A PROTOTYPE MANAGEMENT SUPPORT SYSTEM: DESIGN, IMPLEMENTATION, AND EMPIRICAL TESTING OF A NATURAL LANGUAGE-LIKE KNOWLEDGE-BASED INTERFACE BETWEEN AN END USER AND A STATISTICAL PROBLEM PROCESSING PACKAGE FOR MICROCOMPUTERS

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NOMENCLATURE

AI	- Artificial Intelligence
CAI	- Computer Aided Instruction
CEO	- Chief Executive Officer
DBMS	- DataBase Management System(s)
DSS	- Decision Support System(s)
EIS	- Executive Information System(s)
KBS	- Knowledge-Based System(s)
KPS	- Knowledge Processing System(s)
LPS	- Language Processing System(s)
MIS	- Management Information System(s)
MSS	- Management Support System(s)
NLP	- Natural Language Programming
PPS	- Problem Processing System(s)
RAM	- Random Access Memory
ROM	- Read Only Memory
SDLC	- System Development Life Cycle
SDS	- Structured Decision System(s)
TPS	- Transaction Processing System(s)

CHAPTER I

INTRODUCTION

Management support systems (MSS) are information technology based systems which support management at the operational, tactical, and strategic levels. The term MSS provides a broad emerging category for support systems based upon information technologies, including but not limited to artificial intelligence, teleconferencing, electronic data bases, graphics work stations, and not limited to computer technologies used for traditional data processing While traditionally associated with the information technologies of computer hardware (the physical components of a computer system) and software (the programs which control the operation of a computer system), MSS information technologies also include communication and methodological tools. (Scott Morton, 1984; Rockart, 1984).

MSS may be classified by the type or function of the support provided A functional classification of MSS includes the more traditional domain of decision support as well as the emerging areas of data support and executive support

The design and implementation of MSS have been driven by advances in technology Two information technologies leading to the increase of MSS are. 1) the hardware and software computer technologies of microcomputers; and 2) the communication and methodological tools of artificial intelligence (AI). The proliferation of the microcomputer, or personal computer, has made computer hardware and software more widely available to users. The emergence of AI technologies is redefining the communication and methodological tools for the human-computer interface. These two technologies -- the microcomputer and artificial intelligence -- and their impacts on MSS are the focus of this study. The application of microcomputer and AI technologies to the three functional areas of MSS -- decision support, data support, and executive support comprise the broad scope of this study

1 1 Information Technologies

MSS supply support to management through the use of information technologies computer hardware; computer software; communication tools; and methodological tools (as suggested in Figure 1 below).

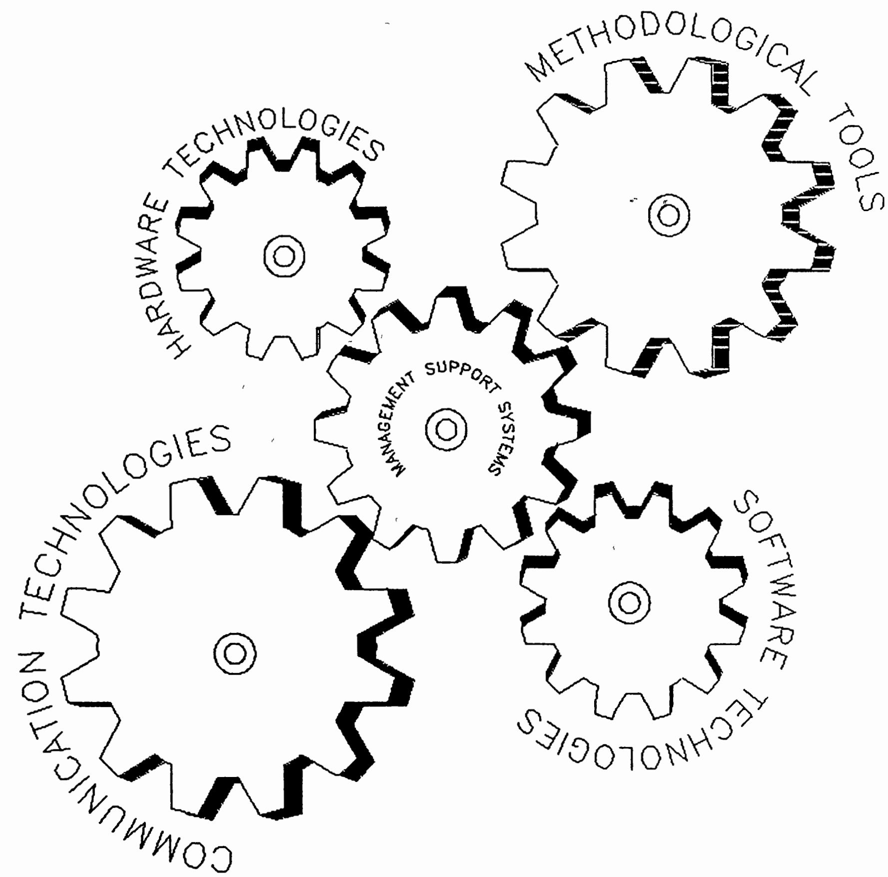


Figure 1. MSS Development is Technology Driven

In his seminal 1971 text, Management Decision Systems, Scott Morton presents a vision of a technology-driven field that "offers the possibility of coupling the manager, at any level, and in any environment, with information and decision-making support from the computer "

1.1.1 Computer Hardware and Software

Almost fifteen years later, Scott Morton cites the unprecedented "information power" of "the ubiquitous personal computer as well as the more traditional time-sharing system " Because of the increasing availability of computer hardware to large numbers of end users "One increasingly finds MSS woven into the very fabric of management." (Scott Morton, 1984, p 13)

Driving MSS development has been the advancement of computer hardware technologies. Since 1940 there have been four generations of modern electronic computer implementations. Based upon the hardware used to control operations, the four incorporate first, vacuum tubes; second, transistors; third, integrated circuits; and the current fourth generation, microprocessors, using very large scale integration (VLSI) to allow tens of thousands of circuit elements to occupy a single silicon chip. The evolution from one generation to another has been marked by increasing speed and processing capabilities and decreasing cost and size. The microcomputer on today's desktop is roughly equivalent in speed and capacity to the roomful of mainframe of ten years ago and costs considerably less.

The first four generations of computer implementations might also be classified by their information processing capabilities as provided by computer software. A first generation adder or counter was followed by a second generation calculator, then a third generation sorter begetting the current fourth generation doer.

Computer software advances have followed the advances in computer hardware There have been four generations of computer programming languages to provide for creation of computer software. Based upon their similarity to binary code (ones and zeroes necessary to direct the switches of computer hardware), the languages are classified as low-level or high-level languages, with low-level languages being more similar to binary code and high-level languages being more similar to conversational language. The four generations include the low-level first generation machine language and second generation assembler language and the high-level third generation programming languages. A fourth generation programming language (4GL) allows the user to specify applications, providing instructions as to what to do rather than how to do it.

The drop in cost and increase in functionality of fourth generation computer hardware (Benjamin, 1982) is bringing about a migration of some MSS software tools from the mainframe to the micro. Among these are: third generation programming languages such as C, COBOL, Pascal, Ada; fourth generation application languages such as IFPS, SAS, SPSS, and SQL; and, fourth generation programming languages such as Prolog and Lisp. In addition to the migration of mainframe software, more powerful microcomputer technology has fostered the maturing of microcomputer spreadsheet application languages from the original VisiCalc to the highly sophisticated multi-dimensional spreadsheets that are on the market today

1.1.2 Communication and Methodological Tools

Both the hardware and software available at the microcomputer level and the increasing availability of mainframe to microcomputer networking offer impetus for a growing number of microcomputer-based MSS applications. Typical of mainframe applications has been the computer professional as intermediary assistant, providing explanation and interpretation of data transformed to information. Most microcomputer implementations which have migrated from the mainframe lack this layer of intermediary support from computer professionals

Keen (1983) cites the advantage of microcomputer-based MSS as an available technological resource which encourages MSS usage, while warning that the lack of an intermediary assistant may present the possibility of microcomputer misuse. Keen proposes a policy for microcomputer use which encourages: 1) use, not control of use; 2) full authority to end users; and 3) the establishment of a coordinator, or intermediary assistant, to provide education and user support. Critical in this policy, which pre-dates the current mainframe to microcomputer software and data migration, is the intermediary assistant who provides education and user support.

A communication design approach which attempts to provide a layer of intermediary support has been user-friendliness -- attempting to assist users in becoming computer literate through a friendly human-computer interface. The emerging technology of AI takes the opposite approach of attempting to provide the computer with user-literacy or an understanding of the user, and an intelligence in problem solving. A computer may be said to be intelligent if it is perceived to perform as a human being might in a similar circumstance.

One direction of AI technology is the construction of computer applications which exhibit abilities associated with human beings. Among these is natural language understanding or natural language processing (NLP), a human-computer interface that allows the user to communicate with a computer-based system in a manner similar to the way that he or she would converse with another human, i.e. in a natural language rather than a programming language. NLP as an MSS communication tool offers a familiar conversational framework for the user Benbasat (1984) includes this conversationality in his working definition of an MSS·

> A conversational, interactive computer-based system used by managers as an aid to decision making in semistructured decision tasks The system supports rather than replaces decision makers. It focuses on the effectiveness of decision making by extending the range and capability of managers' decision processes. It applies to decision tasks that have sufficient structure to allow computer support but for which human judgment is essential (p. 47).

Suggesting that an MSS in its simplest form consists of "the decision maker (manager) with a problem to solve, a computer and analytical tools, and the interface between the manager and the computer," Benbasat's definition (p. 48) of an MSS encompasses the decision support function but also allows for additional types of support provided by the communication interface and methodological, or analytical, tools.

Another AI technology, expert or knowledge-based systems (KBS), offers the promise for emulating the level of intermediary assistance missing in the microcomputer applications. The purpose of a KBS is to offer advice or solution alternatives for problems in a particular area The advice is comparable to that which would be offered by a human knowledgeable in that problem area because the system is programmed to follow the human reasoning used by an expert to deduce certain findings as reached through judgment based on experience Some have gone so far as to suggest that the combination of available hardware and software technologies with the communication and methodological tools of AI will, in the foreseeable future, be able to carry out management at middle or lower levels, replacing managers at those levels (Trappl, 1985, pp. 37-38). However, the development goal of MSS is not the replacement of managers, but rather the <u>support</u> of managers. In order to emphasize that support goal, the term knowledge-based system (KBS) will be used rather than expert system.

Methodological tools, such as the data analysis of statistics and the decision analysis of operations research, may be made available to the user with the AI technology of KBS, providing a design for knowledge engineering that mimics the intermediary assistant's support for the MSS user. In statistical or operations research modeling, this might include suggesting possible data interpretations or encouraging the use of various methodological approaches. Two directions are emerging in the application of AI to statistical data analysis: 1) making statistical software more accessible to the statistically naive user; and 2) the provision of a statistical assistant for professionals. (Gale, 1986).

1.2 Three MSS Support Functions

MSS may be classified according to the type of support offered managers -- decision support, data support, and executive support. While MSS provide support to management, management information systems (MIS) use computer resources to perform transaction processing, providing information, through a formal reporting system, to accomplish managerial-decision support (Davis and Olson, 1985). The interrelationships among the three support functions of MSS and between MSS and MIS are suggested in Figure 2.

MSS makes use of internal data stored in the firm's MIS as well as data external to the MIS (and perhaps the firm) MSS may provide for one or more of the three support functions decision support, data support, and executive support. Hence, all decision support systems are management support systems, but management support systems encompass more than the traditional decision support system. As the technology emerges, MSS may offer support in other areas as well. While useful in areas other than MSS, KBS may be incorporated into MSS to offer support in any of the three MSS functional areas, as discussed below.

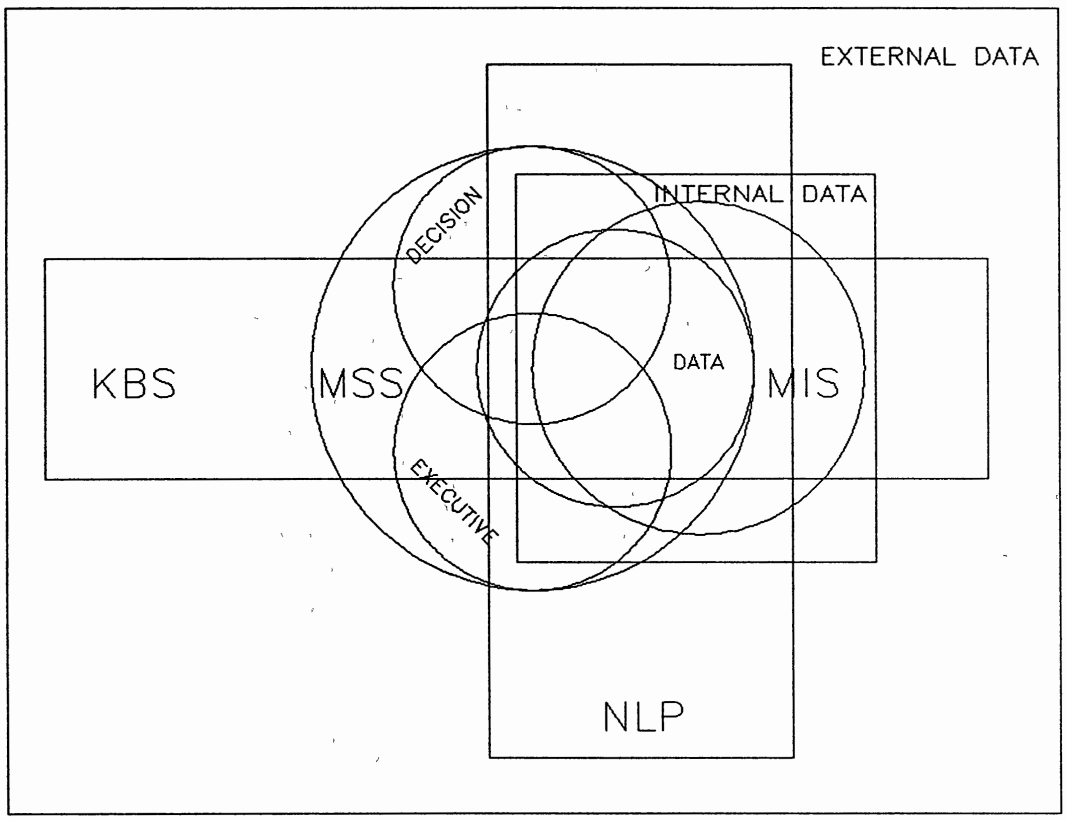


Figure 2. Interrelationships of MSS, MIS, and KBS

1.2.1 Decision Support

Much of the recent MSS work has been done in the area of DSS, or decision support systems (Keen and Scott Morton, 1978; Bonczek, Holsapple, and Whinston, 1980b; Sprague and

Carlson, 1982). This subset of MSS focuses upon computer software that provides support for a specific decision or class of decisions, with a model orientation for the decision process

A general broadening of the decision support function has occurred with the development of KBS. Early KBS were primarily to assist professionals in performing some detailed technical task. Examples include: MYCIN (Shortliffe, 1976; Buchanan and Shortliffe, 1984) used by medical doctors to identify a particular bacterial infection; PROSPECTOR (Duda, Gaschnig, and Hart, 1979) used by geologists; and DENDRAL (Lindsay, Buchanan, Feigenbaum, and Lederberg, 1980) used by chemists for analyzing chemical spectrograms. Only recently have KBS been applied in business settings, such as R1, Digital Equipment Corporation's computer configurer (McDermott, 1980).

1.2.2 <u>Data Support</u>

Data in the business setting have been maintained through MIS databases The growth of relational databases and active query languages has made MIS-maintained data more easily accessible by end users. While traditionally in the purview of transaction processing, to the extent that these systems provide internal information to support managers they offer the data support function of MSS.

External databases also offer data support. Like KBS, external databases were initially developed for licensed professionals such as attorneys (e.g. LEXIS and WESLAW). More recently databases have been maintained specifically for business use (e g Dow-Jones Information Retrieval Service).

AI technologies have impacted data support, as well as effecting advances in MIS KBS have been developed to aid in data retrieval through extended searches of external databases. NLP query languages have been developed for MIS database searches.

1.2.3 Executive Support

Focused upon a manager's information needs across a range of areas, the majority of executive support systems are oriented toward data retrieval and manipulation. The emergence of executive support systems, also called executive information systems (EIS), is currently being driven by: 1) advances in MIS which facilitate mainframe data retrieval, 2) software designed specifically to encourage executive access to and use of data; and 3) increasingly powerful personal computers. Incorporating various operations research and statistical tools as a methodology for data manipulation, EIS software is touted as specially designed systems "so simple that even CEOs can use them" (Gelfond, 1988, p. 84).

1.3 The Emerging MSS Environment

Bonczek, Holsapple, and Whinston (1980b) suggest that a DSS consists of three components: 1) a problem processing system (PPS), 2) a knowledge processing system (KPS), and 3) a language processing system (LPS) Sprague and Carlson (1982) list three functions of a computer-based support system: 1) model manager; 2) data manager, and 3) dialogue manager. Combining these elements and expanding the definition to include: 1) the inference of AI; and 2) the human-machine interaction to aid not only in decision-making but in supporting managers with information, moves to the overarching category of an MSS in all its functions, with AI inference providing executive support and aiding decision support, and the accessibility of human-machine interaction facilitating data support.

This MSS definition parallels the design specifications of a fifth-generation computer. Heralded as bringing the dawn of "the second computer age" (Business Week, 1982), the fifth-generation computer will provide "the transition from information processing to knowledge processing, from computers that calculate and store data to computers that reason and inform" (Feigenbaum and McCorduck, p. 1).

Offering the hope of the evolution of computer as thinker, this new generation of computers had its beginnings at an international conference in October, 1981, in Tokyo The term fifth generation computer and its initial designs were the product of two years of research by the Japan Information Processing Development Center (JIPDEC)

The basic configuration of a fifth generation computer as proposed by JIPDEC has 1) an external interface; 2) software; and 3) hardware. The essence of the Japanese plan can be seen as three subsystems: 1) knowledge base; 2) problem solving and inference; and 3) intelligent interaction between human and machine using a fifth generation programming language similar to natural language.

While the fifth generation computer may have little architectural similarity with existing computer systems, its essence bears strong resemblance to the emerging field of MSS and appears to offer all the capabilities necessary for MSS, offering design specifications for an MSS implementation.

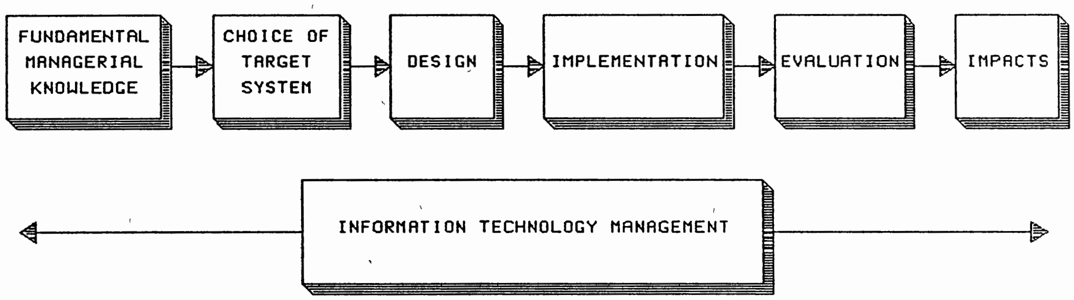
One major area of interest in developing MSS is the role of the intermediary assistant in microcomputer usage and in statistical interpretation. Carlson (1983, p. 65) describes the discretionary use of support systems. He emphasizes the importance of the framework in which information is presented and inputs are given, whether provided by a computer interface or an intermediary assistant.

Critical then to MSS usage is the framework or interface between the support system and the user. Bennett (1983) distinguishes between a presentation language through which the system communicates with the user, and an action or command language, through which the user interacts with the system. Typical of the presentation language are charts, graphs, tabular formats, and the types of helps, prompts and error messages the computer system gives the user. Alternatives for the action language include the type of language (command versus natural language, menu interfaces, etc.) and data entry options (keyboard, mouse, lightpen, audio input).

Accepting the challenge of integrating new technologies, the purpose of this study is to apply information technologies of AI, specifically in the areas of NLP and KBS, to the personal computer information power available to managers in the construction of a prototype management support system using the methodological tools of statistics. The rationale for such a prototype is three-fold, related to the three functions of an MSS: 1) to aid decision support through a knowledge-based intermediary computer assistant, 2) to provide for data support through the ability to import data from external sources; and 3) to facilitate executive support through statistical data analysis. The combination of mainframe computing power in a microcomputer environment coupled with the intermediary assistance of AI offers the promise of continued growth and use of MSS at all levels of management. Specific objectives for the study are detailed below.

1.4 Objectives of the Study

A generic MSS planning and implementation process includes the six steps shown in Figure 3. This process offers a framework for stating the objectives of the study.



Source: Rockart (1984, p. 100).

Figure 3. Management Support Systems Process

1.4.1 Fundamental Managerial Knowledge

1. Specify a heuristic for prototyping a microcomputer-based MSS following the design implications of the fifth generation project and considering fundamental managerial knowledge. The prototype MSS will:

a. provide for decision support through a knowledge-based assistant to aid in model selection;

b. provide for data support in the importation of external data and the explanation of data types in natural language;

c. provide for executive support in assessing the output of statistical modeling and taking into consideration the preferences of the user; and

d. provide for the acceptance of user commands in natural language and the presentation of results in a natural language narrative form.

1.4.2 Choice of Target System, Design, and Implementation

2. Implement this heuristic in a prototype microcomputer-based MSS using statistical analysis as a target system. Design and implementation of the MSS will include.

   a. a problem processing system - model manager, making use of Edu-Stat, a microcomputer-based statistical problem solving system coded in Turbo Pascal,

   b. a knowledge processing system - data manager to:

      1). allow for data management using NLP for both data manipulation and data explanation;

      2). offer intermediary assistance in model selection, dialogue direction, and data manipulation; and

      3). allow for learning from the user new terms and personal preferences.

   c. a language processing system - dialogue manager which allows for both menu and NLP action languages and a narrative presentation language.

1.4.3 Evaluation

3. Empirically test the efficacy of the prototype's NLP action language and menu action language usability in a laboratory experiment.

4. Empirically test the efficacy of the prototype's functionality as a support to management by measuring user manipulation of statistical procedures and results in a problem set

1.4.4 Impacts

5. Survey the satisfaction of users and compare and contrast levels of satisfaction between those using the NLP and menu action languages.

6. Use the results of evaluation and testing to reflect upon the impacts of AI technologies upon the design, implementation, and usefulness of the MSS prototype

1.5 Microcomputer MSS Design and Implementation Concerns

Concerns to be addressed in the design and implementation of an MSS in a microcomputer environment using the information technologies of AI and statistics include 1) detailing the limitations of the microcomputer hardware and software technologies; 2) creating a knowledge system for the data manager and determining the knowledge acquisition process for providing the necessary intermediary assistance; 3) identifying and selecting the statistical problem solving system as a model manager; and 4) integrating the dialogue manager using both a menu and an NLP human-computer interface including definition of the presentation language, action language, and vocabulary selection for the parser.

1.5.1 Microcomputer Limitations

While the fifth generation project offers a procedural goal for the prototyping endeavor, implementation of a microcomputer-based MSS will be limited in a number of areas by the fourth generation machine.

Testing of the prototype MSS will be accomplished using PC-class microcomputer hardware with 640 kilobytes of random access (internal) memory (RAM) and a fixed or hard disk drive for external storage. The central processing unit (CPU) and internal memory capacities will constrain the execution speed of the MSS. Limited internal memory capacities will constrain the performance of NLP in terms of selection of the grammar, execution of the parser, and storage of vocabulary. Due to the memory limitations, program segments will need to be overlayed, being moved from secondary storage into internal memory as needed, further degrading execution speed. The trade-off of speed versus storage within the microcomputer environment will be a major implementation consideration.

1.5.2 The Model Manager: a Statistical Problem Processing System

The Turbo Pascal source code for Edu-Stat (Young, 1986) has been selected as the statistical problem processing system Young describes Edu-Stat as "a statistics package developed to take advantage of the power of microcomputers and to provide an instructive environment for students taking basic statistics or research." The program can calculate a variety of descriptive statistics, perform t-tests of two means, regression and correlation analysis, and analysis of variance. In addition, there are a number of miscellaneous routines available for calculation of factorials, combinations, and permutations, and calculation of hypergeometric, binomial, Poisson, and exponential distributions.

Edu-Stat offers a rich subset of statistical problem processing tools. The availability of the source code will allow the implementation of Edu-Stat as a model manager, facilitating the development process of the prototype MSS. Provisions must be made for recognizing the statistical limitations of the Edu-Stat model manager within the prototype MSS and for directing users to more appropriate alternatives when necessary.

1.5.3 The Data Manager: Knowledge Acquisition

The methodological tools of statistics, like the hardware and software technologies of computers, often require the abilities of an intermediary assistant. AI technologies offer the hope of providing some intermediary assistance through both the presentation language and the assistance of a KBS.

The knowledge-engineering process, capturing the knowledge to provide this intermediary assistance, will require an understanding of various statistical strategies Huber (1986, p. 291) suggests that a typical application of statistics includes: 1) identification of a statistical procedure appropriate for the applied problem; 2) execution of the procedure, and 3) interpretation of the results. While all three require knowledge in statistics, each may also require knowledge in the applied field. Statistical knowledge must be provided in the knowledge base of the data manager, and capturing that knowledge is a major implementation component A secondary implementation component is providing the prototype with the flexibility to learn from the user in order to understand the applied field's relationship to the data.

1.5.4 The Dialogue Manager: NLP Presentation and Action Languages

Edu-Stat has a nested menu-driven action language and uses a tabular format for its presentation language. Data manipulation and model management is directed by a SAS-like action language. With a nested menu-driven action language the user must traverse several full-screen menus in order to select a final menu option. The creation of a pull-down menu-driven action language will allow users to see the full array of system functions on one screen The comparison of this pull-down full-screen menu-driven presentation with an NLP presentation and action languages is a major focus of the study. The availability of the source code will allow the interfacing of Edu-Stat's model management to the NLP code.

Development of the NLP dialogue manager requires design of metagrammar, selection of vocabulary, and implementation of the parser subject to microcomputer constraints and provisions for extending the vocabulary and grammar mentioned above.

1.6 Significance of the Study

To the extent that this study is involved in developing an MSS design heuristic and implementing it in a working prototype, it is exploratory research. The integration of the emerging technologies of computer hardware and software and communication and methodological tools to design and implement an MSS incorporating decision, data, and executive support using the AI technologies of NLP and KBS subject to the constraints of a microcomputer offers the exploratory significance of this study.

Anecdotal evidence has suggested that a natural language user interface would facilitate novice computer users in their use of computer systems, and similarly, a knowledge-based intermediary assistant would facilitate novice statistical users in their use of statistical methodological tools. A controlled test of the efficacy of a natural language like action language versus a pull-down menu action language for both novice and expert computer users and of the efficacy of a knowledge-based computer intermediary assistant for statistics users provides the empirical significance of this study

The possibility of classifying users on the basis of their initial use of a computer system and providing an appropriate interface based upon this initial usage in an intelligent manner offers one of the potential implications of this study. Recognizing the heterogeneous nature of the user community, with different cognitive and learning styles and different levels of expertise through software implementation could lead to more functional and usable software design

A review of related literature is provided in Chapter II. An MSS design heuristic is provided in Chapter III. The experimental design for testing the efficacy of the MSS is given in Chapter IV. Analysis of experiment results, as given in Chapter V, offers information as to the impact of these technologies on MSS development, particularly in the areas of:
1) microcomputer hardware and software implementations using the communication tools of NLP; 2) the intermediary assistance provided to the user by a KBS; and 3) integration of the three MSS support functions of decision, data, and executive support using the methodological tool of statistics. Summary, conclusions, and implications for further research are provided in Chapter VI.

CHAPTER II

REVIEW OF RELATED LITERATURE

Classifications of individual and corporate managerial functions have emerged during the past forty years as organizational theories. At the same time, cognitive and behavioral theories of decision making, problem solving, cognitive style, communication, and information processing have provided a major definition of the managerial function These two schools of research form a specific foundation for the technical development within business of management support systems (MSS) and a general foundation for applications of artificial intelligence (AI)

Because of the relatively recent emergence of these schools of research, the first section of this chapter reviews an organizational taxonomy of management. The second section focuses upon the cognitive and behavioral support for the processes of decision making, problem solving, cognitive style, communication, and information processing The third section discusses general systems theory and its specific application to providing information Following sections review systems as technical and conceptual tools providing support to management, and address concepts relating to the intermediary assistance aspect of management support The last section reviews empirical studies attempting to test the efficacy of computer-based support systems and reports the diversity of conclusions.

As the focus of this study is the design, implementation and empirical testing of a specific MSS using the two information technologies, the microcomputer and AI, contributions of interest are those related to the general design and implementation of computer-based information systems and to the particular design and implementation of: 1) MSS in each of its three functional areas -- decision, data, and executive support; 2) knowledge-based systems (KBS) and computer-aided instruction (CAI); and, 3) natural language processing (NLP) As the methodological tool of statistics is the topic domain of this study's prototype MSS, examples relating to the domain of statistics are cited. The final section emphasizes the need for more integrated approaches and explores the specific task of using information technologies in statistical problem processing to provide the intermediary assistance currently lacking in the microcomputer environment.

2.1 Management and the Need for Information

Literature related to the functions of management, the levels of support needed by managers for decision making and problem solving, and the systems in which managers operate offer an overview of the need for and the importance of management support systems, while indicating the foundation for MSS development and the emerging integration of information technology based support systems within business

Henry Fayol (1949) identifies five functions performed by managers. 1) planning what is to be done; 2) organizing appropriate structures to accomplish the plan; 3) staffing the organization with appropriate staff and coordinating their activities; 4) directing staff toward accomplishing the plan; and, 5) controlling activities so that planned objectives may be met Each of these functions includes a level of decision making: 1) deciding what is desired for a future course of action; 2) deciding the form of the administrative structure, or system; 3) deciding who will operate the system, and within the system; 4) deciding duties to be performed and how to motivate that performance; and, 5) deciding how to measure the results

Anthony (1965) suggests that these decision-making tasks can be categorized as a hierarchy within an organization, classifying three levels of the management process 1) strategic planning, "deciding on objectives of the organization, on changes in these objectives, on the resources used to attain these objectives, and on the policies that are to govern the acquisition, use and disposition of these resources"; 2) management control, assuring "that resources are obtained and used effectively and efficiently in the accomplishment of the organization's objectives"; and, 3) operational control, "assuring that specific tasks are carried out effectively and efficiently."

Ahituv and Neumann (1986) incorporate Anthony's Model with Fayol's classifications (Table I), noting that each function is performed at each managerial level, but that the scope of the function may vary at each level.

Managers act as individuals or in consort to plan, organize, staff, direct, and control the long-range strategies, medium-range resources, and day to day operations of organizations The scope of the managerial function, the planning horizon, and the amount of needed information narrow moving down the hierarchy from strategic to tactical to operational. Similarly, the nature of the decision making task shifts, moving from unstructured, to semi-structured, to structured.

TABLE I

MANAGEMENT FUNCTIONS AT THE VARIOUS MANAGERIAL LEVELS

	MANAGERIAL LEVELS		
MANAGEMENT FUNCTIONS	Strategic Planning	Management Control	Operational Control
Planning	Long-range	Medium-range	Short-range
Organizing	General framework	Departmental level	Small unit level
Staffing	Key persons	Medium-level personnel	Operational personnel
Directing	General and long-range directives	Tactics and procedures	Daily, routine activities
Controlling	Aggregate level	Periodic control and exceptions	Regular, continuous supervision

Source: Ahituv and Neumann (1986, p. 114).

