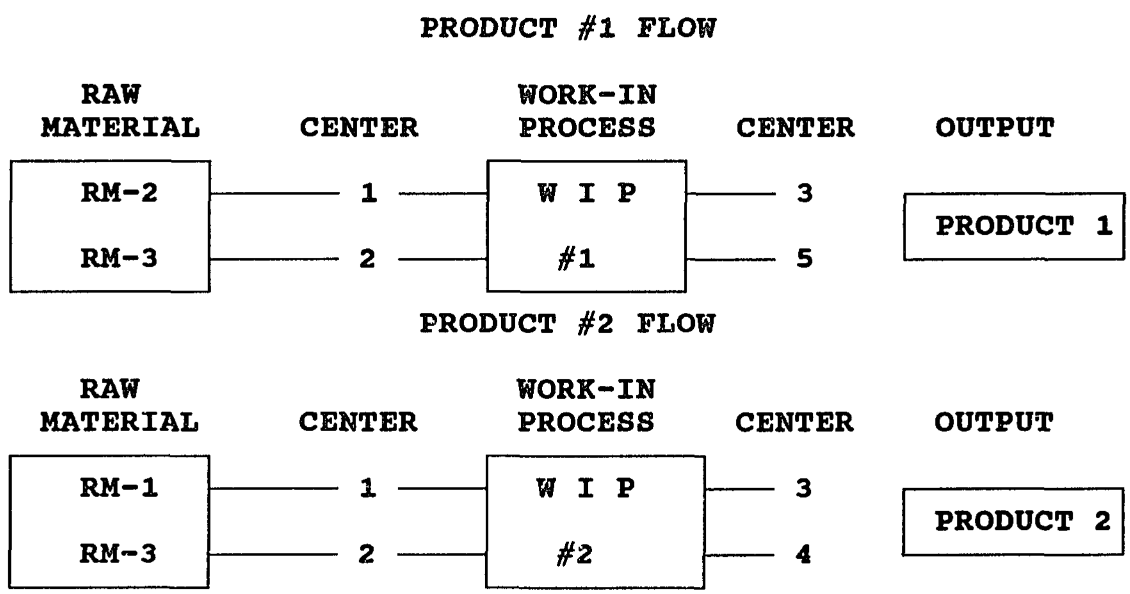
Although the game is comprehensive, the average undergraduate student can "handle" its complexity. As an additional benefit, the game is available on the microcomputer. This greatly facilitates its application in the classroom environment.

The participants are usually divided into small teams. The size of the team is determined by several factors - class size, knowledge of participants, etc.. The study limited team size to one individual. This was done to minimize problems that would arise from having teams composed of individuals with different cognitive styles and backgrounds.

The game assumes a particular product flow. This flow is presented in Figure B.1.

FIGURE B.1

PRODUCT FLOW FOR DECIDE-P/OM GAME



The simulation has two versions. The first version, the one that will be used in this research, assumes that the prices for the two products are given - $25 for Product #1 and $15 for Product #2. The second version requires the participants to make decisions regarding the price of the products. The former version is used, in this work, since it more accurately reflects the reality of the production environment in which pricing is a decision variable for the marketing department.

The simulation has three raw materials. Raw material #2 (RM-2) and raw material #3 (RM-3) are required to produce Product #1. Raw material #1 (RM-1) and raw material #3 (RM-3) are required to produce Product #2. The specific requirements are given in Table B.1.

TABLE B.1

RAW MATERIAL PER UNIT OUTPUT REQUIREMENTS

	PRODUCT #1	PRODUCT #2
RM-1	0	4
RM-2	7	0
RM-3	4	8

The raw materials are ordered in lots of 1,000 units. The costs for raw materials #1, #2, and #3 are $400, $750, and $500 per lot, respectively. The ordering cost for each order is $50,000.

Carrying costs are 10 percent of the inventory value per period. It is assumed that the maximum number of lots that can be ordered of raw material #3, in any period, is 7,000 lots. Raw material #1 and raw material #2 have a history of consistent quality. The historical defect rate of raw material #1 is 1 percent, and the historical defect rate of raw material #2 is 2 percent. Defect rates for the third raw material varies widely - having a range between 1 percent and 30 percent.

There are two labor pools in this simulation - skilled and unskilled labor. Both sets of workers can be assigned to any of the five work centers. Skilled workers are more productive and they are the only workers that can be assigned overtime. The productivity and cost figures for the two classes of workers are given in Table B.2.

TABLE B.2

LABOR REQUIREMENTS FOR WORK-IN-PROCESS AND FINISHED GOODS HOURS PER UNIT

PRODUCT #1 WORK-IN-PROCESS			PRODUCT #1 FINISHED GOODS		
CENTER	UNSKILLED	SKILLED	CENTER	UNSKILLED	SKILLED
1	.2	.1	3	.4	.2
2	.4	.2	5	.4	.25

TABLE B.2 (CONTINUED)

PRODUCT #2 WORK-IN-PROCESS			PRODUCT #2 FINISHED GOODS		
CENTER	UNSKILLED	SKILLED	CENTER	UNSKILLED	SKILLED
1	.4	.25	3	.5	.2
2	.5	.2	4	.25	.1

TABLE B.3

WAGE RATES FOR PERIOD 1

SKILLED WORKER (REGULAR TIME)	$12.00/HOUR
SKILLED WORKER (OVERTIME)	$18.00/HOUR
UNSKILLED WORKER (REGULAR TIME)	$ 7.00/HOUR

One of the key activities of the simulation is the allocation of these types of labor to the five production centers. The number of hours available for scheduling is determined by the number of workers. There is a pool of 575 unskilled workers for all time periods. The pool of skilled workers is variable due to losses attributable to retirement. This loss can be countered by expending funds on a training program. There is a direct relationship between the amount expended upon the training program and the number of unskilled workers that "become" skilled workers. The exact nature of this direct relationship is not specified to the participants.

The simulation incorporates maintenance decisions. Inadequate maintenance will lead to higher levels of downtime; it is assumed that a well-managed work center will have ten percent downtime. Maintenance expenditures must consider labor scheduling at each particular center. Larger expenditures will be deemed necessary as production scheduling approaches capacity.

Production capacity at any of the five work-centers can be increased by capital expenditures. The simulation assumes an annual depreciation of ten percent (or more accurately, it assumes a 2.5 percent depreciation each quarterly period). Capital investments equal to depreciation are required to maintain capacity of a center. Levels of capital investment greater than depreciation will increase capacity in a linear fashion; however, very high levels of capital investment will affect downtime adversely.

If the participant decides to set up a quality control program for raw material #1 he/she must specify the sample size and the acceptance level to "pass" a shipment. There are two costs associated with this sampling plan: sampling cost and the cost of rejecting an acceptable lot. To control the reject rate for Product #1 the participant must specify upper and lower quality control values and specify the number and size of samples to be taken. The maximum number of samples that can be taken is 50 and the maximum sample size is limited to 100. There are costs associated with this quality control program. One cost is associated with sampling; another is related to adjusting the production process when it is out of control. A third cost is that for false adjustments, that is, when the production process was in control but was stopped.

APPENDIX C

The Decision Support System used in this dissertation was built using the STORM system of programs and the LOTUS 1-2-3 package. Users of this system were provided with a diskette that contained data on the past twenty periods' sales, prices, economic indices, prices of a related good, and market indices for both products. This material was in a form that was usable by the regression module in the STORM package. The disk also had a linear programming model that could be accessed by the STORM package. This linear programming model was given in the DECIDE-P/OM text and was designed to allocate the three types of labor to the five work centers. In addition, the diskette contained a worksheet that was designed by the author to work with the LOTUS 1-2-3 package.

This Appendix will review the sequence that a subject used to employ the decision support system. It will also provide outputs from a hypothetical work session.

The first activity the user had to employ was the forecasting of demand for both products. Using the STORM package and the supplied diskette the user entered into the STORM regression module. The user then called up from the supplied diskette a file which contained the past data for the first product. Since the user had already played several decision periods for the game s/he was required to enter sales, price, economic index, related good price, and market index data for the periods for which decisions had not been made. (Remember, half of the users first employed the decision support system in decision period 3 while the other half first used it in period 5.)

Once the new data was entered the multiple regression module was executed. This was done to determine the relationship between sales (the dependent variable) and price, economic index, the price of a related good, and market index (the independent variables). The results of one of these analyses is given in Tables C.1 and C.2.