Observations of chief executive officers (CEOs) (Mintzberg, 1973) and information systems managers (Ives and Olson, 1981) suggest that managers spend a great deal of time in verbal communication, working at an unrelenting pace and participating in a plethora of activities, most characterized by brevity, variety, and fragmentation. The implication is that many managerial decisions are unstructured and take place in a highly unstructured environment, resulting in the need for integration of multiple functions to meet the information needs of a manager's cognitive style on a timely basis (Davis and Olson, 1985).

2.2 Support for Decision Making

The process of decision making and problem solving has been regarded as a central task of management and thus a principal area for support. Some suggest that ignorance or lack of interest in how decisions are made is "a serious weakness of the whole study of management" (Keen and Scott Morton, 1978, p. 15), while others see the transmission of information as more critical to the activity of management, avoiding labeling managers as decision makers (Winograd and Flores, 1987, p. 144).

The gathering of information and the process of decision making is cognitive in nature. Supporting managers in their decision making and information gathering requires an understanding of decision making, cognitive processes, and cognitive styles.

2.2.1 Decision Making

Herbert Simon (1960) describes decision making as a central task of management science, and a process of three sequential, potentially iterative, phases: 1) intelligence, involving problem identification and data collection; 2) design, generating alternative solutions and planning for alternative courses of action; and, 3) choice, selecting a solution and implementing and monitoring its application. At any point in the process, one may return to a prior phase for additional information or upon rejection of information.

Decisions to be made are either: 1) structured, decisions based on clear logic, generally of a quantitative nature and involving a short time horizon, 2) semi-structured, where most but not all problem solving steps are structured; or, 3) unstructured, suggesting the use of heuristics, trial and error, or intuition for decisions generally involving a long time horizon The knowledge of outcomes, or the understanding of what will happen if a particular course of action is taken may be seen as: 1) deterministic for structured decisions, where the outcome is known with certainty; 2) probabilistic for the semi-structured decisions, where a probability of occurrence or risk factor may be ascertained for each outcome; and, 3) random for unstructured decisions, where no probabilities may be determined and the outcome is uncertain. The problem-solving process is an attempt to reduce the difference between possible solutions and the goal in order to select not necessarily optimal but satisficing (March and Simon, 1958) solutions which meet the aspiration level of the decision-maker, in a kind of means-end analysis

As an example of a decision making process, the user of a typical statistical analysis software package (e.g. SAS, SPSS, BMDP, etc.) must: 1) select the data, 2) determine an appropriate statistical technique, 3) issue the analysis commands, 4) interpret the results, and 5) recommend a decision (Remus and Kottemann, 1986). Steps 1 and 2 involve the intelligence aspect of decision making (Simon, 1960), including problem identification and data collection; step 3 involves design, interacting with the system to generate alternative solutions and planning for alternative courses of action; and steps 4 and 5 involve choice, selecting a solution and implementing and monitoring its application (Figure 4) The process involves not only the primary decision task (the process of actually making the decision), but also secondary decision tasks (the process of deciding how to decide) (White, 1975). The tasks require both the user's know-what knowledge, an understanding of the topic domain of statistics, and the user's know-how knowledge, an ability to interact with the system (Bullinger and Faehnrich, 1984).

Steps 1 and 2 involve primary decisions, or actually beginning the decision. These decisions require a knowledge of the topic domain of statistics. Steps 3 and (to some extent) 1 require a knowledge of computer systems in general and experience with the specific computer system. Steps 4 and 5 involve the primary decision of acting upon the results or seeking further analysis.

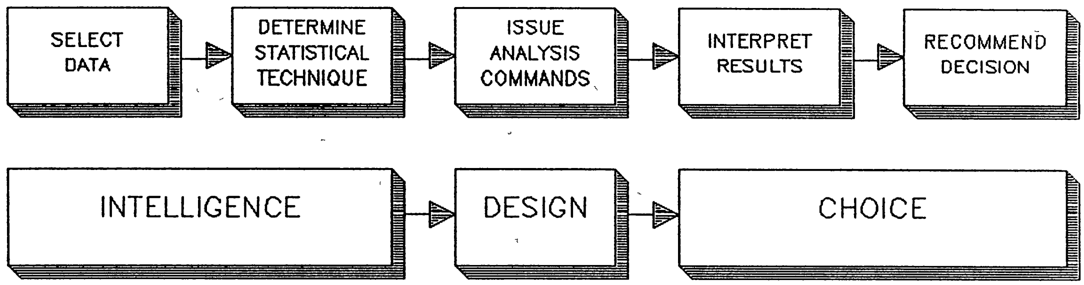


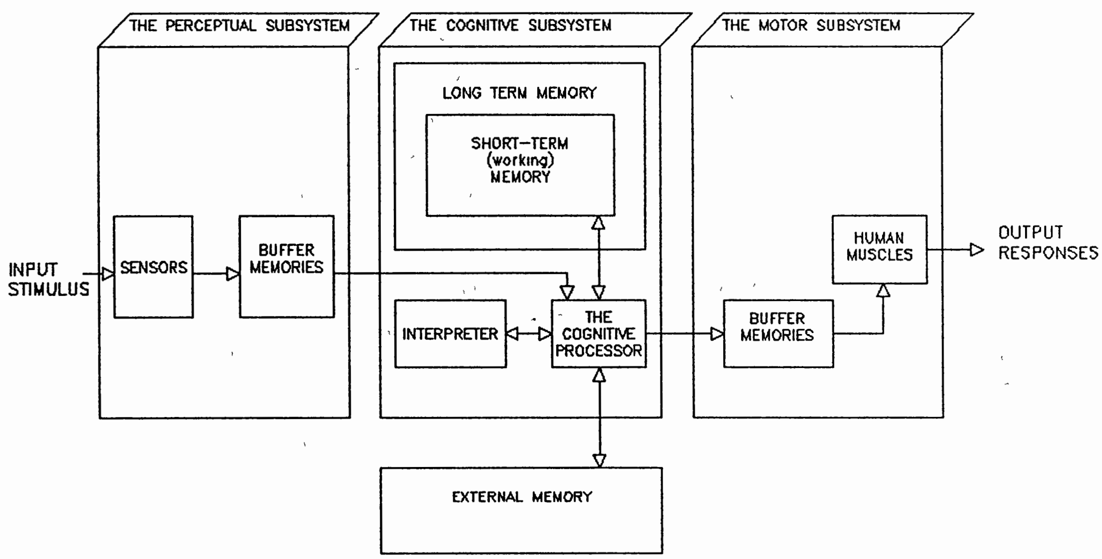
Figure 4. Tasks within the User-Space

Knowledge of the topic domain is the basis for interpreting the results. The dichotomous knowledge categories of know-what and know-how suggest the need for both functionality and usability within the system. Know-what corresponds to a knowledge of the topic domain of the system, referring to 1) the user's pragmatic knowledge or conceptual knowledge of the application (choosing an appropriate statistical technique) and 2) the user's domain knowledge as it relates to details of the functionality of the internal design of the application (interpreting the results). Know-how refers to the user's ability to interact with the computer (providing the data and issuing the analysis commands), relating to usability and corresponding to knowledge of computer systems in general and experience with the specific computer system.

Simon's decision making theories have been seen as integral both to an understanding of management science and the support of problem solving; and, to the foundations of AI Simon suggests that structured and semi-structured decisions are programmed decisions which can be simulated by computer, while unstructured decisions are nonprogrammed, with no possibility of consistent machine replication (1965).

2.2.2 Cognitive Processes

The gathering of information is a cognitive process. Cognition is the intellectual process by which information or knowledge is gained about perceptions or ideas Newell and Simon (1972) offer a formal model of human information processing (Figure 5) in which data are received from the environment through receptors or sensory input of the perceptual subsystem, processed by the cognitive subsystem (brain), using and storing information from memory, either short-term (STM), long-term (LTM), or external (EM). Following processing, information then is returned to the environment through effectors of the motor subsystem (e.g. physical, spoken, or written communication). This process is sequential and serial, each step occurring in its own time and one step following another.



Source: Adapted from Newell and Simon (1972).

Figure 5. A Formal Model of Human Information Processing

Problem solving involves both short-term and long-term memory Theorists tend to agree that the capacity of short-term memory is limited. Miller (1956) proposed a short-term memory model suggesting a discrete buffer containing 7 plus or minus two items, or symbols of information each of which indicates the amount of information needed to make one either/or decision. As the number of symbols of information grow arithmetically, the number of available alternatives for decision making grows exponentially. For example, two symbols of information allow for decisions among four alternatives, three symbols of information provide for eight alternatives, and so forth.

Others have suggested a variability in this discrete short-term memory buffer depending upon the complexity or connectivity of the items being considered (Norman and Bobrow, 1975), proposing a resource allocation model. Just as the complexity or connectivity of items being considered has its effect on short-term memory, so does the organizational aspect of information have its affect on long-term memory. Miller refers to this as chunking, or organizing information into related sets. For example pairings of items would allow the memory capacity to be increased by chunking from a maximum of seven symbols of information to seven symbol, or fourteen items.

Other human memory organization schemas have been proposed, among them the frame concept (Minsky, 1975), used in the computer memory implementation of Smart-Stat, and scripts (Schank and Abelson, 1977).

Mowen (1990) offers a hybrid memory model using a multiple-store approach consisting of sensory, short-term, and long-term memory storage systems. The implication of the model is that information overload can occur, and research suggests that too much information, although frequently desired by managers, can result in poorer decision making (Ackoff, 1967; Malhotra, 1984; Dolinsky and Feinberg, 1986).

Both the primary know-what task of actually making a decision and the secondary task know-how task of using a computer system in deciding how to decide occupy the cognitive activity of a computer assisted decision-maker. Psychological theory indicates that

> ... the completion of a mental activity requires two types of input to the corresponding structure: an information input specific to that structure, and a nonspecific input, which may be variously labeled "effort," "capacity," or "attention " To explain man's [sic] limited ability to carry out multiple activities at the same time, a capacity theory assumes that the total amount of attention which can be deployed at any time is limited (Kahneman, 1973, p 9)

The overloading of the capacity for short term memory is related to the concept of a limited attention capacity. The main attributes of attention are:

> 1) Attention is limited, but the limit is variable from moment to moment. Physiological indices of arousal provide a measure that is correlated to the momentary limit.
>
> 2) The amount of attention or effort exerted at any time depends primarily on the demands of the current activities. While the investment of attention increases with demands, the increase is typically insufficient to fully compensate for the effects of increased task complexity.
>
> 3) Attention is divisible. The allocation of attention is a matter of degree. At high levels of task load, however, attention becomes more nearly unitary.
>
> 4) Attention is selective, or controllable. It can be allocated to facilitate the processing of selected perceptual units or the execution of selected units of performance. The policy of allocation reflects permanent dispositions and temporary intentions. (Kahneman, 1973, 201)

Some activities require less effort than others. The activity of reading, for instance, requires little effort. Once attention is focused upon the activity of reading, the effort is merely a necessary condition for some end to be achieved, that is the pattern matching of the symbols of the words and the recognition of their meaning While perceptual activity requires effort (Kahneman refers to this as $demand_1$), the demands for effort are slight.

Other activities demand greater effort (Kahneman refers to this as $demand_2$). These are typified by choices, decisions, rehearsal, and the mental manipulation of stored symbols. (Kahneman, 1973, 196-200).

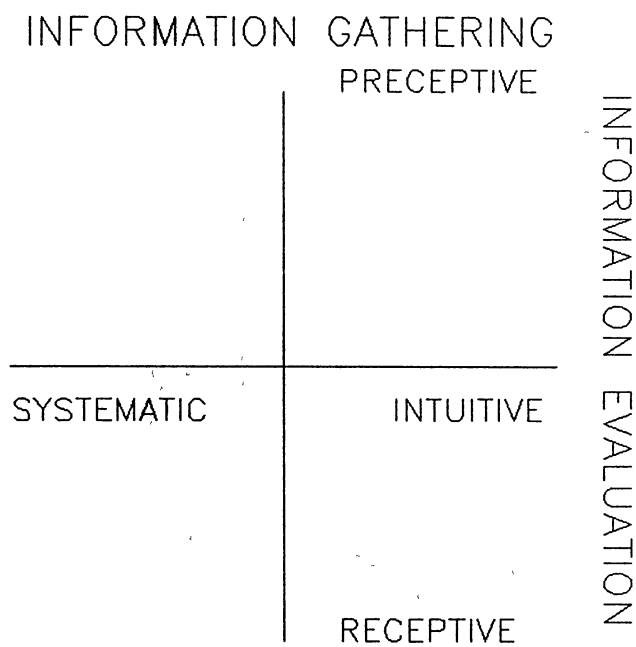
These two types of demands affect the acquisition of knowledge. Alba and Hutchinson (1987) posit that knowledge (specifically consumer knowledge) has two major components· familiarity, characterized by the amount of experience, and expertise, characterized by the ability to perform a task successfully. Simple repetition improves task performance by reducing $demand_1$ effort. As familiarity increases, expertise is enhanced as the ability to analyze information, isolating that which is most important, improves, thus reducing $demand_2$ effort

In a computer-based decision environment, these two demands may be seen as effort relating to the usability (or ease of use, $demand_1$) and the functionality (or usefulness, $demand_2$) of computer-based decision support (Goodwin, 1987; Davis, 1989). Users select computer systems that are useful, that is systems which provide functions needed to accomplish a task (Goodwin, 1987). Selecting the functionality of a computer system to accomplish a task may occur because it is the only way to get the job done, but more likely the choice is made with the expectation that the computer will be useful in accomplishing the task better or faster. The user depends upon the computer system's usability to facilitate and alleviate the amount of $demand_1$ effort allowing the focus of $demand_2$ effort on the system's functionality. Faced with simultaneous multiple activities, it is the secondary task of addressing the computer system, of deciding how to decide, that initially receives the user's primary attention Because the capacity for attention is limited, focusing upon the secondary task diverts attention from (or limits the capacity of attention for) the primary task of actually making the decision.

Cognitive theories of short-term memory, long-term memory, and problem solving offer a framework for understanding the problem of dealing with simultaneous multiple activities in human-computer interaction. In addition, learning theory may play a role in the resolution of demands for attention in situations of simultaneous multiple activities As the user's familiarity increases, expertise moves from novice to expert levels of computer abilities, the effort demanded to learn the system, the know-how areas, diminishes because the awareness of the information input increases. A minimal effort required to use the system, to decide how to decide, allows focusing more effort upon the demands of the primary task of actually making the decision.

2.2.3 Cognitive Styles

An overview of how managers' minds work (McKenney and Keen, 1974) suggests that the process of organizing and changing information during the decision making process can be classified as a cognitive style (Figure 6), which differs from individual to individual (and from organization to organization). This style ranges across two continuums, one for information gathering and the other for information evaluation. The gathering of data dimension runs from the preceptive extreme, generalizing about the environment by focusing on relationships among data items, to the receptive extreme, focusing on details to derive specific knowledge about the environment. The problem solving dimension presents systematic (or algorithmic) approaches at one extreme and intuitive (or heuristic) approaches at the other. Understanding the cognitive style of the manager is a prerequisite to determining their needs for problem solving support



Source: McKenney and Keen, (1974, p 82)

Figure 6. Model of Cognitive Style

Research by Myers and Briggs, among others (Keirsey and Bates, 1984; Evans and Simkin, 1989), provides additional classification of cognitive style across sixteen distinct group represented by combinations of four pairs of temperament types. introversion-extroversion, sensing-intuitive, thinking-feeling, and judging-perceiving (Table II).

TABLE II

FOUR MAJOR PAIRS OF THE MYERS-BRIGGS COGNITIVE STYLE TYPE INDICATOR

EXTROVERT VS. INTROVERT	
Extroversion probably means you relate more easily to the outer world of people and things rather than to the inner world of ideas You like variety and action; are often good at greeting people, are often impatient with long slow jobs; often act quickly, sometimes without thinking, like to have people around, and usually communicate freely.	Introversion means you relate more easily to the inner world of ideas than to the outer world of people and things You like quiet for concentration, tend to be careful with details, dislike sweeping statements, have trouble remembering names and faces, dislike telephone intrusions and interruptions, work contentedly alone, and have some problems communicating
SENSING VS. INTUITIVE	
Sensing means you would rather work with known facts than look for new possibilities and relationships You dislike new problems unless there are standard ways to solve them, like an established way of doing things, enjoy using skills already learned more than learning new ones, seldom make errors of fact, tend to be good at precise work, and are patient with routine details	Intuitive means you would rather look for possibilities and relationships than work with known facts. You like solving new problems, dislike doing the same thing repeatedly, enjoy learning a new skill more than using it, work in bursts of energy powered by enthusiasm, with slack periods in between, reach a conclusion quickly, and are impatient with routine details
THINKING VS. FEELING	
Thinking means you base your judgments more on impersonal analysis and logic than on personal values You do not show emotion readily and are often uncomfortable dealing with people's feelings; may hurt people's feelings without knowing it, like analysis and putting things into logical order, tend to decide impersonally, sometimes paying insufficient attention to people's wishes, and are able to reprimand people or fire them when necessary	Feeling means you base your judgments more on personal values than on impersonal analysis and logic You tend to be very aware of other people and their feelings, enjoy pleasing people, even in unimportant things, dislike telling people unpleasant things, tend to be sympathetic, and like harmony
JUDGING VS. PERCEIVING	
Judging means you like a planned, decided, orderly way of life better than a flexible, spontaneous way. You work best when you can plan your work and follow the plans, like to get things settled and finished; may decide things too quickly, and may dislike to interrupt the project you are on for a more urgent one.	Perceiving means you like a flexible, spontaneous way of life better than a planned, decided, orderly way You adapt well to changing situations, do not mind leaving things open for alterations, may have trouble making decisions, and may start too many projects and have difficulty in finishing them

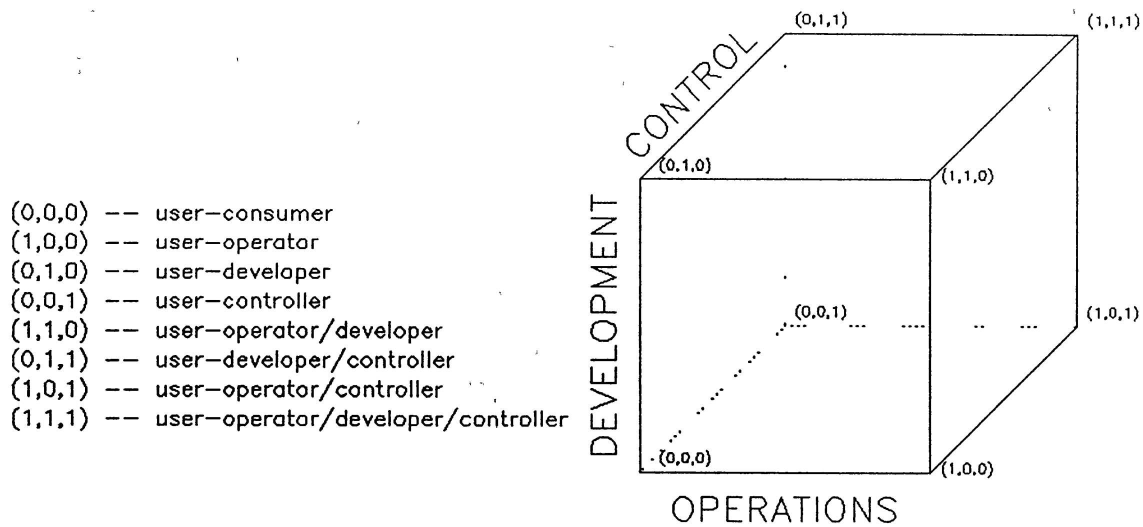
Source: Myers and Briggs as cited in Evans and Simkin (1989, p. 1327)

The importance of cognitive style in the delivery of information has been debated (Benbasat and Taylor, 1978; Huber, 1983) with the major emphasis being that individuals and groups of individuals are the users of information and the focus must be upon the specific needs, styles, and temperaments of each user.

Rockart and Flannery (1983) cite the emergence of microcomputer technologies as an avenue of communicating information for decision making They emphasize the need to understand managers as users of information in order to determine their needs for education, support, and control. They identify six types of end-users of computing power and information 1) nonprogramming end users; 2) command-level end users; 3) end-user programmers, 4) functional support personnel; 5) end-user computing support personnel; and, 6) data processing programmers. In supporting these users in their computing and information needs, they emphasize: 1) Anthony's distributed organizational structure which allows for localizing support, 2) the provision of a wide range of products for problem solving, 3) the development of a substantial education program in methodologies, languages, programming, and system selection; and, 4) the development of data migration techniques to make necessary company data accessible.

Users must be supported on the basis of their ability, novice to expert, and their operational, developmental, and control requirements of computing needs Cotterman and Kumar (1989) have expanded upon the taxonomy above and others to provide a user cube (Figure 7), indicating ranges of expertise across the functional dimensions of computer operations, development, and control. Novices are different from experts in that experts 1) are more knowledgeable about a subject domain, and 2) an expert knows how to apply and use this knowledge more effectively than does a novice (Kolodner, 1984, p 95)

One definition of the novice user suggests a user with no prior computer experience (at which point, a user ceases to be a novice at the first instance of computer use). As previously noted, most management computer users are casual users, seeking the functionality of the computer system. These casual users may be classified as novice users on the basis of their frequency of computer usage, as opposed to expert users who make use of computers on a regular basis.

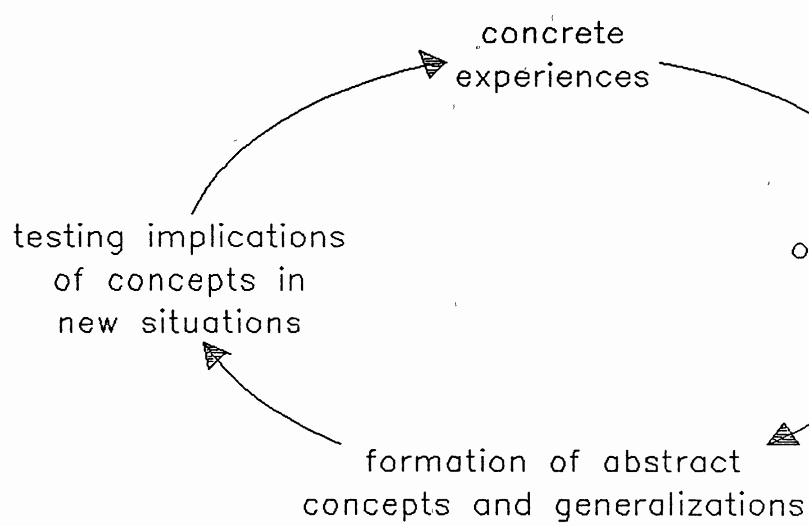


Source: Cotterman and Kumar (1989)

Figure 7. User Cube

Schneider (1982) offers five levels of computer users according to the chunk size assumed to be employed: parrot, someone having minimal knowledge of the computer system whose input merely follows the instructions; novice, someone who attaches specific, but not complex, meaning to input; intermediate, someone who collects items into larger statement chunks; expert, someone who recognizes the interconnection of statement chunks; and master, and individual who is able to create new objects and functions. The implication is that the chunk size increases through a learning process.

Combining the characteristics of problem solving with characteristics of learning, Kolb, Rubin, and McIntyre (1971) suggest that concrete and abstract approaches to problem solving and the active and passive learning that occurs during that problem solving provides an iterative learning/problem solving process (Figure 8). They suggest that this learning cycle is continuously reoccurring, governed by individual needs and goals, and highly individual in both direction and process. Four stages of this process include: 1) concrete experience, offering the raw data of experience, dilemmas, or problems which initialize the learning cycle, 2) reflective observation, providing individual observation of and reflection upon initial choices; 3) abstract conceptualization, moving initial experience and reflection toward the formulation of generalizations and concepts; and, 4) active experimentation, stimulating further new concrete experiences and beginning the cycle again as new learning is gained.



Source: Kolb, Rubin, and McIntyre (1971)

Figure 8. Learning/Problem Solving Process

Effective support for problem solving is enhanced by information: 1) about decision making methods and techniques; 2) about the availability and accessing of data; and, 3) about managerial cognitive style and learning style. The questions of which information (Gorry and Scott Morton, 1971), how much information (Ackoff, 1967), and who uses that information (Mason and Mitroff, 1973) are all critical questions to be considered in the design of systems which deliver information and support management.

2.2.4 Cognitive Implications

Supporting managers in decision making, problem solving, communication, and information gathering requires an understanding of decision theory and cognitive processes at both the organizational and individual levels. Systems that provide information must be built upon these concepts. At the individual level, the usability, or ease of use, and the functionality, or usefulness, of the system will affect the value of the support. Because of the need to both know-how to use the system and to know-what is involved in the domain of the system, attention can be divided in the multiple tasks of using the system and using the products of the system, resulting in information overload. Users of the system may have various levels of familiarity and expertise with one or both of these tasks. Through increased exposure to a process, learning occurs, thereby increasing expertise.

2.3 Systems for Providing Information

General systems theory suggests that a system is a set of interrelated entities that work together for a common purpose in such a synergistic way that it may appear that the whole is greater than the sum of its parts. A taxonomy of systems would include classifications of abstract (either procedural or conceptual) or concrete (either physical or social), open or closed, natural (living) or artificial, deterministic, probabilistic, or random; simple or complex, open loop or closed loop.

The interrelationships of systems, and of systems as subsystems of larger systems, suggest the existence of models, principles, and laws applicable to all systems or subsystems (von Bertalanffy, 1956; Ahituv and Neumann, 1986). For example, Miller (1978) suggests that living systems evolve as a result of a shred-out principle at the exchange of matter-energy and of information in such a way that evolved systems are more complex than their predecessors while including elements of the latter. The evolutionary process of information and energy exchange from the organism (individual) level to the group and organization levels might be characterized as the system of management.

The exchange of information and energy within management systems suggests that they are open systems. In order for management systems to evolve, they must allow for the importation of energy and information from the environment to expand the boundaries of decision making and to avoid the inevitable entropic collapse of a closed system (Katz and Kahn, 1978).

Churchman (1971) suggests nine conditions to be met in order for an entity to be a system. These conditions are a purpose, a measure of performance, a client, components which coproduce the performance measure performance, an environment which coproduces the measure of performance, a decision maker who can change the performance measures, a designer who seeks to affect the decision maker, a design intent on maximizing value to the client, and a realizable design. For a system to achieve its purpose requires the client (user), the decision maker, and the designer.

This overview of management, support, and systems emphasizes the importance of information for decision making and problem solving. The delivery of necessary, useful, and timely information is a systems task. The determination of which information, which decision making model, and which type of support depends upon the level of management, the cognitive style of the manager, and the structure of the problem to be solved. The design of systems depends upon the interactive role of the user, the decision maker, and the designer

2.4 Information System Design Methodologies

Just as systems are evolutionary, the approaches to information system development are also evolving (Alavi, 1984b). The traditional Systems Development Life Cycle (SDLC) approach (Blumenthal, 1969; Enger, 1981) is being supplanted by new approaches

SDLC provides a top-down, multi-stage process for definition, construction, and implementation including: 1) system definition; 2) requirements definition; 3) evaluation, 4) system design and development; and, 5) implementation (Figure 9) SDLC offers a systematic, rigid, sequential process which has been praised for being comprehensive, broad in scope, and easy to understand. SDLC has been criticized for being troublesome, complex, costly, and time-consuming (Ahituv and Neumann, 1984).

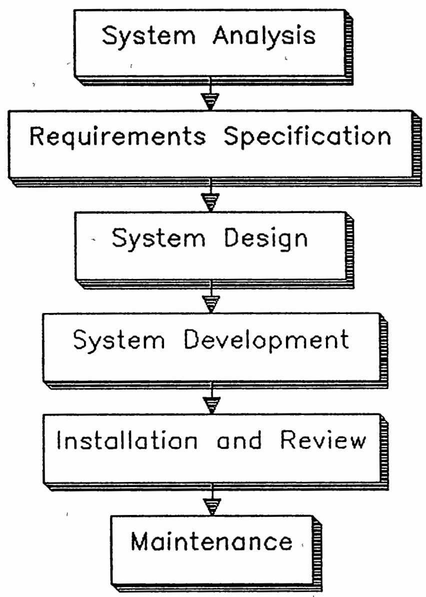


Figure 9. System Development Life Cycle Approach

Because of the criticism of SDLC, a number of variations and modifications of the concept have been proposed. Among these are: evolutionary development (Lucas, 1978), a bottom-up approach used when system requirements are not completely known; heuristic development (Berrisford and Wetherbe, 1979); adaptive design (Keen, 1980), a process of learning, experimentation, and evolution; and, the portfolio approach (McFarlan, 1981). The variations and modifications lead to the current prototyping paradigm Naumann and Jenkins (1982) identify four steps in the prototyping process: 1) identify user's basic requirements;

2) develop a working prototype; 3) use the prototype; and, 4) refine the prototype (the iterative step).

A prototype is a working system which may or may not become the full-fledged or actual production system. Its purpose is to test out assumptions, both of external design (how the system is viewed by the user) and internal design (how the system makes use of software resources). It is created more quickly than systems constructed according to SDLC (in days or months, rather than years) and is relatively inexpensive to build (Sprague and McNurlin, 1986, p. 242).

Prototyping is an iterative process (Figure 10) concentrating on subsets of the capabilities envisioned for the actual production system by combining selected resources As each subset is considered, its feasibility is assessed. If there is some mismatch or incapability, necessary changes are made as feasible. If it is not feasible to make the needed changes, objectives are revised to conform to available resources or a decision is made to consider abandoning the project (Holsapple and Whinston, 1987, p. 159)

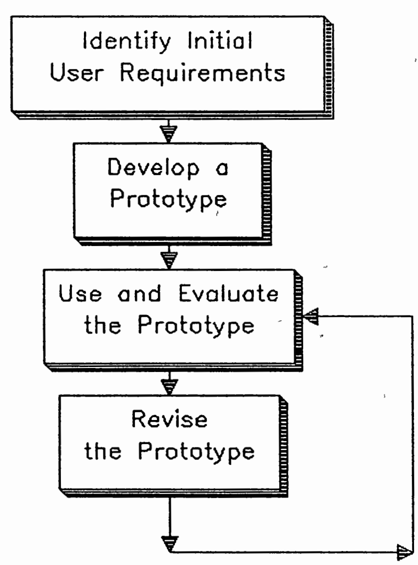
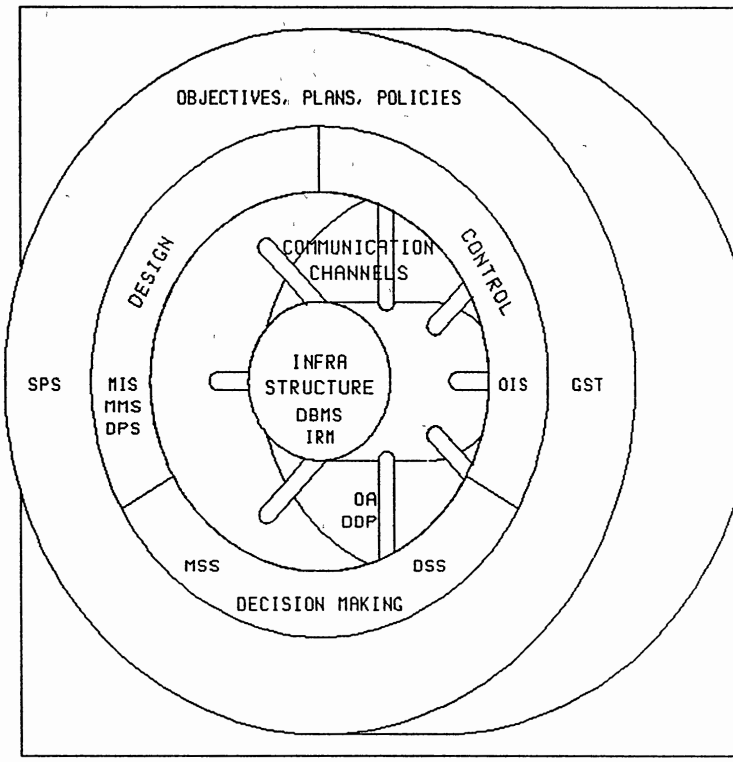


Figure 10. Prototyping Approach

2.5 Technical Tools for Supporting Management

The evolution of information design methodologies has paralleled the development of numerous computer-based systems to deliver information within organizations. Sankar (1984) presents the relationship of these systems as an information wheel (Figure 11)



Source: Sankar (1984, p. 129)

Figure 11. Information Wheel

Sankar describes the interaction:

The hub of an information wheel is made of data base management systems [DBMS] and information resources management [IRM]. The spokes are made of office automation [OA] and distributed data processing [DDP]. The rim is made of management information systems [MIS], data processing systems

> [DPS], model management systems [MMS], operational information systems [OIS], and decision support systems [DSS]. The tire is made of strategic planning systems [SPS] and general systems theory [GST].
>
> When the physical wheel is revolving, the parts cannot be easily distinguished Similarly, the different information systems cannot be easily differentiated in a dynamic organization that is moving and changing in order to meet its objectives. (Sankar, 1984, p. 127).