TABLE C.1

REGRESSION OUTPUT FROM STORM FOR PRODUCT 1

VARIABLE	COEFFICIENT	STD. ERROR	T VALUE	TWO-SIDED SIG. PROB.
CONSTANT	4.217E+005			
X2	-60036.9979	14707.078	-4.0822	0.000981
X3	14600.8044	4115.919	3.5474	0.002925
X4	11049.9914	3137.668	3.5217	0.003083
X5	- 2185.6102	3624.517	-0.6030	0.555512

WHERE X2 was the price
X3 was the economic index
X4 was the price of a related good
X5 was the market index

TABLE C.2

ANALYSIS OF REGRESSION FOR PRODUCT 1

R-SQUARED = 0.8224
STANDARD ERROR OF ESTIMATE = 40029.738

ANALYSIS OF VARIANCE

SOURCE	SS	df	MS	F value	prob.
REGRESSION	1.113E+11	4	2.783E+10	17.369	0.00002
RESIDUAL	2.404E+10	15	1.602E+09		
TOTAL	1.354E+11	19			

One can see from these results that the sales of the first product were strongly related to price, the economic index, and the price of a related good but not impacted in a significant way by the market index. Should the user wish, he or she could use some combination of these four independent variables and rerun the regression, that is, eliminate the market index and run a three independent variable model. The user, when satisfied with the results, would print a copy of the output so that s/he would have available the regression coefficients. The user would then repeat the same procedure for the second product. A sample output for the second product is given in Tables C.3 and C.4.

After obtaining the regression coefficients for each product the user was in a position to forecast sales by using the next period's price and the forecasts for the economic index, the price of the related good, and the market index - all of which are given on the output of the

TABLE C.3

REGRESSION OUTPUT FROM STORM FOR PRODUCT 2

VARIABLE	COEFFICIENT	STD. ERROR	T VALUE	TWO-SIDED SIG PROB
CONSTANT	5.661E+005			
X2	-10043.0164	184.873	-54.324	0.000000
X3	1392.8523	188.763	7.378	0.000002
X4	-39892.6563	1230.665	-32.416	0.000000
X5	- 57.8042	117.235	- 0.494	0.629109

WHERE X2 was the price
X3 was the economic index
X4 was the price of a related good
X5 was the market index

TABLE C.4

ANALYSIS OF REGRESSION FOR PRODUCT 2

R-SQUARED = 0.9955
STANDARD ERROR OF ESTIMATE = 1418.567

ANALYSIS OF VARIANCE

SOURCE	SS	df	MS	F value	prob.
REGRESSION	6.647E+09	4	1.662E+09	825.792	0.00001
RESIDUAL	3.019E+07	15	2.012E+06		
TOTAL	6.677E+09	19			

last decision. The user can either calculate the forecast for sales by hand or employ a segment of the LOTUS worksheet. The LOTUS forecast approach will be presented.

The user accessed the LOTUS system and was instructed at the beginning screen (see Table C.5) on how to move to the forecasting segment.

TABLE C.5

OPENING SCREEN FOR THE LOTUS ELEMENT OF THE DECISION SUPPORT SYSTEM

```
*******************************************
**        DECISION SUPPORT SYSTEM        **
**                  FOR                  **
**            DECIDE P/OM GAME           **
**                  BY                   **
**           DAVID  T.  CADDEN           **
*******************************************
```

INSTRUCTIONS	**- HIT ALTERNATIVE KEY AND I**
FORECASTING	**- HIT ALTERNATIVE KEY AND F**
FIRST TIME USE	**- HIT ALTERNATIVE KEY AND A**
SECOND TIME USE	**- HIT ALTERNATIVE KEY AND B**
THIRD TIME USE	**- HIT ALTERNATIVE KEY AND C**
FOURTH TIME USE	**- HIT ALTERNATIVE KEY AND D**

The system presented a screen and the user inputted the coefficient values derived from the regression module. The user also supplied the price, economic index, price of a relative good, and market index for all prior decision periods. (An example of this screen is given in Table C.6.) This last collection of data was requested so that forecasts based upon the regression model could be calculated not only for the decision period under consideration but for all prior decision periods. These series of forecasts enabled the user to evaluate the performance of the regression model over several periods. In addition to the numerical output the system could provide a graph of the forecasted and actual values. Again this was done so that the user could evaluate the accuracy of the forecasts from the regression model.

TABLE C.6

SCREEN FOR THE FORECASTING MODULE

COEFFICIENTS

	INTERCEPT	PRICE	ECONOMIC INDEX	RELATED PRICE	MARKET INDEX
P1	______	______	______	______	______
P2	______	______	______	______	______

PERIOD	PRICE	ECONOMIC INDEX	RELATED PRICE	MARKET INDEX	FORECAST	ACTUAL
1	______	______	______	______	______	______
2	______	______	______	______	______	______
3	______	______	______	______	______	______
4	______	______	______	______	______	______
5	______	______	______	______	______	______
6	______	______	______	______	______	______
7	______	______	______	______	______	______
8	______	______	______	______	______	______

After the user obtained the forecasts for the two products he/she then returned to the STORM system. One of the most difficult tasks in the DECIDE-P/OM game was the allocation of the types of labor to the five work centers. In addition to requiring a sufficient amount of labor to meet the demand this task involved not violating several constraints - such as work center capacity and total available labor. This problem lends itself to being solved by linear programming. The DECIDE-P/OM text specified a linear programming model to solve the scheduling problem. this model's structure is given in Table C.7

TABLE C.7

LINEAR PROGRAMMING MODEL FOR SCHEDULING LABOR TO THE WORK CENTERS

VARIABLE DEFINITION

```
X(1)   = # OF UNSKILLED HRS. USED IN P1 AT CENTER 1
X(2)   = # OF UNSKILLED HRS. USED IN P1 AT CENTER 2
X(3)   = # OF UNSKILLED HRS. USED IN P1 AT CENTER 3
X(4)   = # OF UNSKILLED HRS. USED IN P1 AT CENTER 5
X(5)   = # OF UNSKILLED HRS. USED IN P2 AT CENTER 1
X(6)   = # OF UNSKILLED HRS. USED IN P2 AT CENTER 2
X(7)   = # OF UNSKILLED HRS. USED IN P2 AT CENTER 3
X(8)   = # OF UNSKILLED HRS. USED IN P2 AT CENTER 4

X(9)   = # OF REGULAR HRS. USED IN P1 AT CENTER 1
X(10)  = # OF REGULAR HRS. USED IN P1 AT CENTER 2
X(11)  = # OF REGULAR HRS. USED IN P1 AT CENTER 3
X(12)  = # OF REGULAR HRS. USED IN P1 AT CENTER 5
X(13)  = # OF REGULAR HRS. USED IN P2 AT CENTER 1
X(14)  = # OF REGULAR HRS. USED IN P2 AT CENTER 2
X(15)  = # OF REGULAR HRS. USED IN P2 AT CENTER 3
X(16)  = # OF REGULAR HRS. USED IN P2 AT CENTER 4
X(17)  = # OF OVERTIME HRS. USED IN P1 AT CENTER 1
X(18)  = # OF OVERTIME HRS. USED IN P1 AT CENTER 2
X(19)  = # OF OVERTIME HRS. USED IN P1 AT CENTER 3
X(20)  = # OF OVERTIME HRS. USED IN P1 AT CENTER 5
X(21)  = # OF OVERTIME HRS. USED IN P2 AT CENTER 1
X(22)  = # OF OVERTIME HRS. USED IN P2 AT CENTER 2
X(23)  = # OF OVERTIME HRS. USED IN P2 AT CENTER 3
X(24)  = # OF OVERTIME HRS. USED IN P2 AT CENTER 4
X(25)  = TOTAL # OF UNSKILLED HRS. USED
X(26)  = TOTAL # OF REGULAR HRS. USED
X(27)  = TOTAL # OF OVERTIME HRS. USED
X(28)  = # OF NEW UNITS OF P1 THROUGH CENTERS 1 AND 2
X(29)  = # OF NEW UNITS OF P2 THROUGH CENTERS 1 AND 2
X(30)  = TOTAL # OF P1 UNITS AVAILABLE FOR SALE
X(31)  = TOTAL # OF P2 UNITS AVAILABLE FOR SALE
```