The blurring effect of spinning the information wheel, where systems tend to blend together as one unit and are difficult to differentiate, is seen in the discussion below in the progression from MIS to DSS to MSS. Each of these technical tools for supporting management appear on the rim of the information wheel.

2.5.1 Management Information Systems

A management information system (MIS) is:

> an integrated, user-machine system for providing information to support operations, management, analysis and decision making functions in an organization The system utilizes computer hardware and software; manual procedures; models for analysis, planning, control, and decision making; and a database. (Davis and Olson, 1985, p 6).

MIS grew from the computerized transaction processing systems (TPS) of the 50's and 60's Assisting the operations level of the organization, TPS capture and validate source data, provide operational information, and update TPS files (Blumenthal, 1969). With the development of database management systems (DBMS), data maintained in TPS files became accessible as information input for management analysis and decision making. A DBMS is a computerized record-keeping system to maintain information and make it available on demand (Date, 1986).

Early hopes were that MIS would offer a single, integrated system to combine all processing for an organization. Skepticism about the ability of such a single system (Dearden, 1966, 1972) focused upon the multitude of problem solving tasks involved, the ability to support decision-making and management planning, and the need for computer professionals to assist in converting data to information. Research into the human-computer interface and other MIS factors is summarized by Dickson, Senn, and Chervany (1977).

Davis and Olson (1985) suggest that MIS as a concept continues to evolve, with related approaches in data processing and extended concepts of decision support systems (DSS) and information resource management (IRM). Rather than evolving as a single system, the MIS concept provides for the integration of organizational information processing. The extended MIS concept of support for decision making has fostered a semantic and conceptual debate Ahituv and Neumann (1986) differentiate the physical structure of information systems in organizations as two subsystems: 1) administrative data processing systems consisting of TPS and structured decision systems (SDS); and, 2) DSS. TPS support the operations of the organization, SDS support decisions at the operational and tactical levels, and DSS support decisions of the tactical and strategic planning levels. Blumenthal (1969) suggests that SDS would replace managers, while DSS would provide for unstructured or semi-structured decision making Others (Rockart and Treacy, 1982; Naylor, 1982) offer the fantasy of CEOs managing from their computer terminals.

The debate over the capabilities of MIS and its differences from its extension, DSS (Naylor, 1982; Blanning, 1983; Watson and Hill, 1983) highlights some of the weaknesses of MIS for management support. Central again is the need for computer skills or the intermediary assistance of computer professionals in order to specify changing information requirements These needs, and the difficulty they present to users, are apparent in the recent migration of a number of mainframe DBMS to microcomputers Douglas (1988, p.38) notes the mainframe mindset of vendors of microcomputer DBMS: "Like their mainframe parent programs, high-end PC databases are complex and, for many users, intimidating products to use."

2.5.2 <u>Decision Support Systems</u>

Decision Support Systems are interactive computer-based systems which provide information and modeling aids to assist users in structured and semi-structured problem solving and decision making. Sprague and Carlson (1982) describe the conceptual components of a

DSS as three management systems: 1) Model Base Management, consisting of a model-base management system (MBMS), modeling command processor, model executor, and database interface; 2) Data Management, through a DBMS, query facility, data directory, and staging elements providing external access; and, 3) Dialog Management, provided by a user interface, request constructor, and control elements. Many of these components exist in an MIS, as noted above in the discussion of the debate over the difference between MIS and DSS. It is the emphasis upon the class of decision making and the changing information needs of the user that distinguishes DSS from MIS (Scott Morton, 1984, Ahituv and Neumann, 1986).

Numerous DSS have been created in both mainframe and microcomputer environments. Their development has been aided by: 1) DSS languages, common high-level computer languages which may be used to develop DSS; 2) specific DSS, systems tailored to a specific decision situation of particular users; 3) DSS tools, software packages (e g. dBase III and integrated systems like Symphony) used to construct DSS available for microcomputers; 4) DSS generators or shells, collections of DSS tools (e.g. IFPS, VisiCalc, and Lotus 1-2-3); and generalized DSS, software packages that provide support for a large class of problems (e.g. SAS, SPSS, BMDP, and Edu-Stat). (Sprague, 1980b; Ahituv and Neumann, 1986)

DSS users are discretionary (McLean and Riesing, 1977; Carlson, 1983) and a DSS has no justification to exist beyond the user's ability and desire to use it. The interactiveness of a DSS seems to enhance its use and effectiveness. Sharda, Barr, and McDonnell (1988) provide a thorough review of the literature related to DSS effectiveness and an empirical test, concluding that DSS users perform more effectively than non-DSS users with only a short-term loss in efficiency. Critical to the success of a DSS is "the judicious interaction between the user and the decision models, and between the models and the database" (Ahituv and Neumann, 1986, p. 178; Cats-Baril and Huber, 1987).

To increase this interactiveness, the next generation of DSS is predicted to be intelligent decision support systems (Bonczek, Holsapple, and Whinston, 1980b). Recent research has focused on this extension of DSS which uses KBS tools of AI to support a limited domain specific problem or class of problems (auditing, Dungan, 1982, and Eining, 1987; income tax, Michaelson, 1982; actuarial consulting, Sivasankaran, 1984; portfolio management, Lee, 1986; audit program planning, Killingsworth, 1987). Where DSS are employed to provide structured decision support, they have been touted as replacements for managers. In limited domains, DSS have been successfully implemented to provide support for semi-structured decision making, although further research is needed to determine ways to increase efficiency and effectiveness. Two critical areas of concern are: 1) interactiveness, or the provision of intermediary assistance, provided by the system; and 2) the transitory nature of information needs for DSS.

2.5.3 Management Support Systems

A management support system (MSS) is an information technology based system which supports management at the operational, strategic, and tactical levels providing decision, data, or executive support. As a term, MSS represents a broad category of information technology based, not just computer-based, systems which support management in the fulfillment of their tasks.

MSS is, broadly speaking, the use of information technologies to support management (Scott Morton, 1984). The MSS concept is not solely computer-based, recognizing that information technologies go beyond the traditional computer data processing, but is grounded in support for management. The shift is from task or decision support to support of individuals throughout the firm who are accomplishing corporate purposes (Rockart, 1984). This support is not only for the cognitive processes required to accomplish corporate purposes, but also for the communication of information. At the same time, the MSS concept builds upon MIS and DSS development and implementation processes, as well as efficiency and effectiveness measures for MIS and DSS to the extent that information technologies offer support for management.

Surveys of information system professionals indicate major information support needs in the 1980's (Dickson, Leitheiser, Wetherbe, and Nechis, 1984; Brancheau and Wetherbe, 1987) including end user computing, competitive advantage, and strategic planning. It is apparent from these surveys that individuals in organizations are expecting more support from the information resources of the firm. As an overarching and integrating entity, MSS attempts to supply that support, even for unstructured and information intensive decision-making processes like those involved in strategic planning (Goul, Shane, and Tonge, 1986; Henderson, Rockart, and Sifonis, 1987). The further integration of information technologies will take advantage of: the emergence of microcomputer technologies to support individuals; data migration links to provide information from MIS; and, existing DSS. It is in using these integrative approaches that MSS will provide both the intermediary assistance and the access to information necessary to support the management function.

2.6 Conceptual Tools for Designing MSS

Providing the intermediary assistance of experts and access to information are two key areas of support for management. The AI technologies of KBS and NLP offer conceptual tools to aid in the design of MSS meeting these support needs, with KBS serving the role of the intermediary assistant and NLP facilitating access to information using natural language.

2.6.1 Knowledge-Based Systems

A knowledge-based system (KBS) is a computer-based system composed of a user interface, an inference engine, and stored expertise (i.e., a rule set, a knowledge base, or an entire knowledge system). Its purpose is to offer advice or solutions for problems in a particular area. The advice is comparable to that which would be offered by a human expert in that problem area because the system is programmed to follow the human reasoning used by an expert to deduce certain findings as reached through judgment based on experience. In order to avoid overstating its capabilities, the term knowledge-based system, indicating reliance upon a set of rules or heuristics as knowledge, is preferred to the more commercial term expert system.

A KBS differs from a conventional computer program in that: "there is a clear separation of general knowledge about the problem (the rules forming a knowledge base) from information about the current problem (the input data) and the methods for applying the general knowledge to the problem (the rule interpreter)." (Duda and Gaschnig, 1981, p. 242).

The development of KBS is facilitated by support software including: 1) shells, standard interface mechanisms and representation languages; 2) AI environments, complete software environments for developing advanced systems; 3) AI languages, such as LISP and Prolog; and, 4) conventional languages, such as Pascal, BASIC, and C.

Baden (1984) cites the flexibility and ease of expression, the human-like processing, and the handling of uncertainty as advantages of KBS. As with DSS, interactiveness is important. Baden sees KBS being used for consultancy, providing checklists to expand decision considerations and refining expertise, and as a training and communication vehicle.

STATCON: the Statistical Consultant (Sechrist, 1987) offers an example of consultancy. A microcomputer based rudimentary KBS application, STATCON is designed to assist in the selection of appropriate statistical tests. Written in Pascal, the menu-driven KBS interrogates the user with questions, generally seeking yes or no responses. Based upon the responses, the program recommends one or more statistical techniques. The opening menu and an example of the program's recommendation for a two interval variable situation are given in Figure 12. User responses are in boldface.

KBS applications in business may not receive the publicity of other KBS because of their potential proprietary nature and the competitive need to protect investments of time and costs involved in their development. Gevarter (1985) estimates that the task of building a KBS takes and average of five person-years. One application that has received considerable publicity is R1, also known as XCON, which assists salespersons at Digital Equipment in configuring computer systems for customers (McDermott, 1980). Other business applications include KBS assistance in auditing (Dungan, 1982; Killingsworth, 1987), credit management (Ben-David and Sterling, 1986), and portfolio management (Cohen and Liberman, 1983). But KBS are limited in applications which: 1) are too simple, less than 10 rules; 2) too complex, over 10,000 rules; 3) are well-structured numerical problems requiring none of the advantages of KBS; 4) rely heavily on the quick response of human senses; and, 5) are in wide and shallow domains, where there may be no specialists. (Baden, 1984, pp. 68-70).

```
                    Select Option From Menu

                      1. Help
                      2. One Variable
                      3. Two Variables
                      4. Over Two Variables
                      5. Quit
```

```
               Treatments for More than Two Variables
Is a distinction made between dependent and independent variables? (y/n): y
Is there more than one dependent variable? (y/n): n
Do you want to use a covariate, i.e. to statistically remove the linear
effect of one (or more) variables from the dependent variable? (y/n): n
Do you want to ignore possible interaction among the variables? (y/n): y
How do you want to treat the dependent variable with respect to scale
of measurement Nominal, Ordinal, Interval? (n/o/i): i
Do you want to treat all the independent variables as interval? (y/n): y
Do you want to treat all the relationships as linear? (y/n): y
Do you want a single measure of the relationship between the dependent
variable and all the independent variables taken together? (y/n): y
Suggested Statistical Measure    Multiple correlation (multiple regression)*
Suggested Statistical Test       F test
Reference                        Hays 1973, 707, 709

                    Press any Key to Continue
```

user responses are shown in **boldface**

Source: Sechrist, 1987.

Figure 12. STATCON Opening Menu and Sample Output

2.6 2 Natural Language Processing

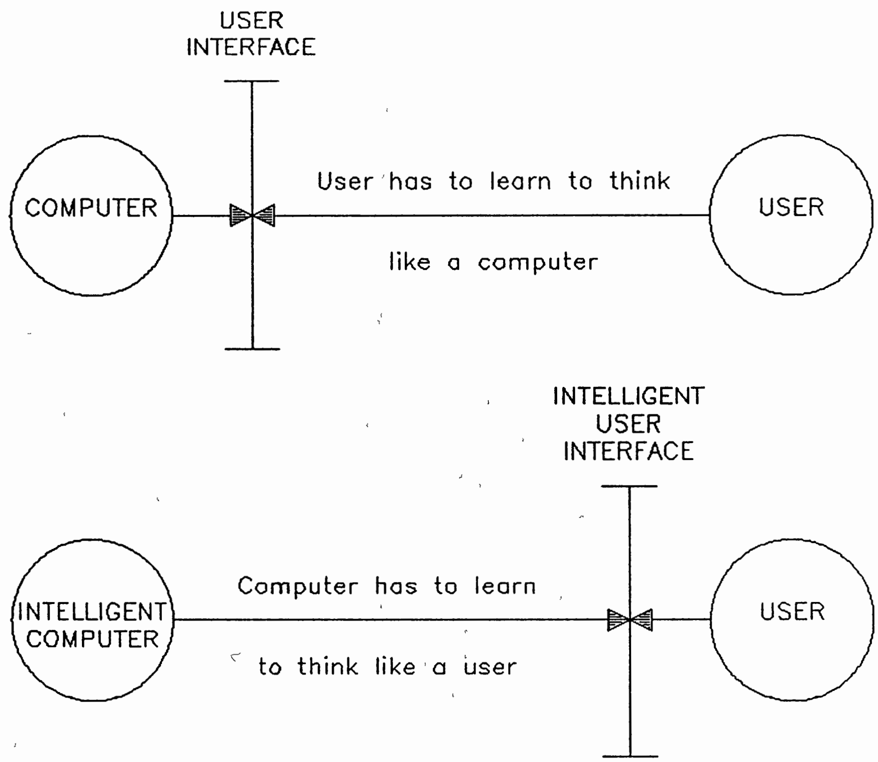
Natural language processing (NLP) includes the two fields of natural language understanding and natural language generation. Natural language understanding, of interest here, investigates methods of allowing a computer to comprehend instructions given by a user in a natural language, such as ordinary English, so that users might communicate with computers more easily. Natural language generation strives to have computers generate ordinary English so that people can understand computers more easily.

Systems for translating natural language into machine usable form make use of knowledge about language (linguistic knowledge) and knowledge about the subject area of communication (domain knowledge) to interpret input. A more formal definition of NLP suggests:

> a kind of user interface that allows the user to carry on a conversation with a computer-based system in much the same way he or she would converse with another human. (Holsapple and Whinston, 1987, p. 341)

Capabilities of the interface include the ability to learn new terms, understand new requests in the context of prior requests, overlook grammatical errors, correct or clarify spelling errors, and carry out actions implied by the conversation (Holsapple and Whinston, 1987) Unlike the traditional user interface consisting of a procedural language (menu driven, command language, etc.) where the user must think like a computer, NLP gives the impression that the computer begins to think like a user (Figure 13).

NLP can be classified at three levels based upon the representation and utilization of linguistic knowledge: syntactic, semantic, and pragmatic. Syntactic analysis explores the arrangement of words and their relationship, semantic analysis explores the meaning of words, and pragmatic analysis attempts to relate the meanings of words and sentences to their surrounding context (Winograd, 1972).



Source: Bishop (1986, p. 125).

Figure 13. Traditional and Intelligent User Interfaces

Hendrix and Sacerdoti (1981) classify NLP systems into three types based upon their representation and utilization of domain knowledge: 1) Type A, no world models, using ad hoc data structures to store facts about a limited domain and performing key word or pattern matching; 2) Type B, explicit world models, using explicitly coded representational models; and, 3) Type C, advanced systems, including information about the goals and beliefs of intelligent entities. Early NLP programs (Type A) were based on pattern, or keyword, searching of the input string, providing for rudimentary syntactic analysis. Weizenbaum's (1966) ELIZA program carried this keyword approach to an impressive, but amusing extreme. Also known as DOCTOR, the program carried on a mock psycho-therapy session with a user by way of a terminal

Figure 14 gives a sample conversation with ELIZA. Machine responses are provided in all capital letters.

Men **are** all alike
IN WHAT WAY
They're always bugging us about **something** or other.
CAN YOU THINK OF A SPECIFIC EXAMPLE
Well, **my** boyfriend **made me** come here.
YOUR BOYFRIEND MADE YOU COME HERE
He says **I'm** depressed much of the time
I AM SORRY TO HEAR THAT YOU ARE DEPRESSED
It's true, **I am** unhappy.
DO YOU THINK COMING HERE WILL HELP YOU NOT TO BE UNHAPPY
I need some help, that much seems certain
WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP
Perhaps I could learn to get along with **my mother**
TELL ME MORE ABOUT YOUR FAMILY
My mother takes care of me
WHO ELSE IN YOUR FAMILY TAKES CARE OF YOU
My Father.
YOUR FATHER
You are like my father in some ways
WHAT RESEMBLANCE DO YOU SEE
You are not very aggressive but I think you don't want me to notice that
WHAT MAKES YOU THINK I AM NOT VERY AGGRESSIVE
You don't argue with me
WHY DO YOU THINK I DON'T ARGUE WITH YOU
You are afraid of me.
DOES IT PLEASE YOU TO BELIEVE I AM AFRAID OF YOU
My Father is afraid of everybody.
WHAT ELSE COMES TO MIND WHEN YOU THINK OF YOUR FATHER
Bullies
DOES THAT HAVE ANYTHING TO DO WITH THE FACT THAT YOUR BOYFRIEND MADE YOU COME HERE

Boldface words are typical of keywords searched for by the program
Underlined words transformed and used to fill out response patterns
CAPITALIZED lines are the program responses

Source: Weizenbaum (1966)

Figure 14. A Sample Conversation with ELIZA

Weizenbaum achieved an amazing level of perceived fluency with two simple tricks. 1) using stock phrases for machine response; and, 2) matching standard patterns (bold-faced words and phrases in Figure 14) with fragments (underlined words or phrases in Figure 14) When a pattern could not be matched, a stock phrase such as "In what way?" would be used When patterns could be matched, they were inserted with fragments of previous input, such as "I am sorry to hear that [fragment]." or "Tell me more about [fragment] " As patterns were matched simple adjustments were made, like changing the word my to the word your.

The apparent fluency of the program's output, brought about by these relatively simplistic tricks, provided results that amazed even the program's designer·

> I was startled to see how quickly and how very deeply people conversing with DOCTOR became emotionally involved with the computer and how unequivocally they anthropomorphized it. . . . Another widespread, and to me surprising, reaction to the ELIZA program was the spread of a belief that it demonstrated a general solution to the problem of computer understanding of natural language (Weizenbaum, 1976, p. 6)

Type B systems explicitly encode knowledge about the domain in a network or frame representation, providing for both syntactic and semantic analysis. A frame is data structure which has slots to be filled for objects and relations appropriate to the situation, becoming one node in a knowledge representation network. Type B systems tend to be limited in their domain The contributions of Chomsky (1965) provided a hierarchy of grammars, or schemes for representing the sentences of a language. His generative-transformational grammar theory provides a framework for the derivation of basic structures of language, by way of transformational rules using a tree structure. Rather than using the actual words, a deep structure was proposed into which the original surface structure might be transformed.

For example, the two sentences "BOB LOVES SUE" and "SUE IS LOVED BY BOB" appear different on the surface, but when an underlying structure is provided, they parse into much the same structure, as can be seen in Figure 15

Chomsky's transformational grammar was not intended as a computational theory, but it grew into a technique for writing recognition grammars known as the augmented transition network (ATN) (Woods, 1970), leading to Type C systems.

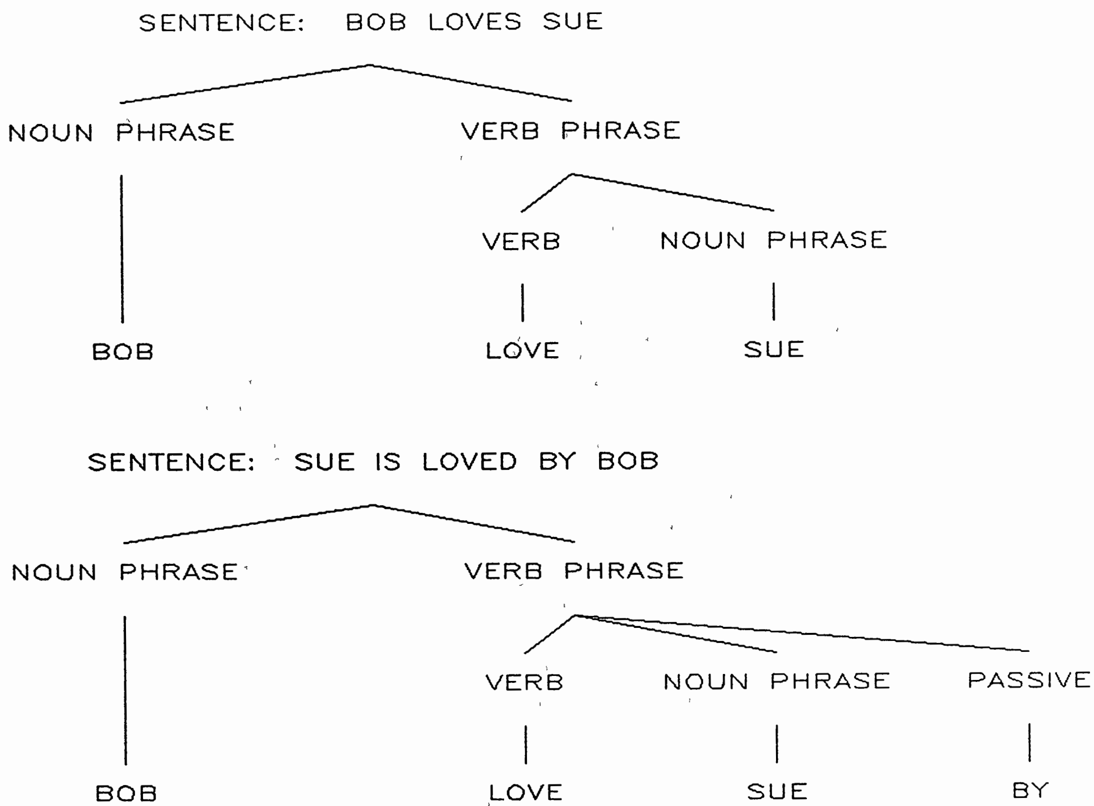


Figure 15. A Transformational Grammar Example

Type C systems use a grammatical relationship to determine the intentions of participants in a communication, offering pragmatic analysis. An early example was the dialogue system of the BLOCKS world of SHRDLU (Winograd, 1972), which held a conversation with the user about a table top world containing building blocks. Using ATN facilities, Winograd translated expressions and commands to address a database of blocks. This arrangement allowed for conversational exchanges such as those in Figure 16

SHRDLU had a very limited domain, over which its syntactic parser constructed structures which were beyond the simple category labellings of an ELIZA. It was an early implementation of procedural semantics which integrated many components, including a database, at a system level.

pick up a big red block
    OK
grasp the pyramid
    I DON'T UNDERSTAND WHICH PYRAMID YOU MEAN
find a block which is taller than the one your are holding and put it into the box
    OK
. . .
what does the box contain?
    THE BLUE PYRAMID AND THE BLUE BLOCK
what is the pyramid supported by?
    THE BOX
how many blocks are not in the box?
    FOUR OF THEM.
is at least one of them narrower than the one which I told you to pick up?
    YES, THE RED CUBE.
is it supported?
    YES, BY THE TABLE.
can the table pick up blocks?
    NO.
. . .
How many things are on top of green cubes?
    I'M NOT SURE WHAT YOU MEAN BY "ON TOP OF" IN THE PHRASE "ON TOP OF GREEN CUBES" DO YOU MEAN:
        1. DIRECTLY ON THE SURFACE.
        2. ANYWHERE ON TOP OF?
2
    THREE OF THEM

* Machine responses are in capital letters

Source: Winograd (1972, pp. 8-15)

Figure 16. A Dialog with SHRDLU

This direction of research moves toward the expressed needs and goals of the fifth generation computer and the implementation of natural language interfaces to information systems. The proposed intelligent human-machine interface for the fifth generation computer includes: 1) NLP; 2) speech synthesis; and, 3) picture and image processing (Tanaka, Chiba, Kidode, Tamura, and Kodera, 1982). Primitive techniques needed for NLP include application domain specific vocabularies, parser and grammar rule development, sentence generation, semantic and pragmatic analysis, and creation of an actual NLP machine.

A number of NLP interfaces have been created, meeting many of the criterion discussed above. IBM's structured query language (SQL) a widely recognized way of addressing a database, has eased the translation difficulties in database queries. Commercial natural language systems for RAMIS II, IDMS, ADABAS, FOCUS, and Vsam on mainframes, Datatrieve and DBMS-32 on minicomputers; and, Guru and KnowledgeMan databases on microcomputers are reported (Holsapple and Whinston, 1987) Additional microcomputer natural language systems are becoming more available (Williamson, 1987), particularly in the area of databases. One recent attempt was the addition of HAL as a limited NLP front-end to Lotus 1-2-3 HAL provides a vocabulary of about 2,000 words and extends the Lotus slash command language to a restricted English-like language, but provides little more than a higher level command language, echoing its English-like commands back to the slash commands (Van Name and Catchings, 1987; Lane, Batsell, and Guadango, 1989). Each of these interfaces share the structural and informational limitations discussed above, in addition to the hardware restrictions imposed by any system.

The advent of new technologies, like speech recognition, promises to free the user from keyboard input and may hasten the development of additional NLP interfaces. Recent implementations report speaker independent machine recognition at 77 percent with a vocabulary limited to 100 words (Bierman, Rodman, Rubin, and Heidlage, 1985) and a 91 percent speaker dependent recognition rate of vocabulary of just over 1,000 words (Erman, Hayes-Roth, Lesser, and Reddy, 1980). Further research may lead to achievement of the 5,000 word vocabulary estimated as necessary for NLP in larger systems (Tanaka, Chiba, Kidode, Tamura, and Kodera, 1982).

As with most development in the area of AI, convenience and cost become mitigating factors Little research has been done comparing the efficiency of NLP over more concise languages or other types of user interfaces. The area of conciseness favors NLP, providing for the fuzzy interpretation of words. The area of fuzzy linguistics and the response to fuzzy queries is a major research area in the application of NLP.

Proponents of natural language interfaces emphasize the range of possible users that could interact with computers without extensive training, and this promise of accessibility is driving the current research. Critics of natural language interfaces point out that concise, rather than natural, languages may be more efficient for many types of problem solving and cite the substantial processing times and development costs of natural language interfaces

2.7 The Need for More Integrated Approaches

Providing access to information and the support of intermediary assistance to management is central to the concepts of MIS, DSS, and MSS. Using MIS and DSS as technical tools for the delivery of requested information and the provision of support moves to the broad purview of MSS. NLP offers a conceptual tool to ease the communication between users and computers. KBS offers a conceptual tool to provide intermediary assistance, including advice, education, and problem-solving support.

The criticisms of MIS and DSS center upon not delivering what was promised While promising a centralization of information resources, most access to data in MIS environments continues to require the intermediary assistance of computer professionals The time required for such assistance is even more frustrating as managers see the relatively immediate response time of their microcomputers and ask "Why?."

While promising to aid in decision making, most DSS environments continue to be limited to the narrow scope of structured and semi-structured decision making. Additionally, DSS use has been saddled by the need to learn a specific command language While NLP has yet to fulfill its promise of a truly conversational user interface, advances have been made in limited domains. Like DSS and NLP, KBS applications are also limited in domain, but have begun to fulfill some of the promise of communication and education The progression of DSS and KBS to MSS is suggested in Table III.

TABLE III

PROGRESSION FROM DSS AND KBS TO MSS

	DSS	KBS	MSS
OBJECTIVE	Assist manager with decision making	Replicate (mimic) and replace manager	Assist manager with information and expertise
DECISION MAKER	The manager	The system	The manager, advised and assisted by the system
MAJOR ORIENTATION	Decision making	Transfer of expertise (manager to machine to manager)	Effective management through information and expertise
QUERY DIRECTION	Manager queries machine	Machine queries manager	Dialogue between manager and machine
QUERY STYLE	Command language	NLP	NLP
CLIENTS	Individual and/or group	Individual	Individual and/or group
MANIPULATION	Numeric	Symbolic	Object-Oriented (both numeric and symbolic)
PROBLEM AREA	Complex, integrated, wide	Narrow domain	Complex, integrated, but narrow domain
DATABASE	Factual knowledge	Procedural and factual knowledge	Procedural and factual knowledge

Source. adapted from Turban and Watkins, 1986, p. 141

While the integration of these conceptual tools is progressing, the challenge of this progression is to fill the gaps in MSS support. Figure 17 highlights these failed promises by indicating the gaps (shaded) of MSS decision, data, and executive support. Most gaps are in the unstructured decision area and at the tactical and strategic levels in the semi-structured decision area. Specific decision making strategies are needed for these gaps

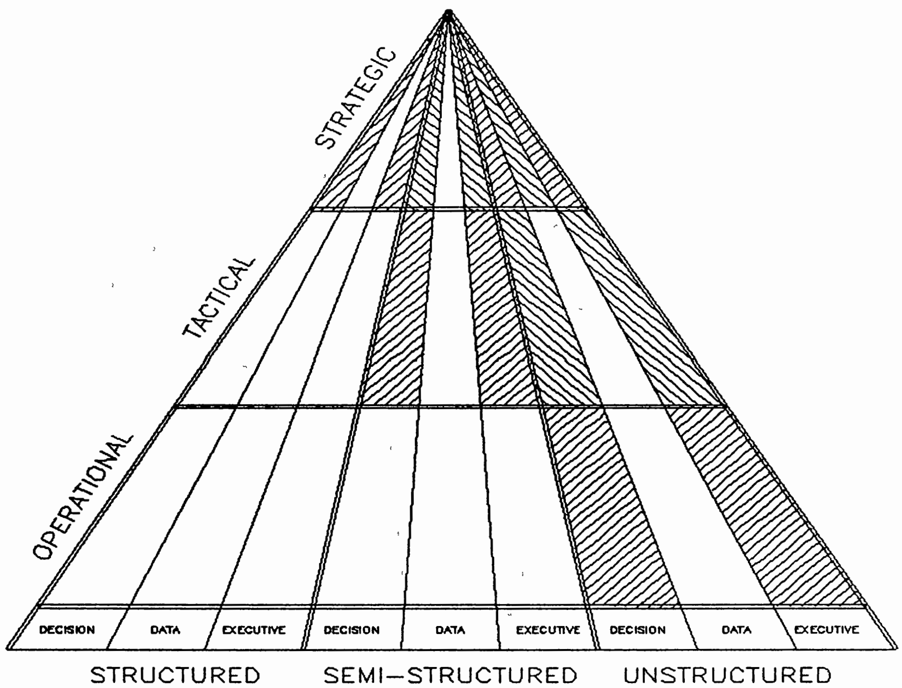


Figure 17. Gaps in MSS Support

2.7.1 Statistics and AI

To the extent that statistical strategies provide for forecasting in uncertain and risk oriented situations based upon current data, these same strategies may offer an additional tool for filling some of the gaps in MSS support. As a "coherent total approach to a data analytic task" Gale (1986, p. 1) defines statistical strategy as answering the questions. 1) "What do I look for?"; 2) "When do I look for it?"; 3) How do I look for it?", 4) "Why do I look for it?"; and, 5) "What do I have to do to look for it?"