OBJECTIVE FUNCTION:

```
MAXIMIZE:  25*X(30) + 15*X(31) - 12*X(26) - 18*X(27)
          - 7.25*X(28) - 5.6*X(29)
```

TABLE C.7 (CONTINUED)

SUBJECT TO:

[CONSTRAINTS 1, 2, 3 ASSURE THAT TOTAL LABOR BY TYPE IS DEFINED]

1. **X(1) + X(2) + X(3) + X(4) + X(5) + X(6) + X(7) + X(8) -X(25) = 0**

2. **X(9) + X(10) + X(11) + X(12) + X(13) + X(14) + X(15) +X(16) - X(26) = 0**

3. **X(17) + X(18) + X(19) + X(20) + X(21) + X(22) + X(23) +X(24) - X(27) = 0**

[CONSTRAINTS 4, 5, 6 PLACE LIMITS ON THE TYPES OF LABOR]

4. **X(25) < 287500**

5. **X(26) < 50000**

6. **X(27) < 25000**

[CONSTRAINTS 7 TO 16 PLACE LIMITS ON THE WORK CENTERS LABOR CAPACITIES]

WORK CENTER 1

7. **X(1) + X(5) + X(9) + X(13) < 44979**

8. **X(17) + X(21) < 22489**

WORK CENTER 2

9. **X(2) + X(6) + X(10) + X(14) < 90265**

10. **X(18) + X(22) < 45102**

WORK CENTER 3

11. **X(3) + X(7) + X(11) + X(15) < 92776**

12. **X(19) + X(23) < 46388**

WORK CENTER 4

13. **X(8) + X(16) < 19079**

14. **X(24) < 9539**

TABLE C.7 (CONTINUED)

WORK CENTER 5

15. X(4) + X(12) < 119730

16. X(20) < 59865

[CONSTRAINTS 17 TO 20 BALANCE LABOR HOURS TO THE NUMBER OF PRODUCTS TO BE PRODUCED]

17. 5*X(1) + 10*X(9) + 10*X(17) + 2.5*X(2) + 5*X(10)
+5*X(18) - X(28) = 0

18. 2.5*X(5) + 4*X(13) + 4*X(21) + 2*X(6) + 5*X(14)
+5*X(22) - X(29) = 0

19. 2.5*X(3) + 5*X(11) + 5*X(19) + 2.5*X(4) + 4*X(12)
+4*X(20) - X(30) = 0

20. 2*X(7) + 4*X(15) + 4*X(23) + 4*X(8) +10*X(16)
+10*X(24) - X(31) = 0

[CONSTRAINTS 21 AND 22 BALANCE THE WORK-IN-PROCESS FOR THE TWO PRODUCTS WITH THE PRODUCTION OF COMPLETED PRODUCTS]

21. X(30) - X(28) = 161191

22. X(31) - X(29) = 138760

[CONSTRAINTS 23 TO 25 PLACE LIMITS ON RAW MATERIAL CONSUMPTION]

23. 4*X(29) < 2269900

24. 7*X(28) < 872200

25. 4*X(28) + 8*X(29) < 2090157

[CONSTRAINTS 26 AND 27 INCORPORATE THE FORECASTED DEMANDS FOR THE TWO PRODUCTS]

26. X(30) < 484956

27. X(31) < 200000

As mentioned, this model was placed on the user's diskette in a form that was readable by the STORM linear programming model. The user called this file up on STORM and then made modifications appropriate for his/her situation. This meant that s/he had to change the labor capacities for the skilled labor regular time and the skilled labor overtime. To do this s/he simply altered the values of the right-hand side for equations 5. and 6. S/he also had to input any changes in the work centers 1 through 5. This was done by altering the right-hand side values for equations 7. to 16. Other changes to the right-hand side values were required. The balance of work-in-process to final production levels were present in equations 21. and 22.

After these changes were done the user could solve the linear program. At that point the user had the forecasts for demand and the labor allocation schedule. The user then accessed the LOTUS template and moved to the Key Results Section. This section is presented in Table C.8. It is an area of the worksheet that the user inputs key results from the last decision period. These values are required to make subsequant calculations.

Once the past decision results are entered the user was then instructed by the system to move to the Raw Material Requirement section of the worksheet. This section of the decision support system required the user to input his/her desired level of production for the two products and the estimate of the useful percentage of raw material 3. It then

TABLE C.8

KEY RESULTS INPUT FORMAT

PERIOD 3 KEY RESULTS

ENDING INVENTORIES

RAW MATERIAL 1	RAW MATERIAL 2	RAW MATERIAL 3
________	________	________
WIP 1	WIP 2	
________	________	
FINISHED GOODS 1	FINISHED GOODS 2	
________	________	

FIXED COSTS	________
MISC. EXP.	________
LIABILITIES	________

PRODUCTION CAPACITIES

	REG.	OVERTIME
CENTER 1	______	______
CENTER 2	______	______
CENTER 3	______	______
CENTER 4	______	______
CENTER 5	______	______

CASH	________
SECURITIES	________
PLANT	________
UNSKILLED WORKERS #	________
SKILLED WORKERS #	________
$ WIP 1	________
$ WIP 2	________
$ RM 1	________
$ RM 2	________
$ RM 3	________
$ PRODUCT 1	________
$ PRODUCT 2	________

computed the necessary inventory ordering policy. This was done by automatically accessing the inventory values supplied to the Key Results section and performing the necessary calculations. Users after examining the results could enter new production values and recalculate the new inventory requirements. The input format of the Raw Material Requirement Form is given in Table C.9

TABLE C.9

RAW MATERIAL REQUIEMENT FORM

	PRODUCT 1		PRODUCT 2
DESIRED PRODUCTION	______		______
BEG. WIP	______		______
NET PRODUCTION	______		______
RAW MATERIAL 1			______
USEFUL FRACTION			0.99
REQUIRED RAW MATERIAL			______
BEG. INVENTORY			______
RM1 ORDER			______
RAW MATERIAL 2	______		
USEFUL FRACTION	0.98		
REQUIRED RAW MATERIAL	______		
BEG. INVENTORY	______		
RM2 ORDER	______		
RAW MATERIAL 3	______		______
USEFUL FRACTION	______		______
REQUIRED RAW MATERIAL	______		______
BEG. INVENTORY	______		______
RM3 ORDER	______		______
TOTAL RM3 ORDER		______	

The user now equipped with forecasts for the demand, the necessary orders for raw material, and the labor allocation schedule is in a position to make his/her decisions with regard to capital investment in each work center, maintenance expenditures, training, and quality control. The entire set of decisions can be entered into the decision form which is presented in Table C.10.

It is critical for the user to be able to evaluate the consequences of these decisions. The most important manner in which they can evaluate the decisions is to have some understanding of their economic impact. To do this the worksheet provides an automatically computed income statement and balance sheet. The only element required of the user is to input the price of the two products into the income statement worksheet and their anticipated defect rates. The income statement (See Table C.11) draws upon the values that were inputted to Decision Form and the Key Results form. It calculates anticipated revenue, changes in inventory, carrying costs, set-up costs and the costs associated with quality control. The worksheet also computes the necessary values to generate a balance sheet which is presented in Table C.12. The decision support system allows the user to examine the economic consequences of his/her decision and then if s/he desires to alter the original decisons it can be done. The user repeats the process until s/he arrives at a satifactory set of decisions.

A flowchart of the process of using the decision support system is given in Figure C.1.