A prime concern of statistics is the analysis of data. As already discussed, MIS provides a technical tool for the storage and delivery of data. An MSS approach using statistical tools would provide a system whereby data may be analyzed to provide support for decision making in semi-structured and unstructured environments.

Requirements for data analysis system (Huber, 1986) include an interactive environment easily accessible by a general purpose programming language providing expert assistance Additional requirements include a laboratory assistant to clean and manipulate data, suggest statistical methods, and interpret statistical results. Huber promotes the educational aspect of a data analysis system:

> I favor an alternative aspect of machine aid: that of extending a human ability into a range where the unaided human fails -- just as a hammer is a primitive but extremely useful extension of the human hand, overcoming some inherent limitations of organical issue. In part, the task is to magnify certain human abilities beyond human range, like the pocket calculator magnifies our arithmetic powers. The real challenge is to invent tools stretching the human mind into directions where we do not have human role models to pattern the extension after. (1986, p. 292).

Orman (1984) reports DSS approaches to avoid information pollution, and thus provide for clean data. Hand (1986) indicates that data cleaning and aims formulation are suitable areas for AI technology assistance in statistics. Additional AI areas for statistics include providing for interpretation of the results. In addition to the intelligence of AI to provide such interpretation, an understanding of statistical methods on the part of the user is necessary Educating the statistically naive user can be an additional task of the intermediary assistant

2.7.2 Computer Aided Instruction

As noted above, an often cited area of support for end users of MIS, DSS, and other computer-based functions is education. One way to provide this education is through computer aided instruction (CAI). When combined with the conceptual tools of NLP and KBS within the framework of MSS, the possibilities for communication of organizational goals and enhancement of managerial skills may be realized (Arden, 1980).

This combination of technologies has provided a transition from CAI to intelligent computer-assisted instruction (ICAI). Kearsley (1987) lists five major paradigms in ICAI research 1) mixed-initiative dialogues, where the learner is engaged in a two-way conversation, 2) coaches, where advice is given to assist in performance, 3) diagnostic tutors, which assist the learners in debugging their work; 4) the microworld, where a learner may explore a specific problem domain; and 5) articulate expert systems which explain their advice and decisions

A popular element of microcomputer software has been the provision of context-sensitive help facilities to alleviate the need for the intermediary assistance of the manual or a human assistant, following the coaching paradigm above. Such support should be typical of an MSS. Statistics is a discipline in need of such help: "Quality statistical expertise is sufficiently rare that any expert system that incorporated statistical knowledge would be almost immediately useful." (Thisted, 1986, p. 267).

2.7.3 The Support of the Intermediary Assistant

Providing necessary information, decision-making advice, and interpretation of results has been the role of computer professionals and statistical professionals. An MSS which provides for decision, data, and executive support will make use of computer hardware and software and communication and methodological tools to accomplish this task The exploratory framework of this study is the design of an MSS and the implementation of a prototype which integrates the interactive capabilities of NLP and provides intermediary support and interpretation from a KBS using the methodological tools of statistics. The experimental focus of this study is the determination of the efficacy of the MSS and each of its elements.

2.8 Empirical Studies Assessing Computer-Based Support Systems

Numerous empirical studies have attempted to identify appropriate dependent measures for assessing the efficacy of computer-based systems Reviews of the empirical research have focused on DSS and Group DSS (GDSS) (Sharda, Barr, and McDonnell, 1988) or a meta-analysis of the empirical studies in a number of computer-based decision support arenas (Alkahldi, 1990). While a number of these empirical studies have been cited previously in this chapter, the purpose here is to review the often divergent conclusions they provide.

Much of the research has attempted to establish the efficacy of computer-based decision support by various combinations of comparison and contrast with non-computer-based decision support. Either the manager is: 1) supplied with no decision support; 2) a computer-based decision support is offered; or, 3) manual decision support (e g. paper-and-pencil techniques) is provided along with the same level of information as for computer-based decision support.

Some researchers test only two of the above conditions: 1) no decision support and decision support (King and Rodriguez, 1978; McIntyre, 1982, Eckel, 1983; Gallupe, 1985; Goslar, Green, and Hughes, 1986); 2) manual versus computer-based decision support (Steeb and Johnston, 1981; Benbasat and Dexter, 1982; Sharda, Barr, and McDonnell, 1988, Zigurs, Poole, and DeSanctis, 1988; Dixon, 1989). Others explore various levels of computer-based decision support (Goul, Shane, and Tonge, 1986) while still others examine all three (Lewis, 1982, Killingsworth, 1987, Eining, 1987; Watson, DeSanctis, and Poole, 1988).

In each of these efforts, the dependent variables tend to center on the decision outcome and the decision process, attempting to measure levels of satisfaction and confidence As previously discussed, these may be seen more generally as system functionality and the system usability as it relates to the decision process (Goodwin, 1987; Davis, 1989). Most measures for these variables tend to be collected through a post-test self-report questionnaire

In attempting to measure levels of confidence in decisions, Dixon (1989) reports a greater level of confidence for those using computer-based decision aids than non-aided decision makers, while Cats-Baril and Huber (1987) negate this effect and Aldag and Power (1986) and Sharda, Barr, and McDonnell (1988) indicate no significant difference. Some studies have reported that the quality of decisions improves with computer-based decision support (Benbasat and Schroeder, 1977; McIntyre, 1982; Cats-Baril and Huber, 1987, Killingsworth, 1987; Dixon, 1989) while others indicate no improvement (Chakravarti, Mitchell, and Staelin, 1979) and still others report no significant effect (King and Rodriquez, 1978; Aldag and Power, 1986)

Just as conclusions about the effectiveness of computer-based decision support have been mixed, so have conclusions relating to other moderating variables, such as mode of presentation and cognitive style. Format of output, tabular versus graphical (Remus, 1984), color (Lucas and Nielson, 1980), level of detail (Benbasat and Schroeder, 1977) have been considered as to their impact on effectiveness. Cognitive style, as measured by the Myers-Briggs Type Indicator (Myers, 1962), has been used in several studies (Bariff and Lusk, 1977, Henderson and Nutt, 1980; Huber, 1983; Kerin and Slocum, 1981; Lucas and Nielson, 1980). The hypothesis that decision makers perform more effectively with computer-based decision aids which match their particular cognitive style (Benbasat and Dexter, 1982) continues to provoke controversy (Slocum, 1978; Huber, 1983), with some researchers suggesting that a decision maker's cognitive style does not remain constant across various decision-making tasks (Dickson, Senn, and Chervany, 1977; Lucas and Nielson, 1980).

Few studies have addressed the impact of natural language as a way of providing for the usability of computer-based decision support. In a recent study (Lane, Batsell, and Guadango, 1989) the effectiveness of a restricted natural-language interface (HAL, for Lotus 1-2-3) over a command or menu interface to a computer-based decision support aid was asserted both for decision process and decision outcome

Empirical testing of the prototype MSS, the design of which is discussed in the next chapter, focuses on two levels of computer-based support, one providing a menu-interface and the other providing a natural language-like interface. As outlined in Chapter IV, measurements of decision outcome employs evaluation of written decision tasks while satisfaction with both decision outcome and decision process employs a post-test self-report questionnaire, similar to that provided by Davis (1989) or Aldag and Power (1986) Measures of cognitive style are assessed using an instrument similar to the Myers-Briggs Type Indicator and keystroke level responses are recorded and analyzed in a manner similar to that used by Card, Moran, and Newell (1980).

CHAPTER III

DESIGN OF SMART-STAT: A PROTOTYPE MSS FOR STATISTICAL ANALYSIS

This chapter describes the methodology used in the design and implementation of the problem processing system (PPS), knowledge processing system (KPS), and language processing system (LPS) of Smart-Stat: a prototype microcomputer based MSS incorporating decision, data, and executive support using the methodological tools of statistics and the AI technologies of KBS and NLP.

Keeping with the assertion that MSS are information technology based and the design and implementation of MSS have been driven by advances in technology, the design of an MSS should begin with a search for existing and emerging information technologies. The design of Smart-Stat is no exception, requiring a search for and acquisition of all of the pieces before assembling the prototype. The first section describes this process. Following sections describe the design and interrelationships of the PPS, KPS, and LPS, with specific attention to data sharing and manipulation. The final section describes the creation of the two interface designs, one using natural language-like commands and the other using a pull-down menu system.

3.1 The Information Technology Pieces of the Prototype

Numerous computer languages and source code for various specific applications were used in developing the final prototype. A listing of the progression from language systems and supplemental code leading to the final prototype (last listing in each column) for the menu and NLP interfaces is provided in Table IV.

TABLE IV

PROGRESSION OF COMPONENT PARTS AND SOURCES LEADING TO THE FINAL ADAPTED PROBLEM, KNOWLEDGE, AND LANGUAGE PROCESSING SYSTEMS AS IMPLEMENTED IN THE INTERFACES FOR SMART-STAT: THE PROTOTYPE MSS

	Menu Interface	Common to Both Interfaces	Natural Language Interface
PPS		Edu-Stat Turbo Pascal 3.0 Turbo Pascal 4.0 Turbo Pascal 5.0 Turbo Pascal 5.5 [Statistical Models] [Data manipulation] [Data transformation, transfer]	
LPS	Turbo Prolog 1.0 Turbo Prolog Toolbox Turbo Prolog 2.0 Advanced Programmer's Guide Turbo Pascal 5.5 [Pull-down menu interface]	Qwik 5.0 [Video] Original Assembly language [Keyboard interpreter]	Turbo Prolog 1 0 Turbo Prolog 2 0 Stonehaven Lexicon Turbo Lightning Turbo Pascal 4 0 Turbo Pascal 5 0 Programmer's Toolkit Turbo Pascal 5.5 [NLP interface]
KPS		Statcon [Consultation text] Lightning Word Wizard [Help System file structure] Original text [Interpret system] [Context-sensitive Help]	

The first acquisition was the problem processing system for the topic domain of statistics. The source code for Edu-Stat (Young, 1986), a microcomputer statistical processing software system, was available from the author. Written in Turbo Pascal version 3.0 (Borland, 1984), Edu-Stat offered a viable beginning A second task was to acquire existing natural language processing software. Since much experimentation in natural language processing was being done in Prolog, Turbo Prolog version 1.0 (Borland, 1986) was acquired along with Turbo Lightning (Borland, 1985), a compatible RAM-resident dictionary, and The Stonehaven Lexicon (Stonehaven, 1988), source code for a natural language processor based upon the Borland Prolog and dictionary products. A subset of the statistical problem-solving capabilities of the Edu-Stat software system was selected as the topic domain for the software, anticipating that implementation of the full statistical capabilities of Edu-Stat might not be an immediately achievable objective due to the overhead for the user interfaces, which were to be written using two languages. Prototyping of the menu interface was begun using code available in the Turbo Prolog Toolbox (Borland, 1987).

During this stage of development, Turbo Pascal was updated to version 4 0 (Borland, 1987), providing tighter executable code resulting from more structured coding through the use of modular units, but removing the capabilities of overlaying code in RAM memory and linking object code from both Pascal and Prolog. The new version allowed the implementation of more statistical techniques but necessitated the focus on one, rather than two programming languages. Natural language processing capabilities similar to those available through Turbo Prolog and the Stonehaven Lexicon were found in the Turbo Pascal based Turbo Lightning Word Wizard (Borland, 1986) and the decision was made to code the prototype in Pascal and assembly language. Borland quickly released Turbo Pascal version 5.0, restoring the overlay capabilities. Source code for a pull-down menu interface in version 5.0 from Advanced Programmer's Guide (O'Brien, 1988) was adapted using Qwik (LeMay, 1988) to allow for the multiple video interfaces being used on current microcomputers. The resulting code was linked to the PPS, providing the first iteration of the menu-interface Informal (alpha) testing was accomplished with various faculty and students to provide guidance for prototype revision

The design of the natural language-like interface began with a survey of undergraduate and graduate students asking for words, phrases, and sentences that might be used in addressing questions related to the topic domain. Input contributed as a result of that survey are shown in Appendix A. Because of the relatively few keywords needed (130), the vocabulary was implemented as an array-based keyword lookup table in random access memory (RAM), enlarged only by the variable names and definitions from the selected data set. Coding was accomplished by adapting a keyword search algorithm from the <u>Programmer's Toolkit</u> (Rugg and Feldman, 1989). Using the same video interfacing code (LeMay, 1988), the keyword search was linked to the PPS as the first iteration of the NLP interface. Informal testing was again accomplished with the assistance of various faculty and students.

Iterative steps for both interfaces included the creation and linking of separate subsystems for error handling, context-sensitive help, interpretation, and consultation. Beta testing was accomplished during the pilot test of the experiment as described in Chapter IV

3.2 Overview of the MSS Design

The specific capabilities of the MSS include: 1) decision support through a knowledge-based assistant to aid in statistical model selection and through CAI to aid in the understanding of statistical methods; 2) data support through importation of external data and the explanation of data in natural language; 3) executive support through the assessment of output from statistical modeling, taking into consideration the preferences of the user. These capabilities are implemented through three subsystems:

1) The problem processing system (PPS) - model manager system of the MSS consists of models for the statistical methodological tools which are used to provide results of statistical analysis requested by the user or recommended by the KBS as affirmed by the user. Accepting problems stated in terms of the LPS, the PPS draws upon the KPS in an effort to produce solutions. The PPS also has models for data transformation and report generation.

2) The knowledge processing system (KPS) - data manager subsystem of the MSS consists of application-specific knowledge for use by the PPS. Using KBS technologies, the KPS assists the user in the selection and correct application of statistical method-

ological tools. Using CAI methods, the KPS assists the user in learning the capabilities and underlying assumptions of the statistical tools. The KPS also contains data, variables, text, vocabularies, rule sets, inference procedures, and error handling routines

3) The language processing system (LPS) - dialogue manager subsystem of the MSS consists of commands accepted by the system (problem statements, or other input to the system) and presentations the system is capable of providing (results, or other output from the system). Using NLP technologies and the vocabularies, data, and text contained in the KPS, the LPS facilitates interaction with the user providing acceptance of user commands in natural language and presentation of results and error messages in a natural language narrative form.

The development process for Smart-Stat follows the prototyping paradigm. Both external design (how the system is viewed by the user, in this case the user-computer interface) and internal design (how the system makes use of software resources, in this case the problem, knowledge, and language processing systems) are considered as factors of usability and functionality. A diagram of the integration of the PPS, KPS, and LPS for the prototype appears in Figure 18 below.

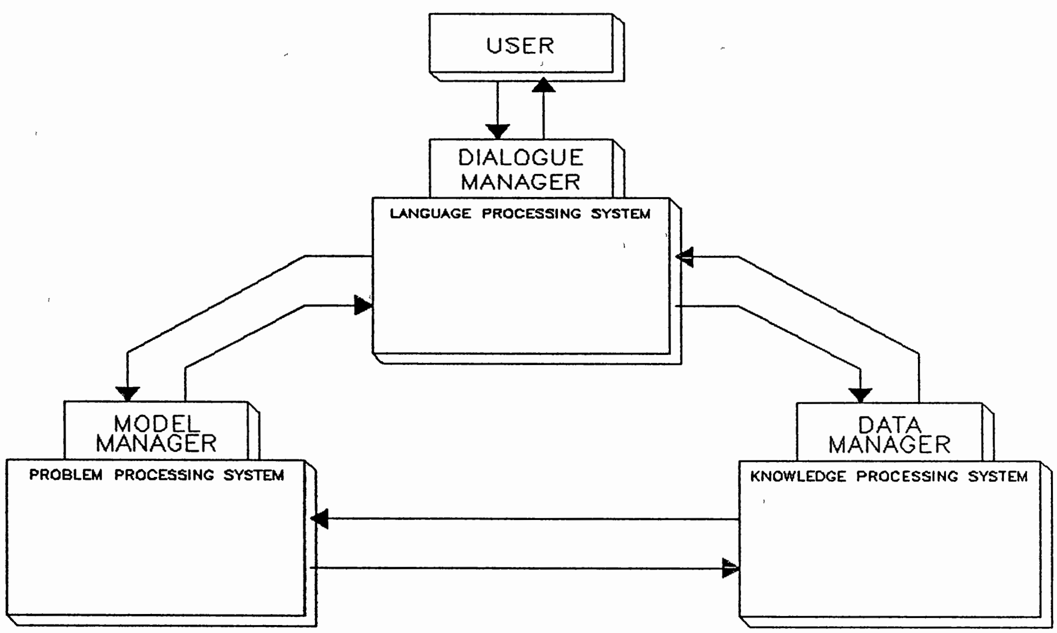


Figure 18. Integrated Structure of the Smart-Stat Prototype

Since Smart-Stat is a statistical analysis tool for casual or novice users (managers or students who have little or no expertise in either computer usage or statistics, or both), as well as for experts, particular concern is taken to identify the user's basic requirements Users of a computer based statistical processing system are faced with primary decisions in the topic domain of statistics and secondary decisions in the functional domain, use of the microcomputer.

Given a problem, the user of a statistical analysis software package must: 1) select the data, 2) determine an appropriate statistical technique, 3) issue the analysis commands, 4) interpret the results, and 5) recommend a decision (Remus and Kottemann, 1986). Each of these steps is facilitated by one or more of the LPS, KPS, and PPS (Figure 19).

Steps 1 and 2 involve primary decisions, or actually beginning the decision These require a knowledge of the topic domain of statistics. For the novice or casual user of statistical tools such knowledge is assumed to be limited to an understanding that statistics may (or may not) be useful. Assistance in this area is facilitated by the KPS.

Steps 3 and (to some extent) 1 require a knowledge of computer systems in general and experience with the specific computer system Some general knowledge of system hardware (disk drives, keyboard, monitor, etc.) and of experience with the computer (typing on the keyboard, entering data, inserting diskettes, etc.) is assumed for the casual microcomputer user (equivalent to a fundamental seminar/class in microcomputer literacy). Experience with the specific computer system is required for providing the data in the appropriate form and for issuing the appropriate commands to the PPS. This area is facilitated by the LPS, and assisted by the KPS is data selection in step 1.

Steps 4 and 5 involve the primary decision of acting upon the output of the PPS, or seeking further analysis. Interpretation of the results, providing the intermediary assistance of the MSS, is implemented through Smart-Stat's KBS, providing information to the user to assist in recommending a decision. Know-how areas are assisted by Smart-Stat's external design of the command language (menu or NLP interface) and it is the efficacy in this is area that is the focus of the experimental study detailed in the next chapter.

The internal design of Smart-Stat offers: a PPS consisting of a subset of statistical methodological tools; the intermediary assistance of a KPS to provide know-what instruction (CAI) and interpretation (KBS); and, an LPS featuring NLP, aiding in know-how by allowing the user to query and manipulate data using a natural language like command language and providing an explanation of results using a natural language presentation language.

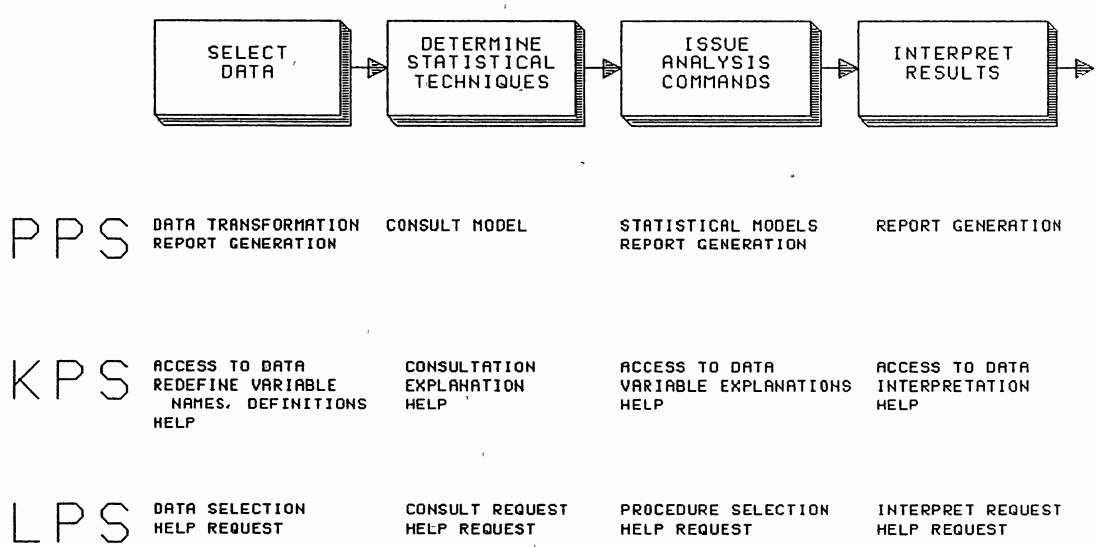


Figure 19. Computer Facilitation of Topic and Functional Domain Tasks

3.3 The Problem Processing System - Model Manager

The problem processing system (PPS) includes models for managing statistical methods, data transformation, and report generation. The major domain of the PPS is the statistical model base supported by the prototype MSS. While the actual production MSS would be capable of dealing with many of the broad domain of statistical methods, design of Smart-Stat is limited to a subset of the PPS provided in the statistical methods of Edu-Stat.

3.3.1 Selection of the Statistical Methods Subset

Raskin (1989) in reviewing existing statistical processing software packages, suggests that basic statistical analysis tools for a "Stat 101 course for the PC" include procedures for descriptive statistics, regressions, analysis of variance, cross-tabulations, and non-parametric tests (1989, p. 104). In order to provide a subset of statistical methods rich enough for functionality but limited enough for efficient prototyping, Smart-Stat's PPS includes computational models for: 1) descriptive univariate statistics (sample mean, standard deviation, variance, minimum and maximum, range, frequency); 2) the related bivariate statistics of correlation and least-squares regression and non-parametric cross-tabs; and, 3) the extended multivariate statistic of multiple linear regression and analysis of variance This subset represents a number of statistical data analysis techniques ordinarily covered in introductory university statistical methods courses. Additionally, the subset provides several operational levels for the implementation of statistical strategy, or determining techniques based upon actual data (Oldford and Peters, 1986), including statistical primitives, least-squares fit on a linear regression model, collinearity analysis, and regression for prediction.

Statistical primitives are useful for data description and understanding, for data cleaning, and for determining whether or not data meet the assumptions of specific statistical methods

Regression deals with determining a quantitative expression, or equation, to describe the linear functional relationship between a dependent variable and one or more independent variables. Correlation offers a measure of the degree of the relationship.

As a functional tool, Smart-Stat assists users in implementing a statistical strategy. The design provides for data manipulation and transformation (collapsing data and creating new variables) and the creation of data subsets based upon selection criteria provided The user may select a specific variable and, using regression, find a prediction equation for that variable from selected independent variables within the data set

Linear regression was selected as a major implementation because previous work in linking AI with statistical data analysis began with regression. Gale (1986) indicates three reasons for selecting regression as a domain for his Regression EXpert system (REX). 1) regression analysis is a widely used data technique; 2) because of its widespread availability, with calculations for regression provided even on some hand-held calculators, it is also widely abused; and, 3) regression is one of the oldest and best studied areas of statistical data analysis, providing a widespread, formalized knowledge of methodological assumptions

Smart-Stat handles simple and multiple linear regression and corresponding correlations providing: 1) decision support in description of the results provided by the PPS system of Edu-Stat; 2) data support in KPS system checking for the validity of model assumptions; and, 3) executive support in explanation of the techniques and of the results through the presentation language and CAI aspects of the LPS.

3.3.2 Statistical Methods Capabilities

Since the principal power of the PPS is implemented using code from Edu-Stat, a brief review (from Edu-Stat Guide, Young, 1986) of the software's capabilities as it pertains to the selected subset of statistics follows.

Among the capabilities of Edu-Stat for univariate statistics are number of cases, sample mean, sample standard deviation, sum, sum of squares, minimum, maximum, and frequency analysis. Frequency analysis processes each variable one data item at a time, allowing for as many as 2,000 different values for a particular variable in a frequency listing Cumulative frequencies and percentages are provided and missing values are recorded

Capabilities of Edu-Stat for correlation include Pearson Product-Moment correlation allowing for pairwise deletion of cases. Means, standard deviations, and probabilities (a two-tailed test that the correlation coefficient equals 0.0) are calculated and may be requested for each variable pair combination.

Edu-Stat regression capabilities allow estimation of the linear relationship between a user specified dependent variable and a list of up to 39 specified independent variables Intermediate regression results are available as each specified independent variable is entered sequentially from the list into the equation, including summary regression statistics and coefficients for variables in the equation. For a requested variable not yet in the equation, an entry t-value, representing the t-value of that variable if it were to be included next in the equation, and associated significance may be obtained.

Stepwise regression is a modification of the sequential regression where, instead of including the independent variable following sequentially in the list, Edu-Stat enters the independent variable having the highest entry t-value. A minimum significance level that a potential variable must meet to be entered in the equation may be specified, and by default the minimum probability is 0.05; or variables may be included in their order of entry significance As additional independent variables are entered in the equation, multicollinearity between independent variables causes the t-values to change for those variable already in the equation Thus it is possible for variables in the equation to have a lower significance level than the minimum specified for inclusion as more variables are added. At present Edu-Stat only performs forward stepwise regression. It does not remove variables that no longer meet the minimum probability for inclusion.

3.3 3 Data Manipulation and Report Generation

Models are available for converting data file input into the format used by the Edu-Stat PPS (known as DTS or DaTa Set files). ASCII (American Standard Code for Information Interchange), or text files, in both fixed and list format, DIF (data-interchange-format by Software Arts, Inc., the creators of VisiCalc) files may be converted to and from DTS files. Additionally, spreadsheet files created by programs like Lotus 1-2-3 and database files created by programs like dBase III+ may also be converted to the DTS format. A DTS file is created from the keyboard through conversion of an ASCII file using a VDF or Variable Definition File, which contains the variable names, labels, and formatting definitions for reading the raw data. The resulting DTS file consists of the actual numeric data from observations in binary form. The DTS file is paired with a NMS or Name Set File, containing variable names, labels, and other information in ASCII. Variable names and labels and dataset titles may be edited and changed by the user.

In addition to creating DTS files from raw data, the Edu-Stat PPS provides for data transformation, allowing the creation of subsets of the data as well as the modification of old variables and the calculation of new ones. Edu-Stat's data transformation language is a command language very similar to that used for data transformations in SAS. Transformations are performed by writing equations similar to FORTRAN or BASIC programming statements A new variable to be created or an old variable from the original data set to be modified is placed by name as a single argument to the left of the equal sign, with the desired conversion stated on the right of the equal sign Conversions may be either numeric, logical, or a subsetting of the data set, and up to ten conversion statements may be processed at one time.

Numeric conversions include models for addition, subtraction, multiplication, division, and exponentiation. Further models are available for the functions of square root, sine, cosine, arctangent, natural logarithms, and base 10 logarithms.

Logical operators include equal, less than, greater than, less than or equal, greater than or equal, and not equal. Both "IF [condition] THEN [conversion]" and "IF [condition] THEN [conversion] ELSE [conversion]" constructs are allowed, provided the conversion may be stated in a simple statement.

Selection of only those observations meeting the specific condition may be accomplished using the subsetting if, which takes the form "IF [condition]."

Reports available from the Edu-Stat PPS include the listing of the contents of a DTS file or the viewing of a file of results. All reports are printed to disk in ASCII format so that they may be either printed at a later time using DOS commands or edited using an editor capable of receiving ASCII text. A simple ASCII text editor is available as a part of the package.

3.4 Knowledge Processing System - Data Manager

The knowledge processing system (KPS) contains the data and the knowledge of the system. Implementation of the KPS requires: 1) a method of accumulating statistical knowledge and strategies needed for expert performance (domain expertise); 2) a structure for representing data and statistical knowledge within the system; and 3) a tutoring process statistical knowledge, considering both novice conceptions (the knowledge and strategies typically used by novices in this domain) and teaching expertise (how effective statisticians or teachers actually instruct users or students in this statistical domain (Bonar, 1984).

Knowledge engineering is a method of accumulating domain expertise involving both the elicitation of reasoning knowledge from a human expert and the representation of that knowledge within a system. Once accumulated, the domain expertise is stored in a knowledge base using an appropriate knowledge representation (a data structure used to organize the knowledge. Domain expertise is made available through the KPS to assist the user in selecting data appropriate to the primary decision, determining corresponding appropriate statistical techniques available within the PPS, checking assumptions related to the appropriate statistical technique and determining the implementation of these assumptions. Selection of data appropriate to user requests requires a knowledge representation for the data capable of interpreting or inferring the statistical nature of data for the KPS and of providing a lexical description of the data to the LPS.

3.4 1 Accumulating Statistical Knowledge

Since the statistical methods domain of Smart-Stat's PPS is a common subset of statistical methodological tools, much of the knowledge concerning judgments on what tests of the statistical methods subset to use and how to properly conduct these tests is gleaned from the human expertise provided in textbooks (Andrews, Klem, Davidson, O'Malley, and Rogers, 1974; Watson, Billingsley, Croft, and Huntsberger, 1988, and others). Formalizations of these rules in existing expert systems, such as Sechrist's STATCON (Sechrist, 1987) and Gale's REX (Gale, 1986) have also been explored. Modified from STATCON and extended from the several texts above, this rule base is implemented as a part of the KPS's consultation function, offering suggested statistical methods to be considered based upon the situations described by the user in response to a series of questions.

3.4.2 Statistical Knowledge Tutelage

Learning objectives for Smart-Stat are that the user would. 1) gain an understanding of statistical methods supported by the system, their application and importance· 2) acquire a vocabulary of statistical terms related to these methods; 3) gain an appreciation of the capabilities (and liabilities) of the methods; and, 4) through the intermediary assistance of the software be supported in the understanding and analysis of data using these methods.

Knowledge of a tutorial nature to facilitate these learning objectives is available to the user in terms of definitions, explanations, and help. Requests for tutorial knowledge may be initiated either by the user or the system. In the menu interface, user-initiated tutoring is accessed from a designated keyboard key to either clarify, explain, or help. In the natural language interface these functions are available in response to user initiated queries

One instance of system initiated tutorial knowledge occurs at any time an inference is made by the system. A prompt offers access to an explanation of the rule set and assumptions related to the recommendations of the KPS. Another example is the statistical output from the system, wherein numerical statistics are provided along with a verbal explanation

3.5 Language Processing System - Dialogue Manager

The language processing system (LPS) - dialogue manager provides the user interface to the system. The LPS consists of both an action, or command language (the problem statements, or other input accepted by the system) and a presentation language (results, or other output the system is capable of providing).

Two separate action language interfaces, one using NLP technologies and the other providing a pull-down menu, have been created and implemented for input to the system. As with the problem processing system, available coding tools (Eagle Software Pascal Windowing) have been used for the implementation.

Both the NLP and menu interface systems make use of the same presentation language for system output, providing presentation of results in a natural language narrative form

3.5.1 Action Language: The User Talks to the Computer

Action languages accept input from the user and direct activities based upon the commands or selections provided. Two separate action language interfaces were created and compared, the first using a menu-interface, and the second using an NLP-interface

Edu-Stat uses a main menu which calls a series of submenus As a result, the user must traverse several menus in order to arrive at the desired functional selection. Recent commercial software interfaces (LOTUS 123, dBASE III Plus) have used pulldown menus which provide the main menu option as a status line at the top of the display and allow the user to scroll through embedded submenus to pinpoint the exact function desired. The menu implementation of Smart-Stat uses this type of menu, providing selection of commands through a point and shoot method using the numeric keypad arrow keys or a mnemonic selection typing the character corresponding to the first letter of the menu selection.

The menu-interface action language system pulldown menu provides a main menu across the top of the screen (Figure 20) with the various options of each submenu presented in an overlaid box upon selection of a main menu item. Selection of a menu item is made by either typing the initial letter or by highlighting the entire item by using the cursor keys of the numeric keypad. Unlike the layered menu system provided in Edu-Stat, where the user is presented a menu and submenu as separate screens and must exit a submenu to return to its parent before entering a second submenu, this menu-interface allows the user to view options on the main menu and all submenus at the same screen, due to the overlaying of submenu boxes. An illustration of the menu interface appears in Figure 21, showing the selection "Frequencies" from the submenu "Univariate" under the main menu selection of "Statistics."

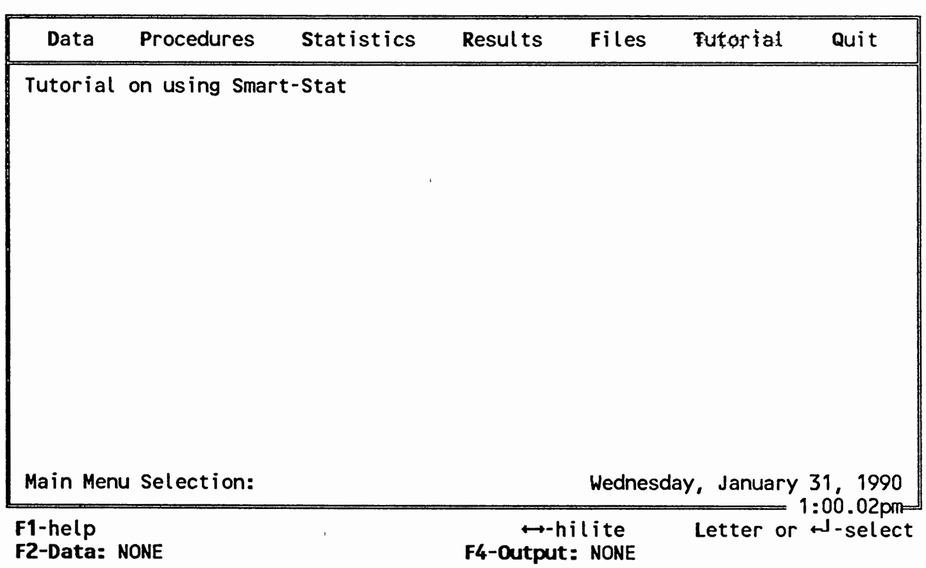


Figure 20. The Smart-Stat Menu Interface Main Menu

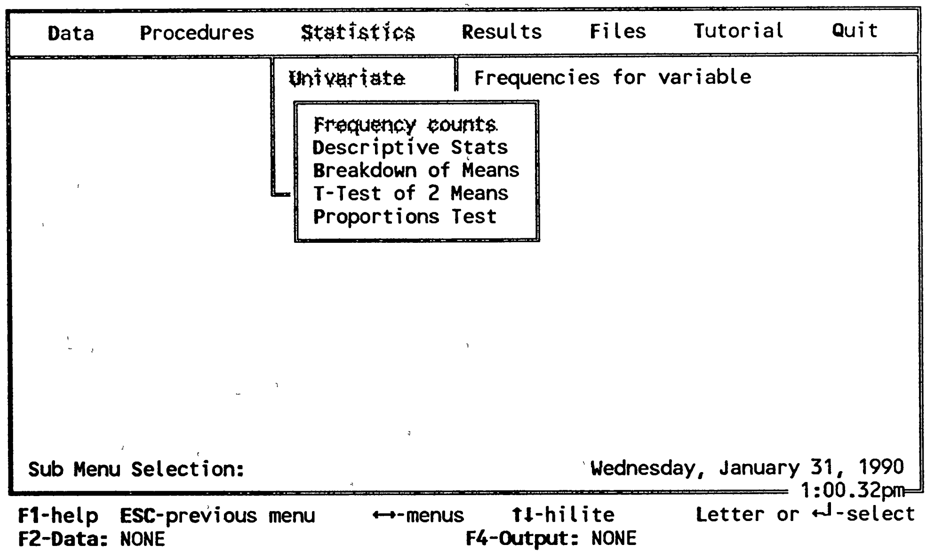


Figure 21. A Smart-Stat Menu Interface Sub Menu

The NLP-interface provides boxes for dialogue. A user dialogue box, and computer dialogue box and a system message box promote this dialogue. The Smart-Stat NLP-interface provides a relatively uncluttered screen anticipating the basic knowledge of a typing conversational words, phrases, and sentences. The initial invitation to the NLP user to begin a dialogue includes encouragement in the system message box to view the tutorial, and a prompt in the computer dialogue box to enter a request or comment (Figure 22).

Key reference points (current data set, function selected, dialogue or command expected, etc.) are provided on screen for both interfaces.

In order to determine the action vocabulary for the NLP interface, a convenience sample of undergraduate and graduate students was employed to survey the words, phrases, and sentences that might be used in addressing questions related to the topic domain (Appendix A) The results from this sample formed the basis for the keyword vocabulary of Smart-Stat's language processing system. Because of the relatively few keywords needed (130 plus access of variable and file names), the vocabulary was implemented as a simple keyword lookup table in RAM memory, enlarged only by the variable names and definitions from the selected data set

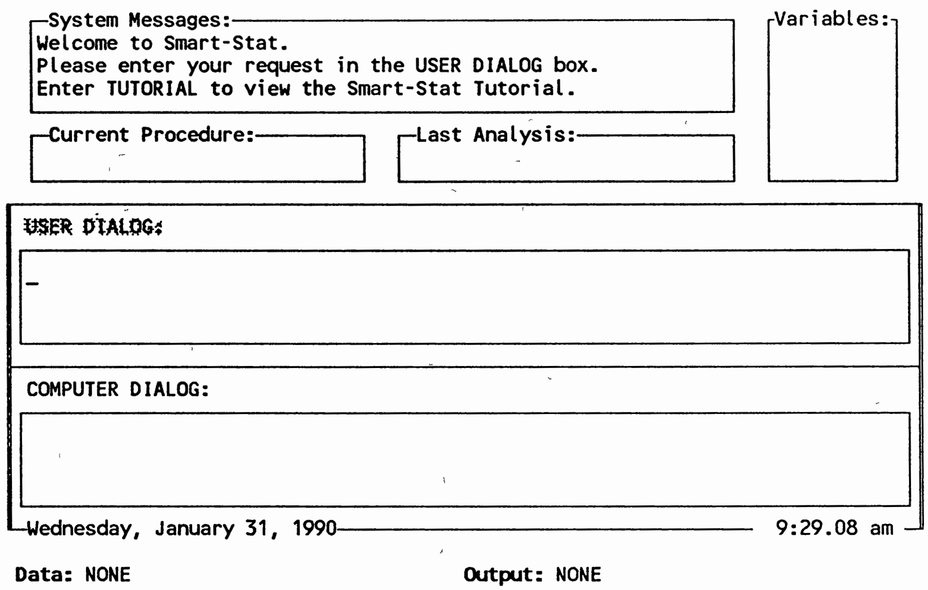


Figure 22. The Smart-Stat NLP Interface Opening Invitation

A three-phase parsing routine, similar to that outlined in Blanning (1986), was employed The first phase is a simple "noise dispersal" or "semantic filtering", looking for key words that would trigger commands according to the keyword vocabulary. If a frame is not sufficiently completed, the second phase seeks to locate items from the enlarged vocabulary created from the current data information (variable names and definitions). Existing ambiguities promote, a third phase, seeking clarification from the user. Beyond this, the NLP has been thoroughly confounded, and requests that the user rephrase the command, using any keywords discovered to suggest a possible command or request. Should the third stage be reached, the request is stored in an "oops" file allowing later review and consideration of further expansion of the natural language vocabulary based upon user requests

3.5.2 Presentation Language: The Computer "Talks" to the User

Both interfaces make use of the same tabular presentation of results, and the same NLP explanatory remarks, based upon the definition of variables contained with the data or provided by the user. Further explanation and instruction is provided regarding the assumptions of the various statistical models. Assumptions of each statistical model are checked at the time of processing an action command for that model. Violations of assumptions, as provided by the KPS are provided to the user through the LPS, are communicated to the user by the program, both in presenting instruction and in assuring the models are used according to correct statistical procedures. Assistance is available for each model through the help features and consult features of both the menu-interface and the NLP-interface.

CHAPTER IV

EXPERIMENTAL DESIGN: TESTING THE EFFICACY OF SMART-STAT

A major design focus of Smart-Stat is concern for the user space defined by know-what and know-how activities. The user is assisted in know-what areas to allow the functionality of the system to emerge, facilitating the primary task of actually making a statistical decision The user is assisted in know-how areas to enhance the usability of the computer system, facilitating the secondary task of deciding how to decide using a microcomputer

The objective of the experiment is to evaluate the relative efficacy of the two MSS command language interface (NLP-interface as compared to the menu-interface) for less experienced to more experienced users of computers. Computer systems may be seen as more or less effective based on: the user's focus of attention and effort; the system's usability and functionality; and, the user's ability, novice to expert. Additionally, cognitive and learning styles may affect a user's perception of the usability and functionality of a particular system.

4.1 Design of the Experiment

Three user microcomputer expertise classifications (low, medium, and high) and the two user interfaces provide a 3 X 2 factorial design. This design was employed to consider multiple dependent measures including attention and effort; system efficacy; domain experience, cognitive style; and, learning style.

4.1.1 The Experimental Task

The experimental task required subjects to use the prototype MSS to complete a statistical problem set (Appendix B) adapted from Brief Business Statistics (Watson, Billingsley, Croft, and Huntsberger, 1988). The problems involve a data set (Appendix C) of 113 observations of individuals who have either been accepted or denied credit at a major department store chain. Ten variables are provided for each observation, including age, sex, marital status, number of years in current job, wage income, spouse's income, additional income, and monthly payment on current debt, and whether or not credit was approved for this observation. The problem set requires the use of descriptive statistics, comparison of means between two classes by a t-test and analysis of variance, cross-tabulation and prediction by regression.

4.1.2 Pilot Study

A pilot study was conducted with 24 individuals who were enrolled in a computer applications course of an evening MBA program at a midwestern, state-supported urban university center during the spring semester of 1990. For the most part, these individuals hold full-time professional positions in various area business organizations. The pre-test instrument was administered and evaluated prior to the actual Smart-Stat interfaces, which was administered two weeks later.

4.1.3 Subjects

The actual study was conducted with 135 undergraduate business students enrolled at a small, private church-affiliated institution located in the mid-west and attracting students from across the country. Subjects included 77 sophomore students enrolled in the introductory business statistics course and 58 juniors and seniors in the management information systems course, both required courses which involve the use of computers in statistical analysis During the period of the test, three of the sophomores withdrew from the course and six chose not to take advantage of the extra credit class points provided for participation, leaving 126 persons who completed the experiment. Two deleted all of their files at the close of the experiment, two succeeded in causing a system crash, and two persons left the experiment early, resulting in 120 usable responses.

4.1.4 Procedures

Each participant completed a self-report assessment of his or her skills in computing, statistics, and keyboarding using the measures in Table V.

TABLE V

SCALE ITEMS USED TO MEASURE RELATIVE SELF-ASSESSED LEVELS OF MICROCOMPUTER, STATISTICS, AND KEYBOARDING EXPERTISE IN PRE-TEST STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

MICROCOMPUTER SKILL EXPERTISE

(Multi-item measure)
C1. I have used microcomputers extensively.
C2. My microcomputer skills are not good. (reversed)
C3. I enjoy using microcomputers.
C4. I am a more experienced microcomputer user than most of my peers.
C5. I own or have easy access to a microcomputer?
C6. If I were to evaluate my microcomputer abilities, I would give myself a grade of . . .
(Single-item measures)
How many courses have you taken which make use of microcomputers?
How many hours per week, on the average, do you estimate you spend using a microcomputer

STATISTICS SKILL EXPERTISE

(Multi-item measure)
S1. I have used statistics extensively.
S2. My statistical skills are not good. (reversed)
S3. I am a more experienced statistics user than most of my peers
S4. I enjoy doing statistics.
S5. If I were to evaluate my statistical abilities, I would give myself a grade of . .
(Single-item measure)
How many courses have you taken which make use of statistics?

KEYBOARDING SKILL EXPERTISE

(Multi-item measure)
K1. I am a faster typist than most of my peers.
K2. My keyboarding abilities are good.
K3. I do not type well. (reversed)
K4. If I were to evaluate my keyboarding abilities, I would give myself a grade of . .
(Single Item measures)
How many courses have you taken in typewriting or keyboarding?
How many words per minute do you estimate that you can accurately type?

The pre-test instrument, which also included demographic data on age and sex, appears in Appendix D. Further demographic information, including grade point average, and number of semester hours completed, was available for each participant. Each participant was provided with a diskette containing computerized versions of the Keirsey Temperament Sorter (Keirsey and Bates, 1984) and the Learning Style Inventory (Kolb, Rubin, and McIntrye, 1971). The Keisey Temperament Sorter offers an approximation of the results (Table II in Chapter II) that might be anticipated from taking the Myers-Briggs Type Indicator Test (Myers, 1962). The Learning Style Inventory assesses a method of learning. These instruments were used to categorize the participants on the basis of cognitive style and learning style for use in post-experiment analysis.

In order to assess expertise levels, three composite scores were calculated, one for each area of expertise, summing items for each measure of relative expertise. These composite scores were arrayed, and percentiles established, allowing the estimation of three groups for each of the three self-assessed expertise measures: microcomputer usage; statistical abilities, and, keyboarding. In addition, the mean composite score and standard deviation was calculated for each measure. Scores for the multi-item measure of computer expertise, of major interest here, were summed to provide an assessment of computer expertise. Based upon the skills assessment, the participant was assigned to one of three computer expertise groups, low, medium, or high, in relation to all subjects in the experiment. Assignment to groups was accomplished using one standard deviation about the mean computer expertise assessment score as the score for the middle expertise group, with the low and high groups comprising the remaining subjects. Similar assignments were made for statistical and keyboarding skills.

Participants in each computer expertise group were randomly assigned to either the menu or the NLP interface group. Each participant was asked to schedule a one-hour time to use a microcomputer package. When arriving for the scheduled time, the participant was given 1) a description of the sample data set and a listing of all the data in the dataset (Appendix C),

2) a problem set to be solved using the dataset (Appendix B), and, 3) written documentation providing a brief introduction to either the NLP prototype MSS (Appendix E) or the menu prototype MSS (Appendix F) to be used to assist in solving the problem set. Participants were asked to use the sample data set to solve as many of the problems as they could, providing their written answers on the problem set. To assist them in this task they were provided with either the menu or the NLP interface version of Smart-Stat. Participants were asked to save their results in a specific file. Each participant was asked to spend about 50 minutes trying to solve the problems in the problem set, following which time they would complete a questionnaire about their experience. During the accomplishment of their task, the software recorded each keystroke, and the time to a keystroke.

Following completion of the problem set, each participant responded to a questionnaire involving multi-item Likert scales for dependent measures related to attitude-towards-MSS (Table VI), attitudes-towards-MSS-process-and-solution (Table VII), and perceived usefulness and ease of use of the MSS (Table VIII). The post-test questionnaire appears in Appendix G

In addition to tabulating the responses on the post-test questionnaire, the written problem set solutions were graded along with the software statistical output. The highest possible score was a 22. Tabulations were made for number of statistical processes and number of correct statistical processes (those necessary to provide answers to problem questions) executed during the completion of the problem set. Also statistics were accumulated from the keystroke records.

TABLE VI

SCALE ITEMS USED TO ASSESS MEASURES OF ATTITUDES-TOWARD-MSS IN POST-TEST STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

CHALLENGE AND ACCOMPLISHMENT

While using Smart-Stat I felt challenged to do by best work.
I really felt like I accomplished something by using Smart-Stat.
I learned a lot using Smart-Stat.
While using Smart-Stat I had to be at my best.

WARMTH OF INTERACTION

I felt frustrated by Smart-Stat. (reversed)
Using a computer to learn seems like a good idea to me.
While using Smart-Stat I felt comfortable.
I enjoyed using Smart-Stat.

POSITIVE AFFECT

Using Smart-Stat was fun.
I am not in favor of computer-aided learning because it is just another step toward depersonalization of learning. (reversed)
Even otherwise interesting material would be boring when presented by the computer. (reversed)
I don't like Smart-Stat. (reversed)

CONFIDENCE IN DECISION QUALITY

My answers for the problems were good ones.
I'm not sure my solution to the problem set was appropriate (reversed).
I'm not confident about my solution to the problem set (reversed).

ENHANCEMENT OF STATISTICAL PROBLEM-SOLVING ABILITY

Answering the problems improved my statistical skills.
Answering the problems was a useful learning experience.
I'll be able to handle future statistical problem situations better because of the approach I used to answer these problems.

Source: adapted from Aldag and Power, p. 579.

TABLE VII

SCALE ITEMS USED TO ASSESS ATTITUDES-TOWARD-MSS-PROCESS
IN POST-TEST STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

SATISFACTION WITH RESOURCE EXPENDITURE

It took too much time to solve the problems (reversed).
The time and effort used to solve the problems were well spent.
The approach used to answer the problems wasn't worth the effort (reversed).

PERCEIVED ACCEPTABILITY OF SOLUTION

People who would be affected by my answers to the problems would probably be satisfied with them.
I might find it hard to get my solution implemented (reversed).
I could easily justify my answers to the problems

PERCEIVED PROCESS STRUCTURE

The approach taken to answering the problems was very structured.
My answering of the problems was systematic.
I answered the problems in a statistically correct manner

PERCEIVED PROCESS ADEQUACY

I wish I had approached the problem set differently (reversed).
I really felt lost in trying to tackle the problem set (reversed).
I may have missed important things in the problem set (reversed).

POSITIVE AFFECT TOWARD PROCESS

I'm pleased with the approach used to answer the problem set
Answering the problem set frustrated me (reversed).
Answering the problem set was interesting.

Source: adapted from Aldag and Power, p. 579.

TABLE VIII

SCALE ITEMS USED TO ASSESS MEASURES OF PERCEIVED USEFULNESS AND PERCEIVED EASE OF USE IN POST-TEST STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

PERCEIVED USEFULNESS (FUNCTIONALITY)

F1. Using Smart-Stat in doing statistics would enable me to accomplish tasks more quickly
F2. Using Smart-Stat would improve my performance in doing statistics.
F3. Using Smart-Stat in doing statistics would increase my productivity.
F4. Using Smart-Stat would enhance my effectiveness in doing statistics.
F5. Using Smart-Stat would make it easier to do statistics.
F6. I would not find Smart-Stat useful in doing statistics. (reversed)

PERCEIVED EASE OF USE (USABILITY)

U1. Learning to operate Smart-Stat would be easy for me.
U2. I would find it easy to get Smart-Stat to do what I want it to do.
U3. My interaction with Smart-Stat would be clear and understandable
U4. I would find Smart-Stat to be flexible to interact with.
U5. It would be easy for me to become skillful at using Smart-Stat.
U6. I would not find Smart-Stat easy to use. (reversed)

Source: adapted from Davis, p. 340.

4.2 Dependent Measures

The efficacy of Smart-Stat and the effect of the two different interfaces are considered in measures of attention and effort, system usability and functionality, topic and functional domain expertise, cognitive style, and learning style.

4.2.1 Attention and Effort

It is posited here that attention focused upon the simultaneous multiple activities of the primary and secondary decision making tasks may bring about a situation of information overload. At this point, the user becomes aroused or more narrowly focused, selecting only one aspect of incoming stimuli such that activities related to the secondary decision of deciding how to decide, of communicating with the system, demand effort, and thus occupy more attention capacity, making less attention capacity available for the primary decision Simply stated, when faced with both the primary and secondary decision tasks, the user pays more attention to getting the system to work (the usability of the system) than to actually getting the solution to the problem at hand (the functionality of the system). If a command language must be utilized or a system specific menu must be followed, the effort required for the secondary decision task might be classified as a $demand_2$ effort. If the same secondary task could be accomplished using natural language the less rigorous requirement of language communication might be thought of as $demand_1$ effort.

Measures of attention and effort include the recording of the number of keystrokes and the time between keystrokes. Users able to focus more attention on the primary task of solving the statistical problem set should require fewer keystrokes and spend less time between keystrokes, indicating a smaller demand of effort for the secondary task of using the computer The reduction of information overload should result in a higher perception of system usability Additionally, "Challenge and accomplishment" (Table VI), "Satisfaction with resource expenditure" provided a measure of effort and "Enhancement of statistical problem-solving ability" (Table VII) provided a measure of the result of this heightened and more focused attention.

4.2.2 Usability and Functionality

Users select computer systems that are useful, that is systems that provide functions needed to accomplish a task (Goodwin, 1987; Davis, 1989). Selecting a computer system to accomplish a task may occur because it is the only way to get the job done, but more likely the choice is made with the expectation that the computer will be useful in accomplishing the task better or faster.

Computer systems with a richer functionality but poor usability may be rejected for systems with less functionality but greater ease of use, or usability, suggesting the interrelationship of usability and an effective functionality. On the other hand, systems with effective usability allow the user to take greater advantage of the actual functionality of the system

System efficacy may be seen as functionality, or usefulness, and usability, or ease of use. Measures of functionality include "Enhancement of statistical problem-solving ability" and "Perceived process structure" (Table VII), and "Perceived Usefulness" (Table VIII) Measures of usability include "Warmth of Interaction" and "Positive affect" (Table VI), "Positive affect toward process" (Table VII), and "Perceived Ease of Use" (Table VIII).

4.2.3 Domain Expertise

Expertise has been expressed as a continuum from novice to expert. Novices are different from experts in that 1) experts are more knowledgeable about a subject domain, and 2) experts know how to apply and use this knowledge more effectively than do novices (Kolodner, 1984, p. 95). Multiple subject domains may participate in providing the knowledge necessary for a complex decision-making task (Alba and Hutchinson, 1987).

Users of the prototype MSS may be classified as novices or experts (or somewhere in between) for the subject domain of the primary, know-what, task of statistical functionality while having an entirely different classification in regard to the secondary, know-how, domain of computer systems. The focus here is the classification of a user in the domain of computer system usage.

Considering both the primary know-what task and the secondary know-how task, the novice computer user requires more effort for the secondary task of accessing system's usability before they are able to focus attention on the primary know-what task of accessing the system's usefulness. For the expert computer user, the effort required for the secondary task is diminished, allowing more attention to be focused upon the primary task

Since users may vary in their domain expertise in using statistics and in using computers, the difference in statistical expertise was adjusted by covarying the measures with the self-report data for "Statistics Skill Expertise" (Table V).

4.2.4 Cognitive Style and Learning Style

The Keirsey Temperament Sorter provides cognitive style classification across sixteen distinct group represented by combinations of four pairs of temperament types: introversion-extroversion, sensing-intuitive, thinking-feeling, and judging-perceiving based on selections to binary choices on seventy questions. The Learning Style Inventory provides classification of concrete and abstract approaches to problem solving and the active and passive learning based on rankings of twenty groups of four words each.

4.3 Hypotheses

A number of hypotheses are suggested based upon a matrix of attention and effort and usability and functionality. Additionally, user expertise, cognitive style, and learning style suggest additional hypotheses for measuring system efficacy.

4.3.1 Attention and Usability

As the usability of the system is perceived to be increasingly satisfactory, less effort is needed for the secondary know-how task of using the system and more attention can be focused upon the primary know-what task of statistical decision making

> Hypothesis 1: Users of the NLP-interface perform more systematic and complete analyses, and score higher on the problem set than do users of the menu-interface.

4.3.2 Effort and Usability

As the usability of the system is perceived to be more difficult, more effort is needed for the secondary know-how task of using the system and less attention can be focused upon the primary know-what task of statistical decision making.

> Hypothesis 2: Users of the NLP-interface have more favorable attitudes toward the usability of the MSS than do users of the menu-interface.

4.3.3 Attention and Functionality

If the functionality of the system is accessible due to satisfactory usability, attention may be focused upon the primary know-what task in such a way to explore the depth of the system's statistical functionality.

> Hypothesis 3: Users of the NLP-interface exhibit more confidence in, and satisfaction with, their statistical decision processes and recommendations than do users of the menu-interface.

4.3.4 Effort and Functionality

If the functionality of the system is less accessible due to poor usability, the effort required for the secondary know-how task of accessing the systems functionality is increased

> Hypothesis 4: Users of the NLP-interface have more favorable attitudes toward the functionality of the MSS than do users of the menu-interface.

> Hypothesis 5: Users of the NLP-interface spend less time using the MSS than do users of the menu-interface.

4.3.5 Attention and User Computer Experience

As the initial attention of the computer user novice is focused upon the secondary know-how task of pursuing the usability of the system, the primary know-what task is slighted. For the computer user expert, a familiarity with computer systems allows more attention to be focused upon the primary task.

Hypothesis 6: More experienced computer users perform more systematic and complete analyses, and score higher on the problem set than do less experienced computer users.

Hypothesis 7: More experienced computer users spend less time using the MSS than do less experienced computer users.

4.3.6 Effort and User Computer Experience

If the NLP-interface requires less effort than that required for the menu-interface, novice users should indicate a preference for the NLP-interface, while expert users who are more familiar with other types of human-computer interfaces should indicate a preference for the menu-interface.

Hypothesis 8: Novice users of the MSS report more favorable attitudes toward the NLP-interface than do expert users.

Hypothesis 9: Novice users of the NLP-interface spend less time using the MSS than do novice users of the menu-interface.

The interrelationship between usability and functionality should also be apparent because of computer experience.

Hypothesis 10: Novice users of the NLP-interface report more favorable attitudes toward the usability of the MSS than do expert users of the NLP-interface.

Hypothesis 11: Novice users of the NLP-interface report more favorable attitudes toward the functionality of the MSS than do expert users of the NLP-interface.

In addition to the cognitive effort required, a physical effort is often part of the human-computer interface. The principal input device for the prototype MSS is the keyboard, and as a result, the motor skills involved with keyboarding are considered. The typing of (relatively) complete sentences to access the MSS functionality as required by the NLP-interface may be a deterrent to those with poor keyboarding skills The additional effort required of those with poor keyboarding skills should affect perceptions of both usability and functionality.

Hypothesis 12: Users of the NLP-interface reporting low keyboarding skills have less favorable attitudes toward the usability of the MSS than do users of the menu-interface who report low keyboarding skills.

> Hypothesis 13. Users of the NLP-interface reporting low keyboarding skills have less favorable attitudes toward the functionality of the MSS than do users of the menu-interface who report low keyboarding skills

4.3.7 Cognitive Style and Learning Style

Persons with temperaments that display extroversion, intuitive, feeling, and perceiving cognitive styles would, based upon the descriptions in Table II, be more likely to adapt to the free-form nature of the NLP-interface, while those displaying introversion, sensing, thinking, and judging temperaments. would be more likely to respond to the more structured nature of the menu-interface.

> Hypothesis 14: Users of the NLP-interface with temperaments of extroversion, intuitive, feeling, and perceiving have more favorable attitudes toward Smart-Stat than do users of the NLP-interface with temperaments of introversion, sensing, thinking, and judging

> Hypothesis 15: Users of the menu-interface with temperaments of extroversion, intuitive, feeling, and perceiving have less favorable attitudes toward Smart-Stat than those do users of the menu-interface with temperaments of introversion, sensing, thinking, and judging.

Persons with concrete experiential learning styles would be less likely to adapt to the free-form nature of the NLP-interface, while those displaying abstract conceptualization learning styles would be less likely to respond to the more structured nature of the menu-interface.

> Hypothesis 16: Users of the NLP-interface with high abstract conceptualization learning styles have more favorable attitudes toward Smart-Stat than do users of the NLP-interface with high abstract conceptualization learning styles.

> Hypothesis 17: Users of the menu-interface with high concrete experiential learning styles have less favorable attitudes toward Smart-Stat than do users of the menu-interface with high concrete experiential learning styles

CHAPTER V

DATA COLLECTION AND ANALYSIS

Self report data were collected on expertise levels prior to usage of the MSS and perceptions of the interaction with the MSS following usage. Cognitive and learning styles were measured prior to the actual experiment. Keystroke data and statistical output, collected during the experiment, were evaluated along with the written solutions to the problem set. Each of these are discussed below.

5.1 Data Collection

Expertise levels for microcomputer usage, statistical experience, and keyboarding were assessed from self report data collected through each subject's completion of multi-likert scaled items using the form in Appendix D.

Dependent measures were collected through each subject's completion of multi-likert scaled items for each measure using the form in Appendix D, adapted from scales provided by Aldag and Power (1986) and Davis (1989). Data were coded on an interval assumed scale of 7 to 1, with 7 representing a high likelihood of the measure, and 1 indicating a low likelihood, as perceived by the subject. Appropriate reversals of negative responses were made to provide for a higher value to indicated a higher positive perception.

Cognitive style was assessed using a computerized version of The Keirsey Temperament Sorter (Keirsey and Bates, 1986), an instrument which offers an approximation of the results (Table II in Chapter II) that might be anticipated from taking the Myers-Briggs Type Indicator Test (Myers, 1962). Scores of The Keirsey Temperament Sorter range from 1 to 10 for introversion-extroversion, and from 1 to 20 for sensing-intuition, thinking-feeling, and judging-perceiving, based upon responses to the 70 questions.

Learning style was assessed using a computerized version of the Learning Style Inventory (Kolb, Rubin, and McIntyre, 1971), with scoring ranging from 1 to 36 for concrete experience, reflective observation, abstract conceptualization, and active experimentation Percentile scores were developed and compared with previous research representing the combined responses of 127 practicing managers and 512 Harvard and M.I.T. graduate students in management (Kolb, Rubin, and McIntyre, 1971, p. 25).

Keystroke data were collected as each participant made use of the MSS. For each occasion that the MSS was waiting for a keystroke, the elapsed time before a key was struck and the key itself were recorded.

Output from the MSS was saved in a file and printed following the experiment Actual file contents were compared with each participant's written answers to the problem set to assess whether a correct procedure was executed in case the participant failed to arrive at the correct answer.

5.2 Analysis of Expertise Measures

Both internal and construct validity should be addressed in a rigorous MIS study (Straub, 1989). For internal validity, reliability for each expertise measure was evaluated using Cronbach's (1951) coefficient alpha, one of three procedures suggested by Churchill (1979). Reliability is "the similarity of results provided by independent but comparable measures of the same object, trait, or construct" indicating an agreement that the efforts to measure the same trait provides maximally similar methods (Churchill, 1987, p. 386). Coefficient alpha levels for items in each of the measures (Table IX) exceed the minimum acceptable level of 0.80 suggested by Nunnally (1978). This confirmed the internal consistency of homogeneity of the measures.