TABLE C.10

DECISION FORM

PERIOD 3 DECISION FORM

RAW MATERIAL 1- ______	PRODUCT 1	PRODUCT 2
RAW MATERIAL 2- ______	UNSKILLED LABOR	UNSKILLED LABOR
RAW MATERIAL 3- ______	CENTER 1 ______	CENTER 1 ______
	CENTER 2 ______	CENTER 2 ______
	CENTER 3 ______	CENTER 3 ______
	CENTER 5 ______	CENTER 4 ______
MAINTENANCE		
CENTER 1- ______	TOTAL ______	TOTAL ______
CENTER 2- ______		
CENTER 3- ______	PRODUCT 1	PRODUCT 2
CENTER 4- ______	SKILLED REG TIME	SKILLED REG TIME
CENTER 5- ______	CENTER 1 ______	CENTER 1 ______
	CENTER 2 ______	CENTER 2 ______
	CENTER 3 ______	CENTER 3 ______
CAPITAL	CENTER 5 ______	CENTER 4 ______
NVESTMENT		
	TOTAL ______	TOTAL ______
CENTER 1- ______		
CENTER 2- ______	PRODUCT 1	PRODUCT 2
CENTER 3- ______	OVERTIME LABOR	OVERTIME LABOR
CENTER 4- ______	CENTER 1 ______	CENTER 1 ______
CENTER 5- ______	CENTER 2 ______	CENTER 2 ______
	CENTER 3 ______	CENTER 3 ______
	CENTER 5 ______	CENTER 4 ______
INPUT CONTROL		
	TOTAL ______	TOTAL ______
AMPLE SIZE ______		
C" ______	DEMAND FORECAST	TRAINING ______
	PRODUCT 1 ______	______
OUTPUT CONTROL	PRODUCT 2 ______	HISTORICAL
		QUALITY CONTROL
# OF SAMPLES ______		DATA REQUEST
SAMPLE SIZE ______		
UPPER LIMIT ______		___
LOWER LIMIT ______		

TABLE C.11

INCOME STATEMENT

	PRODUCT 1	PRODUCT 2	TOTAL
PRICE			
QUANTITIY			
REVENUE			
DEFECTS			
DEFECTIVE SALES REVENUE			
TOTAL REVENUE			
BEG. INV. FIN. GOODS			
DIRECT LABOR			
RM1 USED			
RM2 USED			
RM3 USED			
NET CHANGE WIP INV.			
VARIABLE OVERHEAD			
ENDING INV. FIN. GOODS			
TOTAL VARIABLE COSTS			
MARGIN			
FIXEC COSTS			
CARRYING COSTS (RM)			
CARRYING COSTS (WIP)			
CARRYING COSTS (FIN. GDS.)			
ORDERING COSTS			
SETUP COSTS			
MAINTENANCE			
TRAINING			
DEMAND FORECAST			
HISTORICAL QUALITY CONTROL			
QUALITY CONTROL PROGRAM			
ACCEPTANCE SAMPLING PLAN			
INTEREST EXPENSE			
MISCELLANEOUS			
DEPRECIATION			
TOTAL FIXED COST			
NET INCOME			

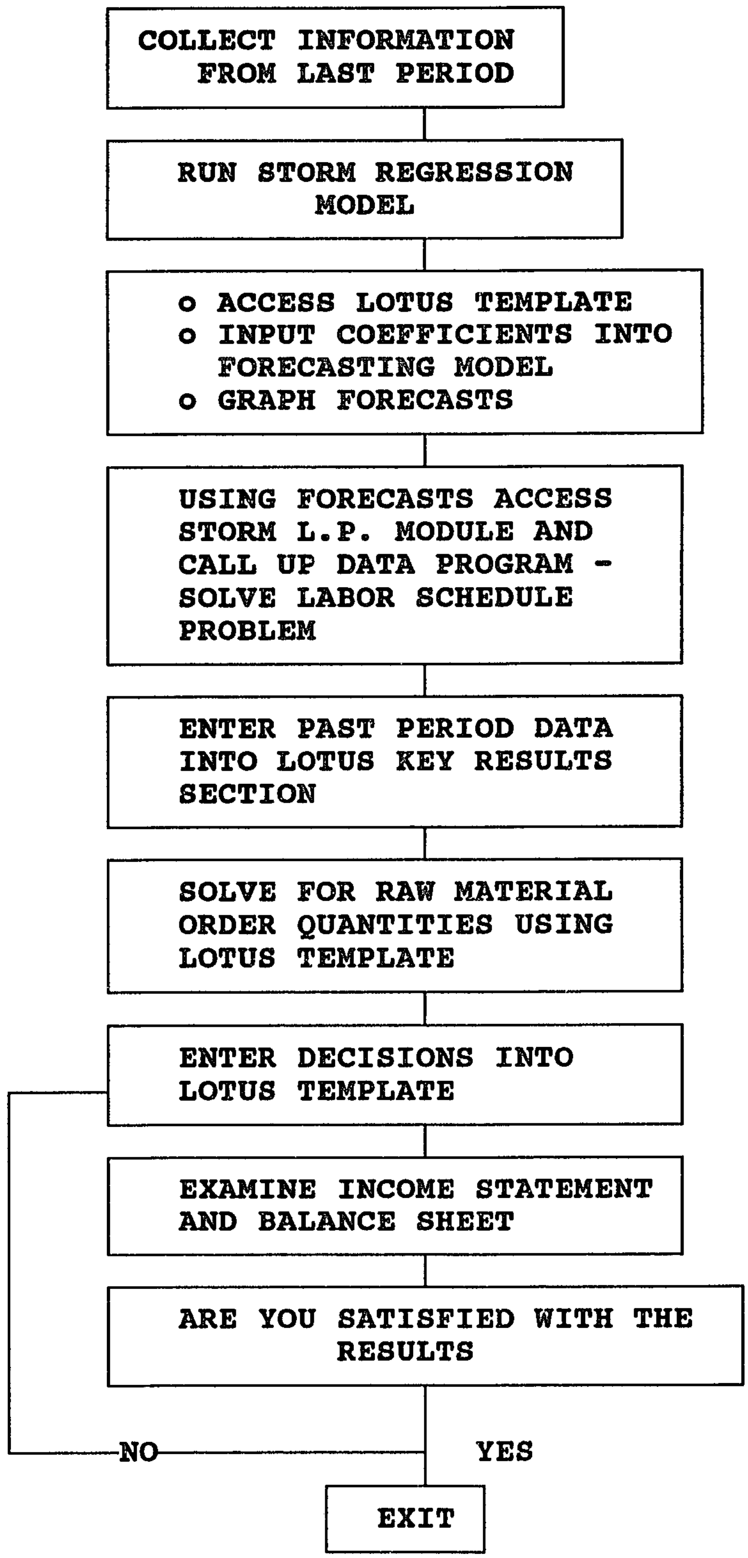
TABLE C.12

BALANCE SHEET

ASSETS		LIABILITIES	
CURRENT ASSETS		LIABILITIES	________
CASH	________		
MKT. SEC	________	EQUITY	________
RM1	________		
RM2	________		
RM3	________		
WIP 1	________		
WIP 2	________		
FIN. GD. 1	________		
FIN. GD. 2	________		
TOTAL INVENTORY	________		
PLANT	________		
TOTAL ASSETS	________		

FIGURE C.1

FLOWCHART



APPENDIX D.

EXPERT SYSTEM DESCRIPTION

In this Appendix, we provide excerpts from the two largest (in terms of the number of rules) expert systems. This should provide the reader with an appreciation of the structure and format of these programs.

The diagnostic expert system requests certain values from the last period's output. It evaluates these values and makes decisions regarding the prior period's decisions. It lists possible problems for the upcoming period and makes suggestions to the user. In addition to listing possible problems it provides a likelihood estimate of the accuracy of its own diagnosis.

The labor scheduling expert system requests data from the prior period. [In retrospect, the author has come to realize that these two systems could have been joined together by a process known as "blackboarding". This would have reduced the total data entry requirements for the user.] It attempts to schedule labor to the least expensive work centers. Should this violate capacity or labor constraints it utilizes a heuristic to reschedule labor so as not to violate those constraints.

Subject:

THIS EXPERT SYSTEM PROVIDES A DIAGNOSIS OF YOUR LAST PERIOD'S DECISIONS.

Author:
DAVID T. CADDEN

Starting Text:
HAVE YOUR LAST PERIOD'S OUTPUT WITH YOU

RULE NUMBER 1:

IF:
```
     [PF1]>0
and  [PF2]>0
```

THEN:
```
     [SO1] IS GIVEN THE VALUE [PF1]-[AP1]
and  [PSO1] IS GIVEN THE VALUE [SO1]/[PF1]
and  [SO2] IS GIVEN THE VALUE [PF2]-[AP2]
and  [PSO2] IS GIVEN THE VALUE [SO2]/[PF2]
```

NOTE:
THIS COMPUTES THE STOCKOUTS FOR THE PRODUCTS

RULE NUMBER 2:

IF:
```
     [UC21]+[SC21]+[OC21]+[UC22+[SC22]+[OC22]=[LC2]
and  [LC2]/[CAP2]<.8
```

THEN:
UNDERUTILIZATION OF CENTER 2 - Probability=60/100

RULE NUMBER 3:

IF:
```
     [PSO1]>.05
```

THEN:
```
     INADEQUATE SALES FOR P1 - Probability=100/100
```

ELSE:
```
     SALES FOR P1 OK! - Probability=95/100
```

RULE NUMBER 4:

IF:
    [PF2]>([RM1}*.25+[WIP2])

THEN:
    INADEQUATE RM1 FOR NEXT PERIOD - Probability=100/100

NOTE:
YOU DO NOT HAVE ENOUGH RAW MATERIAL 1 INVENTORY FOR NEXT PERIOD.

RULE NUMBER 5:

IF:
    [PF1]>([RM2]*.14+[WIP2])

THEN:
    INADEQUATE RM2 FOR NEXT PERIOD - Probability=100/100

NOTE:
YOU DO NOT HAVE ENOUGH RAW MATERIAL 2 INVENTORY FOR NEXT PERIOD.

RULE NUMBER 6:

IF:
    [PF1]+[PF2]>([RM3]*.25+[WIP1)+([RM3]*.125+[WIP2])

THEN:
    INADEQUATE RM3 FOR NEXT PERIOD - Probability=100/100

NOTE:
YOU DO NOT HAVE ENOUGH RAW MATERIAL 3 INVENTORY FOR NEXT PERIOD.

RULE NUMBER 7:

IF:
    [UC11]+[SC11]+[OC11]+[UC12]+SC12]+[OC12]=[LC1]
and [LC1]/[CAP1]<.8

THEN:
    UNDERUTILIZATION OF CENTER 1 - Probability=60/100

RULE NUMBER 8:

IF:
[UC31]+[SC31]+[OC31]+[UC32]+[SC32]+[OC32]=[LC3]
and [LC3]/[CAP3]<.8

THEN:
UNDERUTILIZATION OF CENTER 3 - Probability=60/100

RULE NUMBER 9:

IF:
[UC42]+[SC42]+[OC42]=[LC4]
and [LC4]/CAP4]<.8

THEN:
UNDERUTILIZATION OF CENTER 4 - Probability=60/100

RULE NUMBER 10:

IF:
[UC51]+[SC51]+[OC51]=[LC5]
and [LC5]/[CAP5]

THEN:
UNDERUTILIZATION OF CENTER 1 - Probability=100/100

RULE NUMBER 11:

IF:
[REJ3]>7

THEN:
IMPROVE INPUT QUALITY CONTROL - Probability=90/100

NOTE:
IF THE REJECT RATE FOR RM3 IS GREATER THAN 10% YOU MUST INITIATE AN INPUT QUALITY PROGRAM.

RULE NUMBER 12:

IF:
[REJ3]>10

THEN:
IMPROVE INPUT QUALITY CONTROL - Probability=100/100

NOTE:
IF THE REJECT RATE FOR RM3 IS GREATER THAN 10% YOU MUST INITIATE AN INPUT QUALITY PROGRAM

RULE NUMBER 13:

IF:
    [DEF1]>8

THEN:
    IMPROVE OUTPUT QUALITY CONTROL - Probability=60/100

NOTE:
THE DEFECT RATE FOR PRODUCT 1 IS HIGHER THAN EXPECTED

RULE NUMBER 14:

IF:
    [DEF1]>10

THEN:
    IMPROVE OUTPUT QUALITY CONTROL - Probability=80/100

NOTE:
THE DEFECT RATE FOR PRODUCT 1 IS MUCH HIGHER THAN EXPECTED

RULE NUMBER 15:

IF:
    [DEF1]>12

THEN:
    IMPROVE OUTPUT QUALITY CONTROL - Probability=100/100

NOTE:
THE DEFECT RATE FOR PRODUCT 1 IS FAR HIGHER THAN EXPECTED

RULE NUMBER 16:

IF:
    [DEF2]>2.5

THEN:
    IMPROVE OUTPUT QUALITY CONTROL - Probability=100/100

NOTE:
IF THE DEFECT RATE FOR PRODUCT 2 IS GREATER THAN 2.5% INITIATE QUALITY CONTROL PROGRAM.

RULE NUMBER 17:

IF:
[PSO2]>.05

THEN:
INADEQUATE SALES FOR P2 - Probability=100/100

NOTE:
YOUR SALES FOR PRODUCT 2 WAS INADEQUATE

RULE NUMBER 18:

IF:
[DC1]>13.22

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT CENTER 1 - Probability=80/100

NOTE:
YOU HAVE AN ABNORMALLY HIGH DOWNTIME AT WORK CENTER 1

RULE NUMBER 19:

IF:
[DC2]>12.64

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 2 - Probability=80/100

NOTE:
YOU HAVE AN ABNORMALLY HIGH DOWNTIME AT WORK CENTER 2

RULE NUMBER 20:

IF:
[DC3]>14

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 3 - Probability=80/100

NOTE:
YOU HAVE AN ABNORMALLY HIGH DOWNTIME AT WORK CENTER 3

RULE NUMBER 21:

IF:
[DC4]>14

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 4 -
Probability=80/100

NOTE:
YOU HAVE AN ABNORMALLY HIGH DOWNTIME AT WORK CENTER 4

RULE NUMBER 22:

IF:
[DC5]>0

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 5 -
Probability=80/100

NOTE:
YOU HAVE AN ABNORMALLY HIGH DOWNTIME AT WORK CENTER 5

RULE NUMBER 23:

IF:
[DC1]>13.22
and [CAP1]>.7

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 1 -
Probability=100/100

NOTE:
YOUR INTENSE UTILIZATION OF WORK CENTER 1 AND HIGH DOWNTIME CLEARLY INDICATE AN INCREASE IN MAINTENANCE EXPENDITURES AT THIS WORK CENTER.

RULE NUMBER 24:

IF:
[DC2]>12.64
and [CAP2]>.7

THEN:
IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 2 -
Probability=100/100

NOTE:
YOUR INTENSE UTILIZATION OF WORK CENTER 2 AND HIGH DOWNTIME CLEARLY INDICATE AN INCREASE IN MAINTENANCE EXPENDITURES AT THIS WORK CENTER.

RULE NUMBER 25:

IF:
    [DC3]>14
and [CAP3]>.7

THEN:
    IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 3 -
    Probability=100/100

NOTE:
YOUR INTENSE UTILIZATION OF WORK CENTER 3 AND HIGH DOWNTIME CLEARLY INDICATE AN INCREASE IN MAINTENANCE EXPENDITURES AT THIS WORK CENTER.

RULE NUMBER 26:

IF:
    [DC4]>14
    [CAP4]>.7

THEN:
    IMPROVE MAINTENANCE EXPENDITURES AT WORK CENTER 4 -
    Probability=100/100

NOTE:
YOUR INTENSE UTILIZATION OF WORK CENTER 4 AND HIGH DOWNTIME CLEARLY INDICATE AN INCREASE IN MAINTENANCE EXPENDITURES AT THIS WORK CENTER.

Subject:
THIS PROGRAM ASSISTS IN THE SCHEDULING OF LABOR.

Author:
DAVID T. CADDEN

RULE NUMBER 1:

IF:
    [NP1]>0

THEN:
    [SP1C1] IS GIVEN THE VALUE .1*[NP1]

NOTE:
IF THE WORK-IN-PROCESS FOR PRODUCT 1 IS REQUIRED THIS PERIOD, WE ATTEMPT TO PRODUCE ALL OUR REQUIREMENTS BY USING THE FIRST WORK CENTER.

RULE 2:

IF:
    [SP1C1]>[RTC1]*[UPC1]

THEN:
    [SP1C1] IS GIVEN THE VALUE [RTC1]*[UPC1]

NOTE:
LABOR ALLOCATED AT THE FIRST WORK CENTER MUST BE LESS THAN OR EQUAL TO THE CAPACITY OF THE WORK CENTER TIMES THE ANTICIPATED PERCENTAGE UPTIME

RULE NUMBER 3:

IF:
    10*[SP1C1]<[NP1]

THEN:
    [UP1C1] IS GIVEN THE VALUE ([NP1]-10[SP1C1])*.2

NOTE:
SHOULD SKILLED LABOR AT WORK CENTER 1 BE INSUFFICIENT TO PRODUCE THE DESIRED WORK-IN-PROCESS FOR PRODUCT 1 THEN WE SCHEDULE THE REQUIRED ADDITIONAL UNSKILLED LABOR.