TABLE IX

CRONBACH ALPHA RELIABILITY OF MEASURES FOR ASSESSING RELATIVE EXPERTISE IN MICROCOMPUTER, STATISTICS, AND KEYBOARDING SKILLS AS USED IN PRE-STUDY AT UNIVERSITY CENTER, TULSA, FEBRUARY, 1990 AND IN PRE-TEST AT VALPARAISO UNIVERSITY, MARCH, 1990

Functional domain expertise (microcomputer usage)
0.88613 (study), 0.91645 (pre-study)

C1. I have used microcomputers extensively.
C2. My microcomputer skills are not good. (reversed)
C3. I enjoy using microcomputers. (attitudinal measure)
C4. I am a more experienced microcomputer user than most of my peers.
C5. I own or have easy access to a microcomputer.
C6. If I were to evaluate my microcomputer abilities, I would give myself a grade of .

Topic domain expertise (statistics)
0.81609 (study), 0.89230 (pre-study)

S1. I have used statistics extensively.
S2. My statistical skills are not good. (reversed)
S3. I am more a experienced statistics user than most of my peers.
S4. I enjoy doing statistics. (attitudinal measure)
S5. If I were to evaluate my statistical abilities, I would give myself a grade of .

Entry expertise (keyboarding)
0.92180 (study), 0.93326 (pre-study)

K1. I am a faster typist than most of my peers.
K2. My keyboarding abilities are good
K3. I do not type well. (reversed)
K4. If I were to evaluate my keyboarding abilities, I would give myself a grade of ..

NOTE: Numbers by each measure are Cronbach's coefficient alpha for the items in the measure.

Construct validity refers to whether or not the measures truly describe what they are intended to describe. Factor analysis, an accepted method for assessing the construct validity of an instrument (Long, 1983; Nunnally, 1967; Straub, 1989), was used to validate that three areas were operative in the experiment A three-factor solution was obtained using eigenvalue greater than one criterion The varimax rotation of the solution (Table X) suggested that all three factors represented high loadings, confirming that the three measures were established

TABLE X

VARIMAX ROTATED SOLUTION FROM FACTOR ANALYSIS OF THE MEASURES USED FOR ASSESSING RELATIVE EXPERTISE IN MICROCOMPUTER, STATISTICS, AND KEYBOARDING AS USED IN PRE-STUDY AT UNIVERSITY CENTER, TULSA, FEBRUARY, 1990, AND IN PRE-TEST AT VALPARAISO UNIVERSITY, MARCH, 1990

	Pre-Test			Pre-Study		
	Factor1	Factor2	Factor3	Factor1	Factor2	Factor3
C1	0.8629			0.8784		
C2	0.8468			0.8121		
C3	0.7835			0.7270		
C4	0.8377			0.9374		
C5	0.6308			0.8200		
C6	0.8461			0.8968		
S1		0.7178			0.8755	
S2		0.8142			0 9016	
S3		0.7707			0.8120	-0.3910
S4		0.7006			0.7469	
S5		0.7752			0.8773	
K1			-0.8803			0.8367
K2			-0.9164			0.9018
K3			-0.9348			0.8951
K4			-0.8584			0.9218

NOTE: Only loadings of 0.35 and above are shown in the table

Variance accounted for by each factor

	Study			Pre-Study		
	Factor1	Factor2	Factor3	Factor1	Factor2	Factor3
Eigenvalue	4.0314	3.3731	2.9674	4.5046	3.8383	3.6535
Percent	26.8758	22.4876	19 7829	30.0309	25.5888	24 3566

In addition, it is a necessary condition that relatively high correlations exist between items of the same measure and that relatively low correlations exist between items of measures that are expected to differ (Campbell and Fiske, 1959; Cronbach, 1971; Straub, 1989) to support convergent and discriminant validity. Items for self-assessed microcomputer, statistics, and keyboarding expertise across the three measures correlate at negative to low levels, supporting discriminant validity between measures, while correlations of items within measures were positively correlated (Table XI).

TABLE XI

CORRELATIONS AMONG INDIVIDUAL ITEMS OF MEASURES USED FOR ASSESSING RELATIVE MICROCOMPUTER, STATISTICS, AND KEYBOARDING EXPERTISE AS USED IN PRE-STUDY AT UNIVERSITY CENTER, TULSA, FEBRUARY, 1990, AND IN PRE-TEST AT VALPARAISO UNIVERSITY, MARCH, 1990

	C1	C2	C3	C4	C5	C6	S1	S2	S3	S4	S5	K1	K2	K3	K4
C1	1.00														
C2	0.73	1.00													
C3	0.57	0.55	1.00												
C4	0.62	0.63	0.56	1.00											
C5	0.45	0.39	0.48	0.41	1.00										
C6	0.69	0.79	0.56	0.65	0.42	1.00									
S1	0.26	0.16	0.23	0.12	0.06	0.12	1.00								
S2	0.12	0.23	0.18	0.06	0.10	0.21	0.47	1.00							
S3	0.15	0.14	0.07	0.11	0.05	0.09	0.48	0.49	1.00						
S4	0.14	0.19	0.28	0.11	0.17	0.11	0.43	0.37	0.48	1.00					
S5	0.16	0.30	0.20	0.09	0.16	0.33	0.50	0.70	0.44	0.44	1.00				
K1	0.08	0.23	0.13	0.20	0.09	0.24	-0.14	-0.02	0.02	0.00	-0.09	1.00			
K2	0.14	0.30	0.16	0.18	0.13	0.30	-0.16	-0.06	0.02	0.03	-0.03	0.79	1.00		
K3	0.07	0.29	0.10	0.09	0.15	0.28	-0.16	-0.01	0.02	0.05	-0.02	0.76	0.84	1.00	
K4	0.07	0.28	0.13	0.13	0.11	0.35	-0.14	-0.06	-0.13	-0.10	0.03	0.68	0.75	0.78	1 00

NOTE: All correlations greater than 0.20 are significant at $p < .025$, n=133, two-tailed test of significance

Several items have positive correlations across measures in the range of .25 to 35 Two of these relate to the self-assessed grade question for each expertise measure. The self-assessed microcomputer grade item (C6), correlates with self-assessed keyboarding grade (K4, .35, p=0.0001), and the self-assessed statistics grade (S5, .33, p=0.0001) This might suggest that participants were relatively consistent in their self-assessed grades were it not for the lack of significant correlation between self-assessed grade for statistics (S5) and keyboarding skills (K4) Means for the three items relating to self-assessed grades on a 0 to 4 scale, 4 being high, were microcomputer abilities, 2.47 (standard deviation 0.88); statistics, 2.41 (standard deviation 0 85), and, keyboarding, 2.84 (standard deviation 0.87). A possible interaction relationship between self-assessed microcomputer expertise and keyboarding expertise is indicated by the slightly positive correlations between self-assessed microcomputer grade (C6) and expressed keyboarding abilities (K2 and K3, with correlations of .30 and .28 respectively, $p < .01$). As these measures are further developed, the relationship between self-assessed microcomputer expertise and self-assessed keyboarding skills deserves consideration.

These expertise measures are a self-report of perception, and the constructs are conceptually related. Thus a degree of caution needs to exercised when assessing the convergent and discriminant validity of the measures. Measures for each domain expertise level (microcomputer usage, statistical expertise, and keyboarding ability) correlate at negative or very low levels supporting discriminant validity All correlations greater than .20 are significant (two-tailed test, $p < .001$).

Further concern was whether the measures were actually measuring skill levels as opposed to simply reflecting attitudes toward a domain. To explore this concern, two variables were created using combinations of the attitudinal and skill items, respectively. A t-test of means indicated that for a difference in attitude, there was a significant difference in attitude but not a difference in perceived skill ($p < .01$). For a difference in perceived skill, there was no significant difference in either attitude or perceived skill ($p < .01$). This indicates that the instrument is measuring perceived skills, unbiased by attitude.

In order to assess expertise levels, three composite scores, one for each expertise measure, were calculated summing items for each respective measure of relative expertise, microcomputer, statistics, and keyboarding. Data for the for the calculation of the microcomputer expertise measure, of major interest in this study, are provided in Table XII

TABLE XII

FREQUENCY ANALYSIS OF COMPOSITE RELATIVE MICROCOMPUTER EXPERTISE SCORE IN PRE-STUDY AT UNIVERSITY CENTER, TULSA, FEBRUARY, 1990, AND IN PRE-TEST AT VALPARAISO UNIVERSITY, MARCH, 1990

	PRE-TEST, MARCH, 1990			PRE-STUDY, FEBRUARY, 1990		
Composite Score	Response Frequency	Cumulative Frequency	Cumulative Percent	Response Frequency	Cumulative Frequency	Cumulative Percent
	LOW MICROCOMPUTER EXPERTISE			LOW MICROCOMPUTER EXPERTISE		
10				1	1	4.17
12	1	1	0.75	2	3	12.50
13	1	2	1.50			
14	3	5	3.76	1	4	16.67
15	2	7	5.26			
16	1	8	6.02			
17	4	12	9.02	1	5	20 83
18	4	16	12.03	2	7	29.17
19	8	24	18.05			
20	9	33	24.81	1	8	33 33
21	8	41	30.83			
22	8	49	36.84			
	MIDDLE MICROCOMPUTER EXPERTISE			MIDDLE MICROCOMPUTER EXPERTISE		
23	11	60	45.11	3	11	45.83
24	4	64	48.12			
25	7	71	53.38	1	12	50 00
26	7	78	58.65			
27	11	89	66 92			
	HIGH MICROCOMPUTER EXPERTISE					
28	4	93	69.92	3	15	62 50
29	5	98	73.68	1	16	66.67
30	10	108	81.20	HIGH MICROCOMPUTER EXPERTISE		
31	6	114	85.71	2	18	75.00
32	5	119	89.47	3	21	87.50
33	4	123	92.48			
34	3	126	94.74			
35				2	23	95 83
36	3	129	96.99			
37	1	130	97.74			
38	2	132	99.25			
39	1	133	100.00	1	24	100.00

	n	Mean	Standard Deviation	Median	Minimum	Maximum
Pre-Study	133	25.0301	5.8955	25.00	12	39
Pre-Test	24	24.7917	8.1826	26.50	10	39

The composite scores for each expertise measure were arrayed and percentiles established, allowing the estimation of three groups (low, middle, and high) for each expertise measure. In addition, the mean composite score and standard deviation was calculated for each measure. For both the pre-study and the actual study, establishing a middle group as one standard deviation around the mean provided for a distribution of about one-third of the population in each of the lower, middle, and higher user expertise categories for each measure The composite scores were collapsed, using the method above, into three categories of microcomputer expertise; low, middle, and high; numbered ordinally 1, 2, and 3 respectively. These categorizations correlated well with self-report data on related single item measures, such as estimate number of hours per week of microcomputer usage (.66, $p < .01$), in that as expertise increased from the low level of 1 to the high level of 3, there was a correlated increase in the estimated number of hours of microcomputer usage.

The three self-assessed microcomputer expertise levels and the randomly assigned interface usage provide the 3 X 2 factorial design, comprising six cells: 1) low microcomputer expertise, NLP usage; 2) low microcomputer expertise, menu usage; 3) middle microcomputer expertise, NLP usage; 4) middle microcomputer expertise, menu usage; 5) high microcomputer expertise, NLP usage; and, 6) high microcomputer expertise, menu usage. The six cells each consisted of a group of 20 participants, together comprising the 120 subjects for the experiment

Groups of similar microcomputer expertise (the three pairs of low, middle, and high expertise) should be significantly different from other microcomputer expertise groups while there should be no significant difference between groups based upon: 1) the random assignment to an interface, 2) self-assessed statistics expertise; and, 3) self-assessed microcomputer expertise. A oneway analysis of variance was used to test the hypothesis of equal means between groups for the six cells used in the experiment. Differences of the mean computer expertise scores were significant ($F=117.5478$, $p=0.0001$, 5 d.f between, 113 d.f. within groups) There were no significant differences in the mean expertise scores for statistics ($F=1.9735$, $p=0.0878$) and keyboarding ($F=0.8426$, $p=0.5223$) for the six cells.

The Tukey multiple comparison procedure was used to determine honestly significant differences of means for the each of the expertise measures of subjects in each of the six cells Cell means for the three microcomputer expertise levels along with the results of the Tukey test (alpha=.05) appear in Table XIII.

TABLE XIII

TUKEY TEST FOR HONESTLY SIGNIFICANT DIFFERENCE OF MEANS FOR LOW, MIDDLE AND HIGH MICROCOMPUTER EXPERTISE GROUPS AS RANDOMLY ASSIGNED TO NLP OR MENU INTERFACE IN STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

Group description	Mean	Group	2	1	3	4	5	6
low microcomputer expertise, menu interface	18.65	Group 2						
low microcomputer expertise, NLP interface	18.80	Group 1						
middle microcomputer expertise, NLP interface	24.55	Group 3	*	*				
middle microcomputer expertise, menu interface	25.05	Group 4	*	*				
high microcomputer expertise, NLP interface	30.85	Group 5	*	*	*	*		
high microcomputer expertise, menu interface	32.60	Group 6	*	*	*	*		

NOTE: Asterisk denotes pairs of groups significantly different (alpha=.05).

The pairs of cells representing low, middle, and high microcomputer expertise groups were homogeneous subsets, significantly different from one another. A similar Tukey procedure indicated no significant differences between the means of statistical expertise or keyboarding ability (alpha=.05) with all six groups forming one homogenous subset (i.e. a subset of group whose highest and lowest means do not differ by more than the shortest significant range for a subset of that size). This indicates that the six groups were similar in statistical and keyboarding expertise, but the three pairs of microcomputer expertise groups, while significantly different from one another, were similar within expertise groups. As indicated by the cell means shown in

Table XIII, the mean composite microcomputer score increased with the level of self-assessed microcomputer expertise.

5.3 Dependent Measures

Following use of the prototype MSS, each participant was asked to complete a 45 item questionnaire. These items represented the two measures of functionality and usability (adapted from Davis, 1989), the three measures for attitudes-toward-MSS and the 7 measures for attitudes-toward-MSS-process (adapted from Aldag and Power, 1986).

As with the expertise measures in the pre-test, Cronbach's coefficient alpha was used to test the reliability of each of the twelve post-test measures. Values for this study and those of the corresponding previous study from which the measures were adapted (Davis, 1989, for the functionality and usability measures; Aldag and Power, 1986, for the attitudes-toward-MSS and attitude-toward-MSS-process) are given in Table XIV.

Coefficient alpha scores for the measures for functionality and usability, although somewhat lower than those reported by Davis, exceed the minimum acceptable level of 0 80 suggested by Nunnally (1978), confirming the internal consistency of homogeneity of these measures. With four exceptions the coefficient alpha scores for the measures adapted from Aldag and Power approximated or exceeded Nunnally's (1978) recommended minimum criterion of .7 for scales in early stages of development, allowing consideration of the measures as initially reliable, but bringing into question the power of estimating relationships based upon these measures. The marginal alpha scores for challenge and accomplishment, perceived acceptability of solution, perceived adequacy of the process, and positive affect toward the process suggest the possibility of underestimation of relationships designated by these measures (Aldag and Power, 1986; Davis, 1989).

TABLE XIV

CRONBACH ALPHA RELIABILITY OF DEPENDENT MEASURES AS USED IN POST-TEST AT VALPARAISO UNIVERSITY, MARCH, 1990

	Cronbach Alpha	
	This study	Previous Study noted
Functionality and Usability (Davis, 1989)		
Perceived usefulness (functionality)	.90452	(.98)
Perceived ease of use (usability)	.91692	(.94)
Attitudes-toward-MSS (Aldag and Power, 1986)		
Challenge and accomplishment	.49959	(.83)
Warmth of interaction	.76696	(.79)
Positive affect	.72174	(.69)
Attitudes-toward-MSS-process (Aldag and Power, 1986)		
Confidence in decision quality	.75906	(.84)
Enhancement of problem-solving ability	.74985	(.89)
Satisfaction with resource expenditure	.73664	(.55)
Perceived acceptability of solution	.55727	(.66)
Perceived process structure	.71099	(.81)
Perceived process adequacy	.66494	(.59)
Positive affect toward process	.55387	(.68)

NOTE: Numbers by each item are Cronbach's coefficient alpha for the measures in the item used in the post-test of this study. Numbers in parenthesis are coefficient alpha scores for similar measures in the works cited with the measure.

Analysis of variance (ANOVA) was used to compare the means for each dependent measure across the three microcomputer expertise levels, the two interface groups, and any possible interactions. In addition, anticipating that statistical ability might be a contributing factor to significant results, analysis of covariance (ANCOVA) was used to regress the contribution of the statistical expertise measure onto the model, thus accounting for its effect, if any. The composite measure for statistical expertise was not a significant covariate for any of the twelve dependent measures. The minimal impact of statistical ability on the results, indicated by the lack of significance for the covariate, may have been a function of the homogeneity of the sample with regard to actual statistical expertise in that almost half of the sample were currently involved in studying statistics, learning new information, and the other half of the sample were one to two years away from their last statistics course, forgetting old information.

Overall, the participants perceived the functionality of the prototype MSS to be high, with a composite mean score of 33.04 for the six items in the measure, or a rating of 5.5 on the seven-point likert scale with one being low and seven being high. There were no significant differences either by microcomputer expertise or by interface, and no interaction effects, suggesting a unified high perception of the MSS's functionality.

A slightly lower overall perception (composite score of 28.80, or 4.8 on the seven-point scale) of the MSS's usability, or ease of use, was marked by a significant difference between user expertise groups among the NLP interface users. The Tukey multiple comparison procedure was used to determine honestly significant differences of means for perceived ease of use showing that the high microcomputer expertise NLP users perceived the MSS's ease of use to be significantly higher (33.30 or about 5.55 on the seven-point scale) than did middle (27.3) or low (25.45) expertise users of the NLP interface. No honestly significant differences between expertise groups (alpha=.05) were found for the menu interface users. The Tukey procedure identified two homogenous subgroups, one of the expert users and the middle expertise menu users, and the other of all but the expert natural language interface users. This calls into question the implicit assumption that because an NLP interface would reduce the amount of $demand_2$ effort necessary to focus attention on the primary task of decision making, it would be preferred by novice, or low microcomputer expertise users as has been anecdotal evidence reported in the literature (e.g. Turban and Watkins, 1986). Where a reduction in potential information overload was anticipated for novice microcomputer users as a result of the NLP, it appears that expert microcomputer users more readily perceived this reduction of information overload. Means, standard deviations, and significance tests for the functionality and usability measures appear in Table XV.

TABLE XV

MEANS AND ANOVA TESTS FOR MEASURES OF FUNCTIONALITY AND USABILITY USED IN STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

Cell means (standard deviations)			Significance Tests			
Dependent Measure	Interface NLP	Interface Menu				
Perceived usefulness (functionality)						
overall mean: 33.0417 (6.0062)				F	df	p
low micro expertise	32.25 (6.08)	30.85 (7.77)	Expertise	2.627	2	.077
middle micro expertise	32.35 (5.63)	33.65 (5.55)	Interface	1.010	1	.317
high micro expertise	36.15 (3.36)	33.00 (6.17)	Expertise X Interface	1.442	2	.241
Perceived ease of use (usability)						
overall mean: 28.8083 (6.9164)				F	df	p
low micro expertise	25.45 (6.86)	26.60 (6.25)	Expertise	7.716	2	.001
middle micro expertise	27.30 (6.41)	30.00 (6.66)	Interface	0.044	1	.834
high micro expertise	33.30 (4.81)	30.20 (7.79)	Expertise X Interface	2.118	2	.125

The three measures of attitude-toward-MSS provided no significant differences between expertise groups or between interface group for the three measures of challenge and accomplishment, warmth of interaction, and positive affect (Table XVI). Overall means for the three four-item measures ranged between 4 and 5 on the seven-point scale. As indicated previously, the low reliability for the challenge and accomplishment measure, as indicated by the coefficient alpha score, may have resulted in minimizing relationships. The lack of significant differences on these satisfaction measures indicate that both interfaces for the MSS provided similar challenge and accomplishment, warmth of interaction, and positive affect for users of various expertise, confirming those studies which conclude no significant differences for computer-based decision support users (Aldag and Power, 1986; Sharda, Barr, and McDonnell, 1988)

TABLE XVI

MEANS AND ANOVA TESTS FOR MEASURES OF ATTITUDES-TOWARD-MSS USED IN STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

Cell means (standard deviations)			Significance Tests			
Dependent Measure	Interface NLP	Interface Menu				
Challenge and accomplishment	overall mean:	17.1667 (2.8707)				
				F	df	p
low micro expertise	16.55 (2.01)	17.40 (1.98)	Expertise	0.570	2	567
middle micro expertise	15.65 (2.98)	18.30 (2.77)	Interface	2.481	1	.118
high micro expertise	18.10 (2.61)	17.00 (3.88)	Expertise X Interface	4.545	2	.013
Warmth of interaction	overall mean:	16.7833 (3.7889)				
				F	df	p
low micro expertise	15.60 (3.93)	16.70 (3.10)	Expertise	1.544	2	.218
middle micro expertise	15.85 (3.79)	17.35 (4.23)	Interface	1.030	1	.312
high micro expertise	17.85 (3.34)	17.35 (4.15)	Expertise X Interface	0.785	2	.459
Positive Affect	overall mean:	19.0333 (3.4372)				
				F	df	p
low micro expertise	17.75 (4.13)	18.70 (3.26)	Expertise	2.036	2	.135
middle micro expertise	18.60 (3.22)	19.65 (3.60)	Interface	0.072	1	789
high micro expertise	20.50 (2.42)	19.00 (3.52)	Expertise X Interface	1 806	2	169

The seven measures of attitude toward MSS solution and process provided no significant differences between interface groups (Table XVII), with the exception of perceived acceptability of solution. Four of the measures: confidence in decision quality, perceived acceptability of solution, perceived process structure, and perceived affect toward process; showed significant differences based upon user expertise levels.

TABLE XVII

MEANS AND ANOVA TESTS FOR MEASURES OF ATTITUDES-TOWARD-MSS-PROCESS USED IN STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

Cell means (standard deviations)			Significance Tests			
Dependent Measure	Interface: NLP	Interface: Menu				
Confidence in decision quality						
overall mean: 10.5667 (2.8247)				F	df	p
low micro expertise	8.90 (2.25)	9.15 (2.39)	Expertise	14.293	2	.000
middle micro expertise	10.39 (2.08)	10.85 (3.00)	Interface	0.851	1	.358
high micro expertise	11.85 (2.81)	12.35 (2.78)	Expertise X Interface	0.039	2	.962
Enhancement of problem-solving ability						
overall mean: 11.7333 (2.6655)				F	df	p
low micro expertise	11.40 (2.53)	11.80 (2.09)	Expertise	2.777	2	.066
middle micro expertise	10.20 (3.27)	12.05 (2.42)	Interface	1.599	1	209
high micro expertise	12.70 (2.13)	12.25 (2.97)	Expertise X Interface	2.002	2	.140
Satisfaction with resource expenditure						
overall mean: 13.2333 (2.9753)				F	df	p
low micro expertise	13.10 (3.26)	13.00 (3.31)	Expertise	1.531	2	221
middle micro expertise	11.75 (3.08)	13.80 (2.97)	Interface	0.389	1	.534
high micro expertise	14.35 (1.81)	13.40 (2.85)	Expertise X Interface	2.792	2	.065
Perceived acceptability of solution						
overall mean: 10.7333 (2.4793)				F	df	p
low micro expertise	9.45 (2.21)	10.55 (1.99)	Expertise	7.074	2	.001
middle micro expertise	9.50 (1.73)	11.25 (2.36)	Interface	10.668	1	.001
high micro expertise	11.20 (2.44)	12.45 (2.86)	Expertise X Interface	0.221	2	802
Perceived process structure						
overall mean: 13.3750 (2.4012)				F	df	p
low micro expertise	12.75 (2.40)	12.90 (2.40)	Expertise	4.364	2	.015
middle micro expertise	12.25 (2.15)	13.85 (2.74)	Interface	2.121	1	.148
high micro expertise	14.20 (1.91)	14.30 (2.23)	Expertise X Interface	1.349	2	.264
Perceived process adequacy						
overall mean: 10.2750 (2.7223)				F	df	p
low micro expertise	9.60 (2.72)	10.00 (2.58)	Expertise	0.963	2	385
middle micro expertise	10.05 (2.61)	10.75 (3.01)	Interface	0.487	1	.487
high micro expertise	10.65 (2.43)	10.60 (3.08)	Expertise X Interface	0.189	2	.828
Positive affect toward process						
overall mean: 12.0083 (2.5977)				F	df	p
low micro expertise	11.55 (2.35)	11.85 (2.41)	Expertise	0.949	2	.390
middle micro expertise	10.90 (2.85)	12.85 (2.74)	Interface	0.679	1	.412
high micro expertise	13.00 (2.47)	11.90 (2.43)	Expertise X Interface	3.592	2	.031

Confidence in decision quality increased as user expertise moved from low to high, with significant difference between low expertise users (8.90 and 9.15) and high expertise users (11.85 and 12.35). The implication of this finding is that differences or lack of differences in perceived confidence in decision quality cited by previous studies (Dixon, 1989; Cats-Baril and Huber, 1987; Sharda, Barr, and McDonnell, 1988; Aldag and Power, 1986) may result from different levels of computer expertise rather than treatments based upon a computer-based decision aid.

Perceived solution acceptability also increased with user expertise, with the Tukey process suggesting homogeneous subsets including the expert and middle levels and the middle and low levels of expertise. Means scores for perceived acceptability of solution were lower for the NLP interface groups than means for the menu-interface group for all expertise groups Again, this implies the importance of considering computer expertise when attempting to assess the effectiveness of computer-based decision support. Relationships relating to positive affect toward the process may have been minimized due to the relatively low reliability of this measure as indicated by Cronbach's alpha.

As with confidence in decision quality, the perceived process structure and positive affect toward process increase as microcomputer expertise increases. These measures might be anticipated to show similar results in that confidence in decision quality may be affected by positive perceptions of the decision process and structure.

The post-test measures of confidence in decision outcome and satisfaction with decision process for the MSS in this study suggest that increases in confidence and satisfaction are more a function of microcomputer expertise, which has not been treated as a variable in previous studies, than of the user interface of the MSS.

5.4 Analysis of Cognitive and Learning Styles

A two-tailed test of proportions indicated that the personality types for the sample population of this study (Study 3 on Table XVIII), as determined by the Keirsey Temperament Sorter, was analogous to the population as a whole (Study 1 on Table XVIII, Bradway, 1964), in regard to two of the four Keirsey temperament scales: Extroversion-Introversion and Thinking-Feeling. A previous study of business students at Valparaiso University (Study 2 on Table XVIII, Cooper and Miller, 1989) employing the Myers-Briggs Type Indicator, showed differences from Bradway's percentages of types for the population at large on all but the Thinking-Feeling A comparison of the Myers-Briggs Types reported by Cooper and Miller with the Keirsey Temperaments from this study reports shows equal proportions on the Sensing-iNtuition and Thinking-Feeling scales. Both studies conducted with undergraduate business students at Valparaiso University (the Cooper and Miller study and this study) show significant difference in proportions from those reported by Bradway for the population at large on the Sensing-iNtuition and Judging-Perceiving scales, despite the fact that two different measurement instruments were used. If these divergent results are typical of undergraduate business students, there is cause for concern in using business students as a sample population for cognitive style studies where results are applied to other population groups.

No significant differences in means of the dependent measures were found which relate to cognitive style as assessed by the Keirsey Temperament Sorter in this study While this seems to confirm the arguments of Huber (1983) that cognitive style is much ado about nothing, it is more likely that lack of significance stems from the relatively smaller sample size than those used for cognitive style studies which have provided significant results. With respect to one item of the microcomputer expertise measure, those having an introverted temperament type reported spending more time per week, on the average, using a microcomputer than those having an extroverted temperament, echoing the work of Turkle (1984).

TABLE XVIII

COMPARISON OF COGNITIVE STYLE PERCENTAGES FOR THE POPULATION AT LARGE WITH A 1989 MYERS-BRIGGS TYPE INDICATOR STUDY AT VALPARAISO UNIVERSITY AND THE KEIRSEY RESULTS FOR STUDY AT VALPARAISO UNIVERSITY, MARCH, 1990

Myers-Briggs Type/ Keirsey Temperament	Study 1	Study 2	Study 3	Test of two proportions 1 vs 2	1 vs 3	2 vs 3
Extroversion	75.00	62.83	79.31	z=2.976	z=1.067	z=2.745
Introversion	25.00	37.17	20.69	p=0.003*	p=0.286	p=0.006*
Sensing	75.00	65.49	65.77	z=2.318	z=2.230	z=0.044
iNtuition	25.00	34.51	34.23	p=0.020*	p=0.026*	p=0.965
Thinking	50.00	58.41	47.50	z=1.778	z=0.529	z=1 643
Feeling	50.00	41.59	46.67	p=0.075	p=0.597	p=0 100
Judging	50.00	62.83	81.90	z=2 712	z=6.832	z=3 231
Perceiving	50.00	37.17	18.10	p=0.007*	p=0.001*	p=0 001*

Study 1 is percentage of types in the population as reported by Bradway, 1964
Study 2 is percentage of Myers-Briggs Types for 113 business students at Valparaiso University as reported by Cooper and Miller, 1989.
Study 3 is percentage of Keirsey Temperaments for the 120 business students at Valparaiso University who participated in this study, March, 1990.
Two-tailed test of proportions, asterisk indicates significantly different proportions, alpha = 0 05

5.5 Analysis of Keystroke Data

As might be anticipated, users of the natural language interface used more keystrokes than users of the menu interface. But users of the natural language interface spent less time between keystrokes, implying that they were able to focus more attention on achieving their desired results after having determined a command or request to issue, rather than spending time having to select items from a menu. This heightened focus on moving toward the task, facilitated by the NLP interface, may be one reason for the higher usability reported by those having high microcomputer expertise, considering the increased positive attitude toward process which is based upon microcomputer expertise.

5.6 Analysis of Answers to the Problem Set

Users of the natural language interface ran fewer unnecessary procedures NLP interface users had a 2 to 1 ratio of procedures run to required procedures, while the ratio for menu interface users was almost 4 to 1. There were no significant differences in the problem set scores of users of the two interfaces. Problem set scores increased with user expertise. This suggests a greater efficiency for the NLP interface, providing more output per unit of input.

Those achieving higher scores made use of the interpret function more than those achieving lower scores, suggesting some efficacy of this feature and affirming the value of intermediary assistance in statistics (Thisted, 1986). The use of help was equally divided between the two interfaces. Further research into the integration of these modes of intermediary assistance is needed.

5.7 Analysis of Gender Differences

While not a major focus of this study, in reviewing the self-assessed expertise scores it was noted that the perceived statistical expertise reported by women was lower than that reported by men, although women achieved higher scores on the problem set (suggesting a higher level of statistical expertise than men). Self-assessed keyboarding expertise reported by women was higher than that reported by men, while self-assessed microcomputer expertise reported by women was lower than reported by men. Whether or not these are functions of cultural gender biases deserves further study.

5.8 Analysis of Hypotheses

Seventeen hypotheses were offered in Chapter IV relating to the interaction between and among the two user interfaces and the three levels of microcomputer expertise. Implicit in each of these was the assumption that a natural-language interface would reduce the effort required for the secondary task of using the computer, allowing more attention to be focused upon the primary task of doing statistics. The data do not overwhelmingly support this assumption, and cases where the assumption is negated are noted. Each of the seventeen hypotheses is tested below in light of the data from the study.

> Hypothesis 1: Users of the NLP-interface perform more systematic and complete analyses, and score higher on the problem set than do users of the menu-interface.

Users of both interfaces performed a number of duplicate or unnecessary procedures. However users of the NLP-interface performed significantly lower ratio of unnecessary to required statistical procedures than did users of the menu interface, suggesting a higher level of decision process, or efficiency for the NLP interface over the menu interface. This efficiency was not operationalized in the decision outcome, in that there was no significant difference in the total score of the users of the two interfaces. NLP-users appear to capture the usability of the system, but the type of user interface did not seem to affect the statistical performance of one group over the other.

> Hypothesis 2: Users of the NLP-interface have more favorable attitudes toward the usability of the MSS than do users of the menu-interface.

There was no significant difference between the two interface groups on the usability measure but there was a significant difference based upon microcomputer expertise, especially for those using the NLP interface. The overall mean perceived ease of use score was 28 80 with a standard deviation of 6.91, indicating a slight positive perception of ease of use from the one-time experience with the MSS. NLP users with high microcomputer expertise reported significantly higher perceived usability than did the middle and low microcomputer expertise users of the NLP. This negates the implicit assumption above, suggesting that the reduction in effort brought by an NLP interface is operationalized in perceived ease of use for those with greater microcomputer expertise. A review of the keystroke logs indicated that high microcomputer expertise users of the NLP interface issued one and two word commands similar in syntax to the command languages of SAS or SPSSX, while low microcomputer expertise NLP users tended to issue requests as extended phrases of complete sentences. Further, in written comments, those with low microcomputer expertise indicated their surprise at the MSS's capability of accepting full sentences, while those with high microcomputer expertise praised the flexibility of the interface. The implication is that the NLP interface offered a level of flexibility, accepting already known command structures issued by those with high expertise and, in this one-time usage, surprised those with low expertise, who only over time might begin to appreciate this flexibility

> Hypothesis 3: Users of the NLP-interface exhibit more confidence in, and satisfaction with, their statistical decision processes and recommendations than do users of the menu-interface.

There was no significant difference between the interface groups on the perceived confidence in decision quality measure. The NLP-interface group indicated a slightly higher measure of perceived solution acceptability (11.42 versus 10.05, $t=-3.1288$, $p=0.002$) than the menu-interface group, although this mean score was slightly below the mid-level of four on the seven item likert scale. Both confidence in decision quality and perceived acceptability of solution were rated significantly higher as expertise increased from low to high. Because of the relative simplicity of the experimental task, it is possible that satisfaction in decision outcome in this experiment is more a function of microcomputer expertise, or the secondary decision task, than of the primary decision task. The fact that, in the absence of complexity, this microcomputer expertise variable impacts significantly on decision satisfaction deserves further consideration in future work, considering that this variable has not been regularly considered

> Hypothesis 4: Users of the NLP-interface have more favorable attitudes toward the functionality of the MSS than do users of the menu-interface.

> Hypothesis 5: Users of the NLP-interface spend less time using the MSS than do users of the menu-interface.

There was no significant difference in the perceived functionality of the two interface groups or the three expertise groups. The overall mean score of 33.0417, or about 5.5 on the seven item likert scale, indicated a positive perception of the MSS's functionality. Users of the NLP-interface did average about three minutes less in their time in using the package (50.16 minutes versus 53.23 minutes, $t=-2.1086$, $p=0.0371$), suggesting less effort on the part of NLP-users. Although not a strictly timed experiment, the fact that there were no differences in total scores and that NLP users took less time to achieve similar results implies a level of efficiency for this interface design.

> Hypothesis 6: More experienced computer users perform more systematic and complete analyses, and score higher on the problem set than do less experienced computer users.

> Hypothesis 7: More experienced computer users spend less time using the MSS than do less experienced computer users.

While there was no significant difference in the ratio of unnecessary to correct procedures run by more experienced versus less experienced users, the more experienced microcomputer users did score significantly higher on the problem set. In an analysis of covariance, statistical expertise was not a significant covariate, suggesting the possibility that the better performance was the result of computer expertise alone. While, as noted above, there was a significant difference in time using the MSS between NLP and menu interface users, the time of use was not significantly different between more and less experienced computer users. The importance of computer expertise as a contributing variable in studying the effectiveness of computer-based decision aids is again apparent.

> Hypothesis 8: Novice users of the MSS report more favorable attitudes toward the NLP-interface than do expert users.

> Hypothesis 9: Novice users of the NLP-interface spend less time using the MSS than do novice users of the menu-interface.

There were no significant differences in the challenge and accomplishment measures or the warmth of interaction measures for novice and expert NLP-interface users There were no significant differences in the amount of time spent with either interface for novice microcomputer users. Coupled with the discussion above, it is again the level of computer expertise rather than the type of interface that seems to affect decision outcome and decision performance.

> Hypothesis 10: Novice users of the NLP-interface report more favorable attitudes toward the usability of the MSS than do expert users of the NLP-interface.

Hypothesis 11: Novice users of the NLP-interface report more favorable attitudes toward the functionality of the MSS than do expert users of the NLP-interface.

It was the more experienced microcomputer users of the NLP-interface who reported a more favorable attitude than did either the middle or low groups of microcomputer users There was no honestly significant difference between the usability expressed by the menu-interface users. Again, in an analysis of covariance, statistical expertise measure did not load significantly on the analysis. There were no significant differences in the perceived functionality of the interfaces, with the six cells comprising one homogeneous group. The discussion of Hypothesis 2 above applies here as well.

Hypothesis 12: Users of the NLP-interface reporting low keyboarding skills have less favorable attitudes toward the usability of the MSS than do users of the menu-interface who report low keyboarding skills.

Hypothesis 13: Users of the NLP-interface reporting low keyboarding skills have less favorable attitudes toward the functionality of the MSS than do users of the menu-interface who report low keyboarding skills.

No significant differences were found based upon keyboarding skills, and the keyboarding measure was not a significant covariate. Although perhaps a function of the sample population, familiar with keyboard as a whole, this would bring into question the need for new input devices such as the mouse which has been couple with new graphical user interfaces

Hypothesis 14: Users of the NLP-interface with temperaments of extroversion, intuitive, feeling, and perceiving have more favorable attitudes toward Smart-Stat than do users of the NLP-interface with temperaments of introversion, sensing, thinking, and judging.

Hypothesis 15: Users of the menu-interface with temperaments of extroversion, intuitive, feeling, and perceiving have less favorable attitudes toward Smart-Stat than those do users of the menu-interface with temperaments of introversion, sensing, thinking, and judging.

Hypothesis 16: Users of the NLP-interface with high abstract conceptualization learning styles have more favorable attitudes toward Smart-Stat than do users of the NLP-interface with high abstract conceptualization learning styles.

Hypothesis 17: Users of the menu-interface with high concrete experiential learning styles have less favorable attitudes toward Smart-Stat than do users of the menu-interface with high concrete experiential learning styles

No significant differences were determined based upon either the temperament measures or the learning style measures. The differences between the sample results and those reported for the population at large deserve further consideration in light of the propensity to compare results using undergraduate business students to other populations. A larger sample size may be necessary to consider cognitive style implications, as indicated by the diversity of results in previous studies and the controversy over the importance of cognitive style to decision process and decision outcome.

5.9 Implications of Results

As with some previous studies by other researchers, this study explores the effectiveness of a computer-based decision aid. The prototype MSS with its two distinct user interfaces provides for comparison of NLP and menu interfaces (Lane, Batsell, and Guadango, 1989) and their relative effectiveness in enhancing decision outcome and decision process. Unique to this study is the use of expertise as an independent variable. Where Lane, Batsell, and Guadango control for expertise by providing training sessions prior to the experiment, this study provides an instrument to assess relative expertise and considers it as a major independent variable.

Finding no significant differences in overall functionality, usability, and confidence in decision quality based upon the user interface tends agree with previous studies (Aldag and Power, 1986; Sharda, Barr, and McDonnell, 1988); and with regard to the effectiveness of computer-based decision support in the areas of decision process and decision outcome, differing with those who report significant differences (Lane, Batsell, and Guadango, 1989). But the significant differences for usability, confidence in decision quality, and perceptions of the decision process based upon microcomputer expertise levels confirms both the need to consider this variable seriously in future research, and to consider more longitudinal studies which take into account expertise acquired through learning over time (Sharda, Barr, and

McDonnell, 1988) and through previous experience with decision aids (Killingsworth, 1987; Aldag and Power, 1986).

The lack of significant differences based upon cognitive and learning styles agrees with those negating the importance of these variables to system design considerations (Huber, 1983, Kerin and Slocum, 1981). Like those studies, this study also suffers from the smaller sample size which may be a contributing factor when considering the potentially large number of variables related to cognitive style (the four Myers-Briggs Types produce sixteen different cognitive style appraisals). The significant differences noted between undergraduate business students (Cooper and Miller, 1989) and the population at large (Bradway, 1964) in regard to cognitive style deserves further study in light of the number of MIS studies that have been empirically validated using student population groups.

The final chapter summarizes the study, providing conclusions, limitations, and directions for further research.

CHAPTER VI

CONCLUSIONS AND SUMMARY

6.1 Accomplishments of the Study

Two successful MSS interfaces were created for the topic domain of statistics. A set of expertise measures were created and validated offering simple method to assess relative expertise levels in a specific domain. Only one significant difference was found between the NLP interface and the menu interface with regard to decision process and decision outcome. The flexibility of the NLP-interface was found to be perceived as enhancing usability more for expert microcomputer users, going against the anecdotal evidence that usability would be enhanced for novices if users could communicate with computers in a manner similar to human conversation, based upon an initial, one-time encounter with a new MSS. A significant relationship between enhanced decision process and outcome and microcomputer expertise was found for measures of both decision process and decision outcome. The lack of significant differences brought about by the two user interfaces and the presence of significant differences between levels of microcomputer expertise indicates a need to include this second variable in further research of this nature.

6.2 Development and Capabilities of the Prototype

The change of information technology that drives MSS development was experienced in the development of the prototype MSS. Three different versions of Prolog and four different versions of Pascal were in use or issued during the two years of prototype development. Each offered measurable advantages over their predecessors, and all of these advantages have yet to be incorporated in the MSS prototype. A significant addition to Turbo Pascal 5.5 is the availability of object-oriented program, allowing the full implementation of some of the design features proposed in Chapter III.

Both computer-aided-instruction and context sensitive help features were accessed by microcomputer users of low to high expertise. Narrative reports of some of the users indicated an appreciation for the interpretation feature as a memory prompting aid in interpreting statistical results, offering a necessary external memory source. The effectiveness of these intermediary assistants need to be studied. Another technology driven user interface design feature, an expanded expert system for statistical method selection, will be further implemented in this MSS and studied as to its use and effectiveness.

Both interfaces were perceived to have a relatively high functionality and usability. With the object-oriented programming, perhaps both functionality and usability can be increased in this area. It is the intention of this researcher to continue development of the prototype MSS.

6.3 New Measurement Instruments

An instrument for assessing self-reported relative expertise in topical domains was created, validated, and implemented in this study. In addition, replication of the validation of Davis' functionality and usability measures (1989) was accomplished. This study confirms that the Aldag and Power measures (1986) need further development to enhance their reliability and validity. There are very few paper and pencil measures for MIS studies, and even fewer that have a high degree of reliability and validity. The three created in this study plus the two others of Davis (1989) should prove useful in further research.

6.4 Limitations of the Current Study

Results of the current study should be viewed with caution because of the apparent homogeneity of the sample population. The size of the sample was not large enough to support robust conclusions based upon cognitive style. The limitations of paper and pencil self-report measures are a concern, especially in the area of assessing expertise. Whether these measures of expertise will remain consistent over different populations deserves further study.

6.5 Implications for Further Research

Further development of the MSS prototypes using object-oriented programming may allow more efficient implementation and enhancement of the features specified for MSS design. The relative homogeneity of the 120 persons in this study sample may have affected the results. A study using 300 students is anticipated for Fall, 1990, providing a test-retest design to allow for comparison of both the first impressions of a new MSS reported here (enhanced by potentially more robust data from the Learning Style Inventory of Kolb, Rubin and McIntyre, 1971) and the learning over time. The larger sample should offer additional opportunity to explore the impact of temperament and learning styles, and to improve the Aldag and Power measures.

The flexibility of a natural language like interface for expert users could be universally implemented to overcome the confounding that occurs when moving from one command specific software package to another in the same topic domain. An NLP front-end for a statistical problem processing package like SAS, SPSS-X, or BMDP might obviate the need to learn the specific nuances of the different command structures.

Similarly, assessing a microcomputer users level of expertise, temperament, and learning style could offer the possibility of creating a software design which was capable of adapting to different users, providing an appropriate interface based upon user assessment. But this study has not indicated the need for an adaptable interface, only for a flexible command structure.

Further refinement of measurement instruments will be necessary in order to facilitate this flexibility. Additional study of the differences in temperament types between business student populations and other populations is also necessary to assess the possibilities of generalizing results from studies such as this.

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APPENDICES

APPENDIX A

SURVEY OF STUDENTS TO DETERMINE LANGUAGE USAGE

IN ADDRESSING STATISTICAL PROCESSING REQUESTS

VALPARAISO AND OKLAHOMA STATE UNIVERSITIES

OCTOBER, 1988

YOUR ASSISTANCE IS APPRECIATED

We are attempting to determine how people might communicate with a statistical software package which could "understand" normal conversation. Please take about five minutes to consider and respond to the following:

> *Imagine that a statistical software package could accept commands and act upon requests typed from the keyboard in natural language (the way you and I speak). A data set, called "TEST.DTS", contains a number of observations for variables "A" through "Z" and is available to the statistical software. Considering the models of univariate descriptive statistics (measures of central tendency, measures of dispersion, etc.) and regression and correlation, what specific commands would you issue or what specific requests would you make?*

List those commands or requests below exactly as you would type them from the keyboard. (e.g. "What is the mean of variable A?" or "How do I do a regression?")
THANKS FOR YOUR ASSISTANCE!

- -

PRODUCTIONS/OPERATIONS MANAGEMENT --JUNIOR LEVEL CLASS AT VALPARAISO UNIVERSITY

1. Show me one standard deviation from mean X
   What is a sample size for these conditions
   What is the 90% confidence interval for these conditions
   I want to use a Normal Curve
   Normalize this evenly distributed data
2. What is the central tendency
5. HELP!
   How do I do a regression
   What steps are necessary
7. How many standard deviate units from the mean does variable B lie
9. How many standard deviations
   Help explain basic concepts
17. What is the standard deviation
    Graph the line of regression for the variables
18. Now type in the population
    What is the sample, population
    What is the probability with a 95% confidence that certain variables will fall above or below certain lines
19. What is the standard deviation of X
    What is the covariance of X
    (if the computer can make a graph)
    Draw a scatter diagram of the variable X
    What is the slope of the line of best fit
20. What is the variance of Set B
    What is the co-varianceof that set
    What is the optimal portfolio of securities
    How can I find the minimum variance of portfolio
    How can I find the correlation coefficient
    How can I find the mean and variance of a two-assetportfolio and what is it
21. How do you find the median
    What is the formula for obtaining the standard deviation
    How do you find the standard deviation of a group of standard deviations
22. What is the average standard deviation for variables B thru F
    What is the standard deviation of variable Z
23. What is a T score, Z score
24. Find mean of X? for short or x-?
    Find derivitive of function (Defunct) d? for short variance?
25. What is the sample size
    What is the sample mean
    What is the population mean
    What is the standard deviation
    What is the median and mode
    What is the correlation coefficient
    What is the population parameter
26. CALC MEAN
    Regress

27. What is the standard deviation of variables A-Z
What is the coefficient of determination
How do I perform a multiple regression
Graphically represent the line determined by the regression
Perform the regression both forward and backward in order then show the least and most important variable in the system
28. What is the standard deviation of X
What is the variance of X
29. What is the standard deviation of the set TEST.DTS
What are the mean, median, and mode of the set TEST.DTS
Give me 2-dimensional graphical representation of the set TEST.DTS
What is the most effective, accurate, statistical representation of TEST.DTS
Is there a pattern within TEST.DTS that can be represented by formula
30. What is the standard deviation
How many variables are there
What is the tree diagram
31. What is the rate of dispersion
Are these independent variables
What is the standard deviation of the variables
Are the variables correlated
What is the range
32. What is the standard deviation of the variable a
What is the correlation coefficient of variable a
What is the sample size
What is the mean, median, and mode of the sample
Is the correlation positive or negative
33. What is the variance for variable R
What is the standard deviation for variable R
How do you calculate the standard deviation
34. Whats the date
What is the covariance of variable H
How do I calculate the range
Whats the cost of a widget

BUSINESS STATISTICS --SOPHOMORE LEVEL CLASS AT VALPARAISO UNIVERSITY

35. What is the standard deviation of variable A
What is the variance of variable A
36. Give a frequency listing for variable A
39. What is the standard deviation of C
What is the mode of the set
40. What is the mean of A
Display the cross tabulation of A
41. What is regression
What is the correllation between A & B
What is the main measure of central tendency of A
What is the main measure of dispersion of variable A
Which variables involve the mean and standard deviation
42. What are the measures of central tendency
How do I get a dispersion
The mean is ________________
43. What is the standard deviation of variable A
44. What is the standard diveation
How do I print the results
Print the results
Do a cross-tabulation
45. Find the standard deviation
What are the given values
Are the values representative of the population
46. How do I do a correlation
What is the standard deviation of ? value
What is the median of ? value
What is the range between A & Z
47. How do I do a regression
How do I do a correlation
What is the measure of central tendancy of ____ (fill in what you need)
Using the descriptive statistics, help me find the mean of X
What is the frequency of _________
48. I would like to access any menu from anywhere in the program

49. How do I do a correlation
What step should be taken after doing ________
What does this value represent
Which approach would be most useful ________ or ________
What steps should I take to accomplish ________
Which variable is constant or ________
What does this prove
Which variables should be used
50. What is the standard deviation of B
How do you set up a cross-tabulation
Which data set do I need to use if I want to cross income with class

MANAGEMENT INFORMATION SYSTEMS --SENIOR LEVEL CLASS AT OKLAHOMA STATE UNIVERSITY

51. What is the mean of data set A
What is the median of data set A
What is the standard deviation of data set A
52. What is the correlation
53. What is the std. deviation of variable A
I'm confused
54. Find the standard deviation
Find R-squared
Be able to calculate SST & SSE
55. Graph the function
LIST & explain various formulas
56. Specific commands
Mean = X
Standard dev. =
57. What is X-bar
58. Mean of A=
Standard deviation of A?
60. I would probably try and use a "short-form" of what I want to type onto the keyboard, such as VAR would be for "find the variables of B", MN would stand for "What is the mean of the variable" or STD would stand for "Find the standard deviation of a variable"
61. infile TEST.DTS
VARLIST 1: A1 B3 C5 D6-8etc.
Mean X, Mode X, Median X
Pearsons X
Z score X
end X
62. I would rather have in the software a list of the statistical things that could be done, and as a user I will have only to key in my choice as #1 or 2 etc
63. File?
TEST.DTS
READY (enter ? for help)
MEAN of A
17.25
etc.
65. I would want a statistics package that would give formula and explanation of formula with a command key that would plug in numerals. Have a problem set for each formula.
66. What is a regression
What is the mean of variable A
What is the standard deviation
68. How do I set up an analyses of various ?
69. Compute measures of central tendency
Compute measures of dispersion
70. What is the acceptable deviation
Is there enough data to make the regression
71. What are the options available in this software package
What is the average of variable Z
72. How should I begin
What is the answer means
73. What is the mean of variable A
What is the std. deviation
What is the confidence interval
What are the t test values in a regression analysis
What are the F values
What is R
What is R-squared
74. Plot the data points
Display the mean, median, mode
Fit the data to curve x

75. Find the correlation coefficient for
I don't know, I can't remember anything about STAT
76. What is the standard deviation of variables A-Z
Calculate the coefficient of determination
77. List mean A
List central tendency A
List Mean a-z(if I wanted all of the means to be listed)
Run regression
78. Locate for variable=c
Calculate the measures of dispersion
Do central tendency for . . .
Use TEST.DTS
79. How would I type in formulas for doing regressions and correlations
80. How do I test the null hypothesis
How do I enter the data to form a regression line

MBA CLASS - UNIVERSITY CENTER TULSA

82. I took the stats class last semester, but do not remember anything
Most help menus aren't specific enough
83. Mean of variable A
Skewness of variable A
Exceedence frequency data for A
1% exceedance frequency of A
84. Variable A mean
Calculate regression formula for A against B
Calculate correlation coefficient for A against B
What is standard deviation of A
What does this mean
Explain statistic
85. I need a 95% confidence interval
Plot the curve showing S.D. intervals
What is the S.D. of the input data
Divide the probability among variable _____ as follows _______
86. What is a measure of dispersion
How do I get a measure of dispersion
What is the correlation between A and Z
Tell me everything you know about H
How did you draw that correlation
What commands can I execute
How does the command ______ work
What
87. Find mean of A
Find deviation of A,B
Correlate Z using A,B,C
88. What is the slope of the regression line
WHat is the intercept
89. Regress Y=AX + B in terms of A and B
What is one standard deviation
WHat is the slope
What is the intercept
What is the mean
What is the frequency
What is the correlation
Estimate B when A = Sc
Help (command or Pf-Key)
90. I'm not a statisician so I don't know any commands other than:
What is the central tendency of data set A
What is the mean of data set A
(You really need to question someone who uses this kind of application all the time)
91. First I would have it menu driven
Correlation B/T A and B etc
Mean and STD dev. of each variable
Frequency default for A
Frequency for ranges of _____,_____,______,_____for A
Linear regression B/T __________, use Data ____ + ____
Exponential regression B/T __________, use Data ___ + ____
For help use F1 key with short explanation graphical interface really helps
92. Discribe variable ______
Help with regression, etc
List standard deviation of A

93. What is a correlation
How do I measure central tendency
How do I measure dispersion
What is the average of variable A
(Response to error message) What does this mean
94. How do I find a correlation coefficient for X
What is the weighted average for variable X
95. When would a regression analysis be run vs. other types of analysis
(In response to a response) What do you want
96. What does R or R-squaredmeasure
What does a regression show or measure
How are the 2 variables correlated
Are the variable significant and if so, why (correlated)
97. Do average of variable A
Do mean of variable A
Do multiple regression Variable 1?
Variable 2?
Variable 3?
Show example
99. How do I do a correlation
What is a central tendency
What is the dispersion
What is the standard deviation from the mean of variable A
100. What level of error does the statistic have
What is the correlation factor between variable A and B
Give the standard deviation
Describe the skew of the model
Tell the factors involved
Response: HELP? What?
101. A:>STAT (call program)
Enter drive letter where data is located _____
Enter data set name
F2 for Dir
(use cursor to select)
List programs to screen (select with cursor)
Enter variable to analyze
F2 for names
(select with cursor)
Summary results to screen
Output results to: ASCII file : Printer
102. I don't think I would use a natural language interface to such a technical application. Instead I would use a rule based expert system to generate the proper command syntax from the answers to questions like.
What statistical analysis to you want?
What is the indepent variable?
What is the dependent variable?
103. Give me the standard deviation of A? B? Z?
I want the mean, median, norm, standard deviation, central tendency of A considering variables A thru Q
Do regressive analysis on A considering variables A thru Z
Given variables A thru Z do ______________________
105. What is the average of variable F
What is the average of variable C compared to variable E
What is the mode of variable G
Response to answer: How do you get that answer?

BUSINESS DATA PROCESSING --SOPHOMORE LEVEL CLASS AT OKLAHOMA STATE UNIVERSITY
106. How do I do regression
Name programs and formulas
Punch in variance or X or standard deviation it will calculate
107. Calculate -dispersion, central tendency
Keep, store, save screen
108. How do I do a regression
109. Calculate the mean of variable A
110. Just type the name of what you are doing
111. Mean of variable A
Regression
116. What is the central tendency of A
What is the dispersion of B
117. What is a correlation
What is the mean of Z
119. Calculate measure of central tendency
Calculate standard deviation
Calculate mean, median, and mode of these numbers
120. ?
How do I do a regression

122. Print the standard deviation of ________________
What is a measure of central tendency
Output the regression to the mean on screen in graph form
What is the correlation coefficient of ____________
What is the standard error
123. Give standard deviation
Give variance
Give the mean
(just be able to type commands out in words)
124. Calculate the mean
Show how to calculate standard deviation
125. Show the calculations for standard deviation
What is the standard deviation for variable A
What is the mean, median, mode of variable A
126. I don't comprehend
127. I think the command title and function would be sufficient.
I also would have a HELP system included where the user could key in ex: HELP REGRESSION or HELP PRINT and a list of functions will appear or a easy step chart
128. Give standard deviation of A
Show work for standard deviation of A
What is the mean of variable A
Show mean, median, mode of variable A
131. Variable A?
Standard Deviation?
Regression?
Probability?
132. Calculate standard deviation
Calculate variable
Calculate x-bar
Apply this equation to the central limit theory
134. How do you find probability of A if given the data . . .
What is variance
Give the eq. step by step
135. How do I make a correlation
136. Find mean of
Find stand dev of
Find median of
Find prob. of
Use find and of
137. What is the probability of Z lying between 20 and 30
What is the mean of the population
138. What is the standard deviation of a #
139. Calculate mean of variable A
Can't remember how to do regression
140. Add all the columns
Print text entered
Check spelling
141. Mean of A
Median of A
Mode of A
(I haven't learned regression and correlation yet)
142. What is the mode of string A
What are the upper and lower quartiles
How do I find the standard deviation of string A
143. Calculate standard deviation
Find the mean of variable A
144. What is the standard deviation of whatever
How do I find the average of
Is it left or right skewed
How do I find the median of
147. What is the answer to this problem
What is the formula
148. What is the mean, mode, median, standard deviation, variance
What is the mean, mod, med, SD, var
149. Showing graphs on normal curves
150. Figure the measures of central tendency for VAR
Show the correlation between <first var>. . .<last var>
List the measures at dispersion for <vars>
Explain the formula for regression
151. What is the curve of all grades
Please print the curve
Change all letter grades positively by 1

153. What is the correlation coefficient for variable A-D
What is the distribution of the grades
Draw a graph of the above distribution
Computer the standard deviation of the following numbers
154. What is the mean, mode, median
What is the variance
Where is the standard normal for the distribution
What is the standard deviation
156. What is the sum of sqs for X and Y
What is the t-test? Give the t-value
What is the P-value? Give the p-value
What is the multiple regression equation? Give the mut. reg. equa.
What is the coefficient of correlation? Give r-cubed.
157. What is the standard deviation
What is the variance
Find the summation of x p (x)
Derive Z scores
Is it discrete or poisson
If discrete is it binomial
Find lambda
158. What is the average
What is the sum of all tests
How many A's are on the first exam
160. Give the average
Copy, variables, constants, ect (in general math terms)
Just to be able to talk to the computer, like a person, through the keyboard
161. What is the poisson rule best used for
What is the binomial formula best used for
Name the various symbols and what they represent
163. What is the class grades using stat class grades
Show a normal distribution for a probability
164. Copy, print, give the average, mean, and mode
Draw a histogram with info given

APPENDIX B

EXPERIMENTAL TASK: STATISTICAL PROBLEM SET

STATISTICAL PROBLEM SET

Please make use of the Smart-Stat program where helpful to answer the following problems. You have one hour to complete this task. Complete as many of the problems as you are able, providing your written answers on the pages provided. If you are unable to complete a problem, please move on the next. While you should make every effort to provide the correct answers, you will not be graded on the results. Thank you for your assistance in evaluating this software.

1. a) Generate a frequency distribution for the variable **JOBINC**, using the data set **STAT.DTS**. What is the median value of JOBINC?
   b) What is the modal value of **JOBINC**?
   c) For what level of job income (**JOBINC**) do about twenty percent earn less and eighty percent earn more than the level?

2. Find the mean and standard deviation of **JOBYRS** for those applicants in the entire dataset (i.e. the applicants in the **STAT.DTS** data set).

3. Generate a cross-tabulation classification table for two variables: **MSTATUS** and **CLASS**, using the **STAT.DTS** data set. The rows of this classification table are married and unmarried, and the columns are credit granted and credit denied. Find the number of people who fall into each of this table's four cells.

4. Use a t-test to test the hypothesis that the population means for **JOBINC** are the same for those who were granted credit and those who were denied credit. The classification variable will be **CLASS**. As your alternative hypothesis, use "Applicants in the two groups do not have equal incomes." Use an alpha value of .02.

5. Find the coefficient of correlation between **TOTBAL** and **TOTPAY** for all applicants (**STAT.DTS**).

6. Use analysis of variance with **STAT.DTS** to test the hypothesis that the population means for the dependent variable **JOBINC** are the same for those who were granted credit and for those who were denied credit (the independent variable **CLASS**). Let alpha =.05.

7. a) Run a regression to find the regression line that would allow the prediction of **JOBINC** for all applicants (**STAT.DTS**) as a linear function of **AGE**. What is the regression equation?
   b) Use the result obtained in step 7.a) to test the hypothesis:
      H_o: B = 0
   against the alternative hypothesis:
      H_a: B does not equal 0
   using alpha =.10.

8. a) Obtain the multiple regression equation in which **JOBINC** is the dependent variable and the independent variables are **SEX, JOBYRS, TOTBAL**, and **MSTATUS**. Use all the applicants (**STAT.DTS**). What is the regression equation?

   b) Using the results of step 8.a), test two separate hypotheses. First, test the hypothesis that **JOBYRS** adds no additional explanatory power to the prediction of **JOBINC**, given that all of the other independent variables are also included in the regression equation. Then test the hypothesis that **TOTBAL** adds no additional explanatory power to the prediction of **JOBINC**, given that all of the other independent variables are also included in the equation. Use:

      H_o: B_j does not equal 0

      and alpha = .05 in these two tests.

9. Build a new data set (using Data Transformations of **STAT.DTS**) containing all applicants who were granted credit (i.e. for all applicants where **CLASS** = 1). Call this new data set **GRANTED.DTS**. Using the **GRANTED.DTS** data set, generate a frequency distribution for **JOBINC**. What is the mean and standard deviation of **JOBINC** for this group?

(SOURCE: Adapted from <u>Brief</u> <u>Business</u> <u>Statistics</u>, Watson, et. al., 1988.)

APPENDIX C

STATISTICAL DATA SET FOR EXPERIMENTAL TASK

STAT.DTS: STATISTICAL DATA SET

The data set presented on the following pages represents a random sample of 113 people who applied for charge account privileges at a well-know department store on the East Coast. Each line of data represents one applicant (one case or observation) and gives ten pieces of information (values for variables) about that person. The nature and measure of the ten variables are discussed in the following list.

CLASS Indicates whether the department store granted credit to the individual. The value 1 indicates credit was granted, and the value 0 indicates it was not. The first 63 people in the list were granted credit, and the last 50 were not.

SEX Indicates where the applicant was male (indicated by a 1) or female (indicated by a 0).

AGE Indicates the applicant's age, listed in years.

JOBYRS Indicates the number of years the applicant had held his or her current job. The value "." (the symbol for a missing value) indicates that the individual was not employed in an income-producing job at the time the application was made.

JOBINC Indicates the monthly income the applicant was receiving from his or her job at the time of application. A value of "." (the symbol for a missing value) indicates that the applicant had no monthly income.