RULE NUMBER 4:

IF:
    10*[SP1C1]+5*[UP1C1]<[NP1]

THEN:
    [OP1C1] IS GIVEN THE VALUE ([NP1]-10*[SP1C1]-
                                5*[UP1C1])*.1

NOTE:
THIS RULE STATES THAT IF UNSKILLED LABOR AND UNSKILLED LABOR AT WORK CENTER 1 IS INSUFFICIENT TO MEET DEMAND THEN SCHEDULE THE NEXT CHEAPEST LABOR WHICH IS OVERTIME LABOR.

RULE NUMBER 5:

IF:
    [NP2]>0

THEN:
    [SP2C2] IS GIVEN THE VALUE .2*[NP2]

NOTE:
IF THE IS A REQUIREMENT FOR WORK-IN-PROCESS FOR PRODUCT 2, WE ALLOCATE REQUIRED LABOR AT THE LEAST COST WORK CENTER.

RULE NUMBER 6:

IF:
    [SP2C2]>[RTC2]*[UPC2]

THEN:
    [SP2C1] IS GIVEN THE VALUE [RTC2]*[UPC2]

NOTE:
THIS RULE MAKES SURE THAT WE DO NOT SCHEDULE MORE TIME AT WORK CENTER 2 THAN ITS CAPACITY TIMES IT'S ANTICIPATED UPTIME.

RULE NUMBER 7:
IF:
    10*[SP1C1]+5*[UP1C1]=>[NP1]
THEN:
    [OP1C1] IS GIVEN THE VALUE 0
    [SP1C2] IS GIVEN THE VALUE 0
    [UP1C2] IS GIVEN THE VALUE 0
    [OP1C2] IS GIVEN THE VALUE 0

NOTE:
THIS RULE MAKES SURE THAT IF THERE IS SUFFICIENT UNSKILLED AND SKILLED LABOR AT WORK CENTER 1 TO MEET THE REQUIREMENTS FOR THE WORK-IN-PROCESS FOR PRODUCT 1 THEN THERE IS NO NEED TO SCHEDULE OTHER LABOR TO MAKE PRODUCT 1.

RULE NUMBER 8:
IF:
    2.5*[UP2C1]+5*[SP2C2]<[NP2]
THEN:
    [SP2C1] IS GIVEN THE VALUE ([NP2]-5*[SP2C2]-
    2.5[UP2C1])*.25
NOTE:
IF THE ALLOCATION OF SKILLED LABOR TO WORK CENTER 2 AND UNSKILLED LABOR TO WORK CENTER 1 IS INSUFFICIENT TO MEET THE REQUIREMENTS TO PRODUCE WORK-IN-PROCESS 2 THEN LABOR IS ALLOCATED TO THE NEXT LOWEST COST CENTER.

RULE NUMBER 9:
IF:
    5*[SP2C2]+2.5*[UP2C1]+4*[SP2C1]=>[NP2]
THEN:
    [UP2C2] IS GIVEN THE VALUE 0
and [OP2C2] IS GIVEN THE VALUE 0
and [OP2C1] IS GIVEN THE VALUE 0

NOTE:
THIS RULE IS TO ASSURE THAT IF THERE IS SUFFICIENT LABOR TO MEET THE REQUIREMENTS FOR WORK-IN-PROCESS 2 THEN THE OTHER WORK CENTERS ARE NOT USED.

RULE NUMBER 10:
IF:
    [FP2]>0
THEN:
    [SP2C4] IS GIVEN THE VALUE 0
NOTE:
IF THERE IS DEMAND FOR FINISHED PRODUCT 2 THEN WE FIRST ALLOCATE THE CHEAPEST WORK CENTER.

RULE NUMBER 11:
IF:
    [SP2C4]>[RTC4]*[UPC4]
THEN:
    [SP2C4] IS GIVEN THE VALUE [RTC4]*[UPC4]
NOTE:
THIS RULE MAKES SURE WE DO NOT SCHEDULE MORE LABOR TIME AT WORK CENTER 4 THAN IT'S CAPACITY TIMES IT'S ANTICIPATED PERCENTAGE UPTIME.

RULE NUMBER 12:
IF:
    10*[SP1C1]+10*[OP1C1]+5*{UP1C1]=>[NP1]
THEN:
    [SP1C2] IS GIVEN THE VALUE 0
    [UP1C2] IS GIVEN THE VALUE 0
    [OP1C2] IS GIVEN THE VALUE 0
NOTE:
IF THE ALLOCATION OF LABOR TO PRODUCE WORK-IN-PROCESS FOR PRODUCT 1 IS SUFFICIENT AT WORK CENTER 1 THEN SHUT DOWN WORK CENTER 2 FOR PRODUCT 1.

RULE NUMBER 13:

IF:
    .2*[NP2]>[SP2C2]

THEN:
    [UP2C1] IS GIVEN THE VALUE ([NP2]-5*[SP2C2])*.4

NOTE:
IF THERE IS INSUFFICIENT LABOR AT WORK CENTER 2 FOR PRODUCT 2 THE SCHEDULE UNSKILLED LABOR AT WORK CENTER 1.

RULE NUMBER 14:

IF:
    [FP1]>0

THEN:
    [SP1C3] IS GIVEN THE VALUE .2*[FP1]

NOTE:
IF THERE IS DEMAND FOR FINISHED PRODUCT 1 THEN SCHEDULE LABOR AT THE CHEAPEST SOURCE.

RULE NUMBER 15:

IF:
    [SP1C3]>[RTC3]*[UPC3]

THEN:
    [SP1C3] IS GIVEN THE VALUE [RTC3]*[UPC3]

NOTE:
LABOR ALLOCATED AT WORK CENTER 3 MUST BE LESS THAN OR EQUAL TO THE CAPACITY OF THE WORK CENTER TIMES IT'S ANTICIPATED UPTIME.

RULE NUMBER 16:

IF:

[.2*[FP1]>[SP1C3]

THEN:

[SP1C5] IS GIVEN THE VALUE ([FP1]-5*[SP1C3])*.25

NOTE:

IF THE ALLOCATION OF SKILLED LABOR AT WORK CENTER 3 IS INSUFFICIENT TO MEET DEMAND THEN ADDITIONAL LABOR IS SCHEDULED AT WORK CENTER 5.

RULE NUMBER 17:

IF:

5*[SP1C3]+4*[SP1C5]<[FP1]

THEN:

[UP1C5] IS GIVEN THE VALUE ([FP1]-5*[SP1C3]-4*[SP1C5])*.4

ELSE:

[OP1C5] IS GIVEN THE VALUE 0

NOTE:

IF SKILLED LABOR AT WORK CENTER 5 AND SKILLED LABOR AT WORK CENTER 3 IS INSUFFICIENT THE SCHEDULE UNSKILLED LABOR AT WORK CENTER 5.

RULE NUMBER 18:

IF:

5*[SP1C3]+2.5*[UP1C5]+4*[SP1C5]<[FP1]

THEN:

[UP1C3] IS GIVEN THE VALUE ([FP1]-5*[SP1C3]-2.5*[UP1C5]-4*[[SP1C5])*.25

ELSE:

[UP1C3] IS GIVEN THE VALUE 0
[OP1C3] IS GIVEN THE VALUE 0
[OP1C5] IS GIVEN THE VALUE 0

NOTE:

IF THE SKILLED LABOR AT CENTERS 3 AND 5 AND THE UNSKILLED LABOR AT WORK CENTER 5 IS INSUFFICIENT IS INSUFFICIENT THEN SCHEDULE UNSKILLED LABOR AT CENTER.

APPENDIX E.

INFORMATION SHEET

NAME: ____________________

ADDRESS: ____________________

____

TELEPHONE: ____________________

1. SEX: FEMALE ____ MALE ____

2. HIGHEST DEGREE EARNED
   - CURRENT UNDERGRADUATE ____
   - B.S. DEGREE ____
   - B.A. DEGREE ____
   - M.S. DEGREE ____
   - M.A. DEGREE ____
   - M.B.A. DEGREE ____
   - DOCTORAL STUDIES ____
   - PH.D. ____

3. UNDERGRADUATE MAJOR ____________________

4. GRADUATE MAJOR ____________________

5. CERTIFICATIONS:
   - CPIM ____
   - CFPIM ____
   - CPA ____

6. YEARS OF FULL TIME WORK EXPERIENCE: ____________________

7. CURRENT JOB TITLE: ____________________

8. HAVE YOU EVER HELD A PRODUCTION/MANUFACTURING RELATED JOB?
   YES ____ NO ____

9. IF YOU ANSWERED YES TO QUESTION 8. PLEASE DESCRIBE THE JOB:

   ____

10. HOW LONG DID YOU HOLD THIS JOB: ____________________

11. DO YOU OWN A COMPUTER? YES ____ NO ____

12. WHAT IS ITS MAKE AND MODEL? ____________________

PLEASE NOTE

POST-USAGE QUESTIONNNAIRE

PLEASE CIRCLE THE NUMBER THAT MOST CLOSELY CORRESPONDS TO YOUR FEELINGS ABOUT THE FOLLOWING STATEMENTS

1. While using the Decision Support System (DSS), I felt challenged to do my best work.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

2. While using the DSS, I really felt like I accomplished something.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

3. I learned a great deal while using the Decision Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

4. I enjoyed using the Decison Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

5. I am not in favor of computer-aided decision devices because it is another step toward depersonalization.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

6. I felt frustrated by the Decision Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

7. Even otherwise interesting material would be boring when presented by the computer.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

8. I didn't like the Decision Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

9. Using the computer in an environment like the game seems like a good idea.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

10. While using the Decision Support System I had to be at my best.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

11. While using the Decision Support System I felt comfortable.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

12. I don't think I know more about decision-making in this game than before.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

13. Using the Decision Support System was fun.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

14. I became dependent on the Decision Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

15. I have personally benefited from using this Decision Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

16. The Decision Support System was extremely useful.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

17. As a result of the Decision Support System, I produced more satisfactory decisions.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

18. All in all, I think that the Decision Support System is important to participating in this game.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

19. Utilization of the Decision Support System enabled me to make better decisions.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

20. The Decision Support System has improved the quality of the decisions that I made.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

21. As a result of using the Decision Support System, I was better able to set my decision priorities.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

22. The Decision Support System led me to greater use of analytical aids in my decision-making.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

23. As a result of the Decision Support System, more relevant information was available for my decision-making.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

24. I would rely upon this Decision Support System if I continued to play this game.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

25. As a result of the Decision Support System, the speed at which I made decisions was increased.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

26. Use of the material generated by the Decision Support System enabled me to organize my decisions more convincingly.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

27. It would be extremely difficult to complete the decision-making process without the information presented by the Decision Support System.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

28. Extremely complex recalculations are necessary to use the information provided by the Decision Support System to make decisions.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

29. The information presented by the Decision Support System is sufficient to complete the required decisions.

COMPLETELY DISAGREE	DISAGREE	SOMEWHAT DISAGREE	NEUTRAL	SOMEWHAT AGREE	AGREE	COMPLETELY AGREE
1	2	3	4	5	6	7

30. What proportion of the information is in the correct form for completion for the game's decisions?

NONE			ABOUT HALF			ALL
1	2	3	4	5	6	7

31. What proportion of the information presented is interpretable, without any recalculation or adjustment, for the completion of the game's decisions?

NONE			ABOUT HALF			ALL
1	2	3	4	5	6	7

32. What proportion of the information presented is essential for, or instrumental in, completing the game's decisions?

NONE			ABOUT HALF			ALL
1	2	3	4	5	6	7

33. To what extent do you actually use the Decision Support System compared to your original expectations?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

34. To what extent could you get along without the use of the Decision Support System?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

35. To what extent does the Decision Support System assist you in performing your job better?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

36. To what extent did you get along better before the Decision Support System was implemented?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

37. To what extent do you actually use the reports or outputs that are provided to you by the Decision Support System?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

38. To what extent do data that you receive from the Decision Support System require correction?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

39. To what extent does the Decision Support System overload you with more data than it seems you can possibly use?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

40. To what extent does the Decision Support System provide report(s) that seem to be just about exactly what you need?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

41. To what extent do you understand what this system does in assisting you in playing the game.

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

42. To what extent is the Decision Support System troublesome for you or difficult to operate with in order for you to accomplish your decision making task?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

43. To what extent would you like this system to be modified or redesigned?

NOT AT ALL	VERY LITTLE	LITTLE	MODERATELY	MUCH	VERY MUCH
1	2	3	4	5	6

PRODUCTION/OPERATIONS MANAGEMENT QUESTIONNAIRE

1. One of the important advantages of a three-period moving average over exponential smoothing is that the former gives heavy weight to the most recent data.

   T ____ F ____

2. The coefficient of determination states the proportion of the variation in the regression equation which is explained by the independent variable.

   T ____ F ____

3. If the latest actual demand is 100 and the last forecast is 110, then if alpha = 0.4, the new forecast is

   a.) 104
   b.) 106
   c.) 105
   d.) none of the above

4. A discounted cash flow analysis is appropriate for capacity planning because the internal rate of return is greater than zero.

   T ____ F ____

5. Hospitals are generally physically laid out as continuous line systems.

   T ____ F ____

6. The master schedule is the basis of other plans that must be carefully coordinated, such as material procurement, plans to hire or lay off workers, and detailed schedules for staffing operations.

   T ____ F ____

7. The essence of aggregate production planning is to absorb fluctuations in demand by

   a.) varying the size of the work force
   b.) using overtime
   c.) using seasonal inventories
   d.) none of the above

8. In the Linear Decision Rule model the admissible shape of cost curves are

   a.) step functions
   b.) higher order polynomial functions
   c.) quadratic functions
   d.) all of the above
   e.) none of the above

9. Fixed reorder quantity systems use the EOQ formula to determine the amount ordered.

   T ____ F ____

10. If the unit holding cost is $0.50, the ordering cost is $50.00, and the annual demand is 20,000 units, what would be the optimal order quantity?

    ____

11. One of the assumptions of the EOQ lot size model is that the demand is equal from period to period.

    T ____ F ____

12. In MRP, the master production schedule is usually frozen in later weeks.

    T ____ F ____

13. The demand for a component may be considered to be independent if it is used in three or more assemblies.

    T ____ F ____

14. Just-In-Time is an inventory control technique that is only appropriate for continuous line operations.

    T ____ F ____

15. Scheduling techniques more useful in intermittent systems are:

    a.) Johnson's rule and the assignment method
    b.) runout method
    c.) truncated LaPlace method
    d.) all of the above
    e.) none of the above

16. Loading schedules help schedulers achieve this objective:

    a.) satisfy customers demand
    b.) meet customer delivery promises
    c.) maintain high operating efficiency
    d.) avoid machinery breakdowns because of processing excessively heavy products
    e.) c or d

17. In LOB, the line balance represents
    a.) what has been produced to date
    b.) what has been shipped to date
    c.) what should have been produced to date
    d.) what should have been shipped to date
    e.) c or d

18. The risk that we accept output as being good product when in fact the process is out of control is known as the consumer's risk.

    T ____ F ____

19. If the process is in fact in control, and based on our information we reject the output, we have made a Type I error.

    T ____ F ____

20. In acceptance sampling we can control the level of output quality from the inspection point.

    T ____ F ____

MANAGEMENT SCIENCE QUESTIONNAIRE

1. The assignment algorithm is a zero-one special case version of linear programming.

   T ____ F ____

2. Which of the following constraint formulations would not be acceptable for a linear programming problem?

   a.) x2 + y < 123
   b.) x + y*z < 20
   c.) 2x + 6y > 1
   d.) all of the above
   e.) none of the above

3. What "attribute" of linear programming would allow for a fractional solution to a linear programming problem?

   a.) Divisibility
   b.) Linearity
   c.) Separability
   d.) all of the above
   e.) none of the above

4. In linear programming the number of variables must equal the number of constraints.

   T ____ F ____

5. In terms of solution time, it doesn't matter if the number of constraints exceeds the number of variables in a linear programming problem.

   T ____ F ____

6. In linear programming, the shadow prices represent the breakeven cost of a limited resource.

   T ____ F ____

7. If in a probabilistic PERT problem, the most optimistic time estimate was 6, the most likely was nine, and the most pessimistic time estimate was 18 what would be the average completion time for the activity?

   a.) 9
   b.) 10
   c.) 12
   d.) 18
   e.) none of the above

8. For the same values given in Question 7, what would be the value for the standard deviation of the activity?

   a.) 6
   b.) 8/6
   c.) 2
   d.) none of the above

9. In probabilistic PERT, what type of probability distribution is assumed for estimating average activity completion times?

   a.) Normal
   b.) Poisson
   c.) Erlang
   d.) Beta
   e.) Unit

10. In the transportation algorithm, one _must_ have a problem in which the demands _exactly_ equal the supplies.

    T ____ F ____

11. In the transportation algorithm, the number of demand centers must equal the number of supply centers.

    T ____ F ____

12. What variation on linear programming might be employed if one had multiple objectives?

    a.) Integer Programming
    b.) Separable Programming
    c.) Goal Programming
    d.) none of the above
    e.) all of the above

13. Significance of zeros evaluations of open squares is that we have not maximized potential improvements when making shifts in the transportation algorithm.

    T ____ F ____

14. In a linear programming problem we are told that firm produces two product - X and Y. It takes 4 hours to produce a unit of X and 3 hours to produce a unit of Y. If there is an upper limit of sixty labor hours what would be a feasible solution?

    a.) X = 0 and Y = 0

b.) X = 15 and Y = 20
c.) X = 10 and Y = 10

15. In simulation models the results are optimal and perfectly accurate.

T ____ F ____

16. If the arrival rate follows the Poisson distribution with a mean value of two units per hour, and the mean service time is ten minutes with a standard deviation of five minutes, what would be the average length of the line?

a.) 0
b.) 0.1
c.) 1
d.) none of the above
e.) all of the above

17. In queuing models services times follow the negative exponential distribution?

T ____ F ____

18. If the times between arrivals follows a negative exponential distribution then arrival rates follow a Poisson distribution.

T ____ F ____

19. In linear programming the optimal solution always lies

a.) within the feasible region
b.) on the edge of the feasible region
c.) beyond the limits of the feasible region
d.) none of the above
e.) all of the above

20. Minimization problems usually have

a.) fewer decision variables
b.) less than or equal to constraints
c.) fewer constraints
d.) b and c
e.) none of the above

APPENDIX F

In Chapter 4, we presented the results of the tests of the various hypotheses. For Hypotheses HA1 to HA12 we presented the results for two of the four questionnaires (Sander's Questionnaire and Larker and Lessig's Questionnaire). In Table F.1 we summarize the results of those hypotheses for the two other questionnaires.

In Table F.2 we present the data (sample size, correlation coefficient, slope of regression, and the residual error) that was required to compute the T statistic and z-transformation.

TABLE F.1

STATISTICAL SUMMARY OF T-TESTS FOR HYPOTHESE HA1 TO HA12 ON THE ALDAG AND POWERS' ATTITUDE-TOWARD-DECISION AID QUESTIONNAIRE AND THE FRANZ AND ROBEY QUESTIONNAIRE

HYPOTHESIS	QUESTIONNAIRE	T-VALUE	LEVEL OF SIGNIFICANCE
HA1.	ALDAG AND POWERS	-5.20	.001
HA2.	ALDAG AND POWERS	4.14	.001
HA3.	ALDAG AND POWERS	-3.73	.001
HA4.	ALDAG AND POWERS	1.60	.115
HA5.	ALDAG AND POWERS	-5.14	.001
HA6.	ALDAG AND POWERS	3.88	.001
HA7.	FRANZ AND ROBEY	4.25	.001
HA8.	FRANZ AND ROBEY	-5.21	.001
HA9.	FRANZ AND ROBEY	-4.18	.001
HA10.	FRANZ AND ROBEY	1.06	.292
HA11.	FRANZ AND ROBEY	3.08	.004
HA12.	FRANZ AND ROBEY	-5.37	.001

TABLE F.2

DATA FOR T-STATISTIC AND Z TRANSFORMATION COMPUTATION

DA - Aldag and Powers' Questionnaire as applied to the decision support system
DF - Franz and Robey's Questionnaire as applied to the decision support system
DL - Larker and Lessig's Questionnaire as applied to the decision support system
DS - Sander's Questionnaire as applied to the decision support system
EA - Aldag and Powers' Questionnaire as applied to the expert system
EF - Franz and Robey's Questionnaire as applied to the expert system
EL - Larker and Lessig's Questionnaire as applied to the expert system
ES - Sander's Questionnaire as applied to the expert system

DEPENDENT VARIABLE	INDEPENDENT VARIABLE	SAMPLE SIZE	CORRELATION COEFFICIENT	SLOPE OF REGRESSION	RESIDUAL ERROR
DA	LOCUS OF CONTROL	66	-.1610	-.4703	135.80
DA	TOLERANCE FOR AMBIGUITY	66	.1253	.1605	137.29
DA	MANAGEMENT SCIENCE	66	.1103	.2966	137.79
DA	P/OM	66	.1584	.4177	135.98
DA	CONCEPTUAL	66	-.0621	-.0538	138.95
DA	BEHAVIORAL	66	-.1886	-.0928	135.11
EA	LOCUS OF CONTROL	66	.1853	.8198	308.09

DEPENDENT VARIABLE	INDEPENDENT VARIABLE	SAMPLE SIZE	CORRELATION COEFFICIENT	SLOPE OF REGRESSION	RESIDUAL ERROR
EA	TOLERANCE FOR AMBIGUITY	66	.0266	.0515	319.63
EA	MANAGEMENT SCIENCE	66	-.2159	-.8792	304.95
EA	P/OM	66	-.3270	-1.3056	285.65
EA	CONCEPTUAL	66	-.1337	-.1754	314.14
EA	BEHAVIORAL	66	.0724	.2049	315.66
DS	LOCUS OF CONTROL	66	-.0578	-.1859	168.67
DS	TOLERANCE FOR AMBIGUITY	66	.1197	.1689	166.81
DS	MANAGEMENT SCIENCE	66	.0896	.2656	167.87
DS	P/OM	66	.1750	.5081	164.06
DS	CONCEPTUAL	66	.0662	.0631	168.50
DS	BEHAVIORAL	66	-.1252	-.0395	168.95
ES	LOCUS OF CONTROL	66	.1537	.6061	248.09
ES	TOLERANCE FOR AMBIGUITY	66	.0748	.1293	252.67
ES	MANAGEMENT SCIENCE	66	-.2063	-.7490	243.28
ES	P/OM	66	-.3123	-1.1113	229.31
ES	CONCEPTUAL	66	.1224	.1431	250.29
ES	BEHAVIORAL	66	.0661	.1671	251.96

DEPENDENT VARIABLE	INDEPENDENT VARIABLE	SAMPLE SIZE	CORRELATION COEFFICIENT	SLOPE OF REGRESSION	RESIDUAL ERROR
DL	LOCUS OF CONTROL	66	.0691	.0833	23.65
DL	TOLERANCE FOR AMBIGUITY	66	.2299	.1215	22.50
DL	MANAGEMENT SCIENCE	66	-.0544	-.0604	23.70
DL	P/OM	66	.1578	.1717	23.17
DL	CONCEPTUAL	66	.1061	.0380	23.49
DL	BEHAVIORAL	66	-.0070	-.0392	23.86
EL	LOCUS OF CONTROL	66	.2451	.3798	36.94
EL	TOLERANCE FOR AMBIGUITY	66	.0282	.0192	39.27
EL	MANAGEMENT SCIENCE	66	-.2085	-.2977	37.59
EL	P/OM	66	-.3332	-.4663	34.93
EL	CONCEPTUAL	66	.1846	.0849	37.96
EL	BEHAVIORAL	66	.1185	.1011	37.52
DF	LOCUS OF CONTROL	66	.0029	.0049	48.44
DF	TOLERANCE FOR AMBIGUITY	66	.1270	.0957	47.66
DF	MANAGEMENT SCIENCE	66	.1615	.2559	47.17
DF	P/OM	66	.1353	.2101	47.55
DF	CONCEPTUAL	66	-.1320	-.0674	47.59
DF	BEHAVIORAL	66	-.1067	-.0828	47.41

DEPENDENT VARIABLE	INDEPENDENT VARIABLE	SAMPLE SIZE	CORRELATION COEFFICIENT	SLOPE OF REGRESSION	RESIDUAL ERROR
EF	LOCUS OF CONTROL	66	.2706	.4808	47.89
EF	TOLERANCE FOR AMBIGUITY	66	.1001	.0779	51.11
EF	MANAGEMENT SCIENCE	66	-.3070	-.5024	46.76
EF	P/OM	66	-.2790	-.4475	47.61
EF	CONCEPTUAL	66	.2322	.1224	48.84
EF	BEHAVIORAL	66	.1415	.1449	47.62

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