ADDINC Indicates the amount of additional income (over and above that received from a regular job) the applicant received each month. The figures listed here most often included income from commissions or rental property.

TOTBAL Indicates the total balance of debt owed by the applicant (exclusive of a home mortgage) at the time of application.

TOTPAY Indicates the total monthly payments the applicant was making on the debt balance listed above.

SPINC Indicates the applicant's spouse's monthly income. Some applicants listed the vale 0, but many applicants merely left this item blank. A blank value is indicated in the data set by "." (the symbol for a missing value).

MSTATUS Indicates the marital status of the applicant. Married applicants are indicated by a 1, and unmarried applicants (single, divorced, widowed) are indicated by a 0.

```
Smart-Stat Listing of Cases

Data Set = Sample Data Set from Brief Business Statistics

CLASS    Granted = 1 Denied = 0        SEX      Male = 1 Female = 0
AGE      Applicant's age in years      JOBYRS   Number of years in current job
JOBINC   Applicant's monthly income    ADDINC   Applicant's additional income
TOTBAL   Total balance of debt owed    TOTPAY   Total monthly payments on debt
SPINC    Spouse's income               MSTATUS  Married = 1 Single = 0
```

Obs	CLASS	SEX	AGE	JOBYRS	JOBINC	ADDINC	TOTBAL	TOTPAY	SPINC	MSTATUS
1	1	1	29	4	1200	200	5645	80	0	1
2	1	0	21	0	450	0	0	0	.	0
3	1	1	23	1	700	0	1798	34	430	1
4	1	1	53	27	2000	0	0	0	.	1
5	1	1	30	5	1200	0	3500	110	.	1
6	1	1	25	3	925	0	828	103	500	1
7	1	1	47	20	1520	100	0	0	.	1

Obs	CLASS	SEX	AGE	JOBYRS	JOBINC	ADDINC	TOTBAL	TOTPAY	SPINC	MSTATUS
8	1	1	23	0	782	0	1626	79	.	0
9	1	1	57	.	.	880	0	0	850	1
10	1	1	34	2	2500	110	6000	70	.	1
11	1	1	22	1	600	0	568	91	.	1
12	1	1	44	8	1250	0	896	49	.	1
13	1	0	53	9	600	755	0	0	.	1
14	1	1	37	1	1200	0	0	176	.	0
15	1	0	33	5	520	210	1000	28	.	0
16	1	1	27	0	834	100	0	0	100	1
17	1	1	27	6	630	0	0	0	400	1
18	1	1	39	0	740	0	880	40	750	1
19	1	0	66	19	550	0	0	0	.	1
20	1	1	35	3	1000	0	0	0	.	0
21	1	1	37	0	1875	0	0	0	.	1
22	1	1	40	11	2000	300	0	0	.	1
23	1	1	24	4	1350	175	0	0	.	0
24	1	1	60	.	.	806	1740	36	.	1
25	1	1	42	3	700	300	500	40	.	0
26	1	1	48	7	4000	1000	18000	461	.	0
27	1	1	31	4	800	0	0	0	500	1
28	1	1	29	3	600	150	0	0	.	0
29	1	0	30	2	1000	0	1050	120	.	0
30	1	1	78	30	1000	1620	0	0	.	0
31	1	1	28	1	520	350	0	0	.	1
32	1	1	22	1	650	0	0	0	250	1
33	1	1	39	5	800	0	0	0	.	0
34	1	1	27	2	1100	0	800	55	.	0
35	1	1	28	6	650	0	287	20	.	1
36	1	1	65	.	.	0	0	0	.	1
37	1	1	56	25	2000	2000	0	0	.	1
38	1	0	22	3	640	85	0	0	.	0
39	1	1	22	6	750	0	0	0	.	0
40	1	1	18	15	850	300	10800	163	150	1
41	1	1	63	6	1916	0	0	0	.	1
42	1	1	28	0	.	0	0	0	.	1
43	1	1	32	1	2000	0	2800	0	.	1
44	1	1	24	0	650	1000	0	0	.	1
45	1	1	24	3	900	0	0	0	300	1
46	1	1	32	0	1450	0	2700	115	.	1
47	1	1	70	.	.	280	0	0	.	1
48	1	1	35	0	700	100	700	60	.	1
49	1	1	29	0	1060	0	457	51	.	1
50	1	1	21	3	900	0	215	88	.	0
51	1	1	28	8	1000	0	0	0	.	1
52	1	1	60	6	2000	0	0	0	.	0
53	1	1	27	2	1025	0	0	0	.	1
54	1	1	29	0	1336	115	0	0	575	1
55	1	1	21	2	900	0	200	43	.	0
56	1	1	50	7	1500	0	0	0	.	1
57	1	1	42	13	3000	0	0	0	.	1
58	1	0	25	1	713	83	0	0	.	0
59	1	1	44	.	.	0	6135	130	1000	1
60	1	1	26	16	1000	0	0	0	.	0
61	1	1	34	13	1374	0	0	0	.	1
62	1	1	22	0	933	0	0	0	.	1
63	1	1	36	2	2200	400	0	0	.	1
64	0	0	34	4	400	0	0	0	1000	1
65	0	1	21	1	540	0	469	46	0	0
66	0	1	40	3	1500	0	360	37	300	1
67	0	1	25	3	865	0	1000	103	500	1
68	0	1	22	9	570	260	200	25	0	0
69	0	1	54	20	1000	0	2400	205	0	1
70	0	0	63	8	600	0	0	0	0	0
71	0	1	28	0	440	0	120	20	0	0
72	0	0	29	0	600	300	0	0	.	0
73	0	0	22	2	350	85	820	57	.	0

Obs	CLASS	SEX	AGE	JOBYRS	JOBINC	ADDINC	TOTBAL	TOTPAY	SPINC	MSTATUS
74	0	1	30	1	1000	0	5146	217	.	1
75	0	1	30	9	600	0	5000	288	.	0
76	0	1	45	11	2225	0	4000	78	0	1
77	0	1	26	2	950	0	500	95	.	0
78	0	1	28	1	400	240	0	0	500	1
79	0	1	40	5	1300	0	9000	200	250	1
80	0	0	25	0	600	43	169	15	.	0
81	0	1	21	0	400	0	0	0	.	0
82	0	1	24	0	755	0	0	0	.	1
83	0	1	21	1	645	0	0	0	300	1
84	0	1	39	1	1000	116	1356	117	.	1
85	0	0	29	5	539	0	220	40	.	0
86	0	1	24	1	400	0	0	0	.	0
87	0	0	23	.	.	0	0	0	.	0
88	0	1	28	2	660	196	890	17	660	1
89	0	1	22	0	1265	0	250	57	.	0
90	0	0	24	2	400	0	50	0	200	1
91	0	1	29	10	1200	0	150	30	.	0
92	0	1	21	0	520	0	0	0	.	0
93	0	1	28	1	300	0	0	0	.	0
94	0	1	22	3	700	0	0	0	420	1
95	0	1	19	3	700	0	0	0	.	0
96	0	1	52	28	755	0	0	0	.	1
97	0	1	32	1	750	310	0	0	450	1
98	0	0	24	0	500	309	0	0	.	0
99	0	1	20	1	900	0	0	0	.	0
100	0	0	20	1	376	0	200	20	.	0
101	0	1	22	1	450	0	3063	106	.	1
102	0	1	23	3	800	0	0	0	.	0
103	0	1	32	10	800	0	2800	104	.	1
104	0	1	35	0	450	0	0	0	.	0
105	0	1	20	2	750	0	0	0	.	0
106	0	1	34	0	600	175	2709	52	.	1
107	0	1	32	2	1800	400	90	460	.	1
108	0	1	35	1	1600	0	3900	163	.	1
109	0	1	26	5	1300	800	765	54	350	1
110	0	1	27	0	660	0	768	64	556	1
111	0	1	23	2	700	0	385	20	.	0
112	0	1	28	2	700	0	297	28	.	0
113	0	1	28	2	1200	0	0	0	500	1

(SOURCE: Adapted from Brief Business Statistics, Watson, et. al., 1988, pp. 562-565.)

APPENDIX D

PRE-TEST EXPERTISE SELF-ASSESSMENT INSTRUMENT

USED AT VALPARAISO UNIVERSITY, MARCH, 1990

NAME: ______________________

Your assistance is requested in a survey of user attitudes. While we are asking for your name on the survey, please be assured that your responses will be kept in strictest confidence. Please check the space above the words which indicate your level of agreement or disagreement with each of the following statements.

1. I have used microcomputers extensively.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

2. My microcomputer skills are not good.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

3. I enjoy using microcomputers.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

4. I am a more experienced microcomputer user than most of my peers.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

5. I own or have easy access to a microcomputer.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

6. I wish my microcomputer skills were better.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

7. I have used statistics extensively.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

8. My statistical skills are not good.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

9. I am a more experienced statistics user than most of my peers.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

10. I enjoy doing statistics.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

11. I wish my statistical skills were better.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

12. I am a faster typist than most of my peers.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

13. My keyboarding abilities are good.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

14. I do not type well.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

15. I wish my keyboarding skills were better.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

16. If I were to evaluate my microcomputer abilities, I would give myself a grade of ...

A	B	C	D	F

17. If I were to evaluate my statistical abilities, I would give myself a grade of ...

A	B	C	D	F

18. If I were to evaluate my keyboarding abilities, I would give myself a grade of ...

A	B	C	D	F

Please answer the following questions.

____ **19. How many courses have you taken which make use of microcomputers?**

____ **20. How many courses have you taken which make use of statistics?**

____ **21. How many courses have you taken in typewriting or keyboarding?**

____ **22. How many hours per week, on the average, do you estimate you spend using a microcomputer?**

____ **23. How many words per minute do you estimate that you can accurately type?**

____ **24. What is your gender?**

____ **25. What is your age?**

APPENDIX E

DOCUMENTATION FOR THE NATURAL LANGUAGE INTERFACE PROTOTYPE

ABOUT SMART-STAT

Smart-Stat assists in making statistical analyses efficiently and correctly. The process of a computer statistical analysis (pictured below) is followed by Smart-Stat and offers an outline for this brief introduction.

```
[select DATA] --> [determine statistical PROCEDURE] --> [do STATISTICS analysis] --> [interpret RESULTS] --> [RECOMMEND DECISION]
```

Smart-Stat allows you to access statistical processes by typing in simple requests. Smart-Stat responds to your requests and provides the results in a separate file which you may view on the screen.

QUICK START FOR SMART-STAT

To being the Smart-Stat program, type **SMART** followed by the **Enter** or carriage return key.

Your data are already stored in a Smart-Stat DTS file called **SMART.DTS**. Simply type the statistical procedure you wish to execute, including the variables you wish to use. You will be prompted for your input data set and asked to name an output print file in which Smart-Stat will store your results. The default name for the output data set is **WORK.PRT**. Please use this name throughout this session, and whenever asked if you wish to **APPEND**, answer **Y**. Once these two files are selected (input data -- output for results), Smart-Stat will complete the procedure you requested.

EXAMPLES:

What is the mean of JOBINC?
Do a regression on JOBINC vs JOBYRS and AGE

USING THE SMART-STAT DIALOG PROCESSOR

Smart-Stat provides two dialog windows, one for your requests and directions to the computer, and the other for the computer responses to these requests and directions. In addition, the screen provides information as to the current data and output files (at the bottom of the screen) and the current and last procedure, and System messages in separate windows.

```
System Messages:                                              Variables:
Welcome to Smart-Stat.
Please enter your request in the USER DIALOG box.
Enter TUTORIAL to view the Smart-Stat Tutorial.

Current Procedure:               Last Analysis:

USER DIALOG:
_

COMPUTER DIALOG:

Wednesday, January 31, 1990                              9:29.08 am

Data: NONE                          Output: NONE
```

SMART-STAT TEXT ENTRY

The requests you enter in the user dialog window give you access to Smart-Stat's statistical processes. Type your request, pressing the carriage return only after you have entered the entire request. SMART-STAT text input works like a small word processor. When entering statements (as in the user dialog window, when in Transform entering transformation equations, or when entering a data set title) you may use the following keys:

HOME - cursor to beginning of entry	**CTRL-LEFT** - cursor to next word left
END - cursor to end of entry	**CTRL-RIGHT** - cursor to next word right
LEFT ARROW - move cursor left	**CTRL-END** - delete from cursor to end
RIGHT ARROW - move cursor right	**DEL** - delete at cursor
BACKSPACE - delete left of cursor	**INS** - toggles insert and typeover mode

EXITING THE PROGRAM

Pressing the **ESC** key quits the current statistical process and returns to the dialog processor screen. Typing **QUIT** from the user dialog window causes Smart-Stat to ask if you are sure that you wish to quit the program. Typing a **Y** or **y** in response to the question will exit the program. Typing any other key will continue the program.

CONTEXT SENSITIVE HELP

Typing **HELP** and a topic will provide help on that topic. Typing **HELP** by itself provides a list of available help topics.

EXAMPLE: **Help regression**

When there is a reverse bar at the top of the screen pressing the **F1** key provides help or additional information about the current process. Pressing the **ESC** returns to the dialog processor.

DATA FOR STATISTICAL PROCESSING

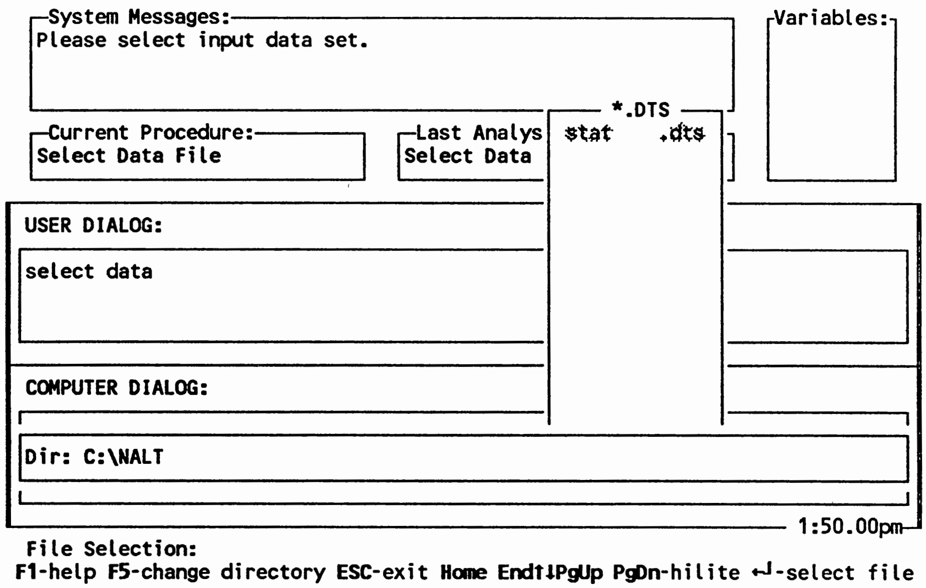
A Smart-Stat dataset consists of up to 64,000 cases (observations) with up to 255 variables for each case. Variables may have either numeric or character values (there is a maximum of 20 character variables per dataset).

Smart-Stat makes use of several files to store the data to be processed and the results of statistical processing. These files are designated by a three letter filename extension.

DTS, or **D**a**T**a**S**et files, contain the numeric values of variables for each case in the data set. Because this data is stored in a binary format you may not read or edit this file with a standard text editor.

NMS, or **N**a**M**e**S** files, contain the variable names and labels for the dataset and character variable data for each case.

When you ask or are asked to **SELECT DATA**, Smart-Stat provides a listing of the data files available.



Use the following keys to move through the file directory listing:

↵ (Enter) - selects highlighted file and exits
Down (Up) Arrow - moves to next (previous) file on current page
Home (End) - moves to first (last) file on current page
PgUp (PgDn) - moves to previous (next) page of file listings
Ctrl–Home (Ctrl–End) - moves to first (last) file in the list
Ctrl–PgUp (Ctrl–PgDn) - moves to first (last) page of file listings
Initial letter - jumps to first file beginning with the letter
F5 - allows you to specify a new drive, directory
ESC - exits without selection

DATA TRANSFORMATIONS

You can create a new data set from an existing one using data transformations. Request a **TRANSFORMATION** and enter the input data set file name when requested. Smart-Stat will then prompt you for an output data set. The default name for an output data set is **WORK**.

You may give the output file the same name as the input file, but it is a good practice to use separate names. Up to 10 data transformation statements may be processed at one time.

Data transformation equations are similar to those written in FORTRAN or BASIC. The equations are of three types:
Subsetting IF statements,
Numeric Transformations,
Logical Transformations.

Subsetting IF Statements consist of an IF statement without a corresponding THEN equation. This statement allows selection of cases to be included in the output dataset.

An example: IF GENDER=1 selects only those observations where GENDER = 1.

SELECTING STATISTICAL TECHNIQUES

Smart-Stat incorporates an expert system to assist the user in determining appropriate statistical techniques. Request **CONSULT**. You will be asked to answer a series of questions. Using your responses, the system will suggest an appropriate statistical technique within Smart-Stat or indicate where further information might be available.

SELECT A STATISTICAL METHOD

Smart-Stat provides numerous statistical methods, including:

UNIVARIATE - frequency counts, descriptive statistics (mean, standard deviation, standard error, minimum, maximum, etc.), breakdown of means, t-test of 2 means, proportions test

BIVARIATE - cross tabulation, correlation (listwise and pairwise), covariation (listwise and pairwise), linear regression, Cronbach's alpha

MULTIVARIATE - multiple regression, analysis of variance, factor analysis

DISTRIBUTIONS - binomial, hypergeometric, exponential, and poisson distributions, plus probabilities for Z, t, F, and Chi-square statistic

OTHER - permutations, combinations, factorials

Simply request the technique and provide the requested information.

SELECTING VARIABLES

When asked to select variables, you will be presented with a listing of variables in the current data set.

```
┌System Messages:──────────────────────────────────────┐  ┌Variables:┐
│Variables listed in variable box                      │  │ NUM      │
│for input file: C:\PASCAL\NAT\STAT.DTS                │  │ CLASS    │
│Press escape to exit.                                 │  │ SEX      │
└──────────────────────────────────────────────────────┘  │ AGE      │
┌Current Procedure:──────┐  ┌Last Analysis:────────────┐  │ JOBYRS   │
│Variable Listing        │  │                          │  │ JOBINC   │
└────────────────────────┘  └──────────────────────────┘  └─ ↑↓more ─┘
┌─────────────────────────────────────────────────────────────────┐
│ USER DIALOG:                                                    │
│ ┌─────────────────────────────────────────────────────────────┐ │
│ │variables                                                    │ │
│ │                                                             │ │
│ └─────────────────────────────────────────────────────────────┘ │
├─────────────────────────────────────────────────────────────────┤
│ COMPUTER DIALOG:                                                │
│ ┌─────────────────────────────────────────────────────────────┐ │
│ │                                                             │ │
│ │                                                             │ │
│ └─────────────────────────────────────────────────────────────┘ │
└─────────────────────────────────────────────────── 1:50.00pm───┘
 Variable Listing:
F1-help F6-description ESC-exit  Home End ↑↓ PgUp PgDn-hilite ↵-Select/unselect
```

Use the following keys to move through variable listing:

Down (Up) Arrow	- moves to next (previous) variable
Home (End)	- moves to first (last) variable on current page
PgUp (PgDn)	- moves to previous (next) page of variables
Ctrl–Home (Ctrl–End)	- moves to first (last) variable in the list
Ctrl–PgUp (Ctrl–PgDn)	- moves to first (last) page of variables
F6	- provides description of highlighted variable
ESC	- exits listing

If variables may be selected, the following keys make selections

↵ (Enter)	- selects/unselects highlighted variable
F3	- select/unselect all variables
F7	- done, process selected variables

VIEW OR INTERPRET RESULTS

The results of Smart-Stat statistical methods are written to PRT files. You may request **VIEW** to see the contents of a PRT file, and then use the **F8** key to receive an interpretation of the results in a PRT file. You may quickly scan through the PRT file indicated at the bottom right of the screen with the following keys:

Down Arrow- scrolls the text up to read the next line down
Up Arrow - scrolls the text down to read the next line up
PgDn (PgUp) - displays the next (previous) screen of data
Home (End) - goes directly to the beginning (end) of the file
ESC - exits the View procedure
F8 - provides an interpretation of the output on the screen
Ctrl-PrtSc - sends the contents in memory to the printer

You may not change the contents or otherwise edit the output print file in this special view mode. If you are sending the results of multiple procedures to the same file, the most recent results will be at the end. Press the End key to go directly to the end of the entire file then use PgUp to locate the beginning of the most recent set of results.

You may send the contents of the file to the printer by holding the Ctrl key down and pressing PrtSc. While the file is being routed to the printer, the text will scroll across the screen. You can cancel the printing process at any time by pressing ESC.

APPENDIX F

DOCUMENTATION FOR THE MENU INTERFACE PROTOTYPE

ABOUT SMART-STAT

Smart-Stat assists in making statistical analyses efficiently and correctly. The process of a computer statistical analysis (pictured below) is followed in the Smart-Stat menu structure.

```
[select]     [ determine ]     [   do     ]     [interpret]     [RECOMMEND]
[ DATA ] --> [statistical] --> [STATISTICS] --> [ RESULTS ] --> [DECISION ]
[      ]     [ PROCEDURE ]     [ analysis ]     [         ]     [         ]
```

QUICK START FOR SMART-STAT

To being the Smart-Stat program, type **SMART** followed by the **Enter** or carriage return key.

Your data are already stored in a Smart-Stat DTS file called **STAT.DTS**. Select the statistical procedure you wish to execute from the **STATISTICS** menu. You will be prompted for your input data set and asked to name an output print file in which Smart-Stat will store your results. The default name for the output data set is **WORK.PRT**. Please use this name throughout this session, and whenever asked if you wish to **APPEND**, answer **Y**. Once these two files are selected (input data -- output for results), Smart-Stat will ask for the variables you wish to consider and then complete the procedure you requested.

USING THE SMART-STAT MENU

The Smart-Stat menu features a horizontal bar, representing selections for the actions above (plus various system settings).

```
 Data   Procedures   Statistics   Results   Files   Tutorial   Quit
 Tutorial on using Smart-Stat




 Main Menu Selection:                        Wednesday, January 31, 1990
                                                              1:00.02pm
 F1-help                          ←→-hilite     Letter or ↵-select
 F2-Data: NONE                    F4-Output: NONE
```

Selections from the horizontal bar may have secondary selections which are given in a vertical *pull down* menu.

```
 Data    Procedures    Statistics    Results    Files    Tutorial    Quit

                      Univariate    | Frequencies for variable
                       Frequency counts
                       Descriptive Stats
                       Breakdown of Means
                       T-Test of 2 Means
                       Proportions Test

 Sub Menu Selection:                           Wednesday, January 31, 1990
                                                                1:00.32pm
F1-help  ESC-previous menu    ←→-menus    ↑↓-hilite    Letter or ↵-select
F2-Data: NONE                          F4-Output: NONE
```

HIGHLIGHTING AND CHOOSING SMART-STAT SELECTIONS

Choose a menu selection by typing the first capital letter in the selection, or by *highlighting* and pressing the **Enter** key. The cursor keys on the numeric keypad (**left arrow, right arrow, up arrow, down arrow**) may be used to *point* to a selection. The selection that is pointed to is *highlighted*. *Highlighting* a selection and pressing the enter key chooses that selection and leads to the next selection or to the activity associated with the selection.

EXITING A MENU

Pressing the **ESC** key quits the current menu and returns to the previous options. If the current menu is a vertical *pull down* menu, **ESC** returns to the previous *pull down* menu or to the initial horizontal menu.

CONTEXT SENSITIVE HELP

Pressing the **F1** key provides help or additional information about the currently highlighted selection. Pressing the **ESC** exits the help screens.

SELECTING DATA FOR STATISTICAL PROCESSING

A Smart-Stat dataset consists of up to 32,000 cases (observations) with up to 255 variables for each case. Variables may have either numeric or character values (there is a maximum of 20 character variables per dataset).

Smart-Stat makes use of several files to store the data to be processed and the results of statistical processing. These files are designated by a three letter filename extension.

DTS, or DaTaSet files, contain the numeric values of variables for each case in the data set Because this data is stored in a binary format you may not read or edit this file with a standard text editor.

NMS, or NaMeS files, contain the variable names and labels for the dataset and character variable data for each case.

When you press the **F2** key, or are asked to select data, Smart-Stat provides a listing of the data files available.

```
                          *.DTS
                       stat     .dts




Dir: C:\MENU\

File Selection:
                                                        1:50.00pm
F1-help F5-change directory ESC-exit Home End↑↓PgUp PgDn-hilite ↵-select file
F2-Data: NONE                         F4-Output: NONE
```

Use the following keys to move through the file directory listing:

↵ (Enter)	- selects highlighted file and exits
Down (Up) Arrow	- moves to next (previous) file on current page
Home (End)	- moves to first (last) file on current page
PgUp (PgDn)	- moves to previous (next) page of file listings
Ctrl–Home(Ctrl–End)	- moves to first (last) file in the list
Ctrl–PgUp(Ctrl–PgDn)	- moves to first (last) page of file listings
Initial letter	- jumps to first file beginning with the letter
F5	- allows you to specify a new drive, directory
ESC	- exits without selection

DATA TRANSFORMATIONS

You can create a new data set from an existing one using data transformations. Enter the input data set file name first. Smart-Stat will then prompt you for an output data set. The default name for an output data set is **WORK**.

You may give the output file the same name as the input file, but it is a good practice to use separate names. Up to 10 data transformation statements may be processed at one time.

Data transformation equations are similar to those written in FORTRAN or BASIC. The equations are of three types:

Subsetting IF statements,
Numeric Transformations,
Logical Transformations.

Subsetting IF Statements consist of an IF statement without a corresponding THEN equation. This statement allows selection of cases to be included in the output dataset.

An example: IF GENDER=1 selects only those observations where GENDER = 1.

SELECTING STATISTICAL TECHNIQUES

Smart-Stat incorporates an expert system to assist the user in determining appropriate statistical techniques. Select **CONSULT**. You will be asked to answer a series of questions. Using your responses, the system will suggest an appropriate statistical technique within Smart-Stat or indicate where further information might be available.

SELECT A STATISTICAL METHOD

Smart-Stat provides numerous statistical methods, including:

UNIVARIATE - frequency counts, descriptive statistics (mean, standard deviation, standard error, minimum, maximum, etc.), breakdown of means, t-test of 2 means, proportions test

BIVARIATE - cross tabulation, correlation (listwise and pairwise), covariation (listwise and pairwise), linear regression, Cronbach's alpha

MULTIVARIATE - multiple regression, analysis of variance, factor analysis

DISTRIBUTIONS - binomial, hypergeometric, exponential, and poisson distributions, plus probabilities for Z, t, F, and Chi-square statistic

OTHER - permutations, combinations, factorials

Simply highlight your selection and provide the requested information.

SELECTING VARIABLES

When asked to select variables, you will be presented with a listing of variables in the current data set.

```
                                                  Variables:
                                                   NUM
                                                   CLASS
                                                   SEX
                                                   AGE
                                                   JOBYRS
                                                   JOBINC
                                                   ADDINC
                                                   TOTBAL
                                                   TOTPAY
                                                   SPINC
                                                   MSTATUS

 Variable Selection:
                                                                  1:50.00pm
F1-help F3-mark all F6-description F7-done ESC-exit ↑↓-hilite ↵-mark,unmark
F2-Data: STAT.DTS                      F4-Output: WORK.PRT
```

Use the following keys to move through variable listing:

Down (Up) Arrow	- moves to next (previous) variable
Home (End)	- moves to first (last) variable on current page
PgUp (PgDn)	- moves to previous (next) page of variables
Ctrl–Home(Ctrl–End)	- moves to first (last) variable in the list
Ctrl–PgUp(Ctrl–PgDn)	- moves to first (last) page of variables
F6	- provides description of highlighted variable
ESC	- exits listing

If variables may be selected, the following keys make selections

↵ (Enter)	- selects/unselects highlighted variable
F3	- select/unselect all variables
F7	- done, process selected variables

VIEW OR INTERPRET RESULTS

The results of Smart-Stat statistical methods are written to PRT files. You may select VIEW to see the contents of a PRT file, and then use the **F8** key to receive an interpretation of the results in a PRT file. You may quickly scan through the PRT file indicated at the bottom right of the screen with the following keys:

Down Arrow- scrolls the text up to read the next line down
Up Arrow - scrolls the text down to read the next line up
PgDn (PgUp) - displays the next (previous) screen of data
Home (End) - goes directly to the beginning (end) of the file
ESC - exits the View procedure
F8 - provides an interpretation of the output on the screen
Ctrl–PrtSc - sends the contents in memory to the printer

You may not change the contents or otherwise edit the output print file in this special view mode. If you are sending the results of multiple procedures to the same file, the most recent results will be at the end. Press the End key to go directly to the end of the entire file then use PgUp to locate the beginning of the most recent set of results.

You may send the contents of the file to the printer by holding the Ctrl key down and pressing PrtSc. While the file is being routed to the printer, the text will scroll across the screen. You can cancel the printing process at any time by pressing ESC.

SMART–STAT TEXT ENTRY

SMART-STAT text input works like a small word processor. When entering statements (as in Transform, or when entering a data set title) you may use the following keys:

HOME- cursor to beginning of entry
END - cursor to end of entry
LEFT ARROW - move cursor left
RIGHT ARROW - move cursor right
BACKSPACE - delete left of cursor
CTRL–LEFT - cursor to next word left
CTRL–RIGHT - cursor to next word right
CTRL–END - delete from cursor to end
DEL - delete at cursor
INS - toggles insert and typeover mode

APPENDIX G

POST-TEST DEPENDENT MEASURES INSTRUMENT USED AT VALPARAISO UNIVERSITY, MARCH, 1990

Please check the space above the words which indicate your level of agreement or disagreement with each of the following statements.

1. While using Smart-Stat I felt challenged to do by best work.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

2. I felt frustrated by Smart-Stat.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

3. Using Smart-Stat was fun.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

4. My answers for the problems were good ones.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

5. Answering the problems improved my statistical skills.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

6. It took too much time to solve the problems.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

7. People who might be affected by my answers to the problems would probably be satisfied with them.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

8. The approach taken to answering the problems was very structured.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

9. I wish I had approached the problem set differently.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

10. I'm pleased with the approach used to answer the problem set.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

11. I really felt like I accomplished something by using Smart-Stat.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

12. Using a computer to learn seems like a good idea to me.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

13. I am not in favor of computer-aided learning because it is just another step toward depersonalization of learning.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

14. I'm not sure my solution to the problem set was appropriate.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

15. Answering the problems was a useful learning experience.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

16. The time and effort used to solve the problems were well spent.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

17. I might find it hard to get my solution implemented.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

18. My answering of the problems was systematic.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

19. I really felt lost in trying to tackle the problem set.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

20. Answering the problem set frustrated me.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

21. I learned a lot using Smart-Stat.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

22. While using Smart-Stat I felt comfortable.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

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

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

24. I'm not confident about my solution to the problem set.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

25. I'll be able to handle future statistical problem situations better because of the approach I used to answer these problems.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

26. The approach used to answer the problems wasn't worth the effort.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

27. I could easily justify my answers to the problems.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

28. I answered the problems in a statistically correct manner.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

29. I may have missed important things in the problem set.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

30. Answering the problem set was interesting.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

31. While using Smart-Stat I had to be at my best.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

32. I enjoyed using Smart-Stat.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

33. I don't like Smart-Stat.

completely agree	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree	completely disagree

34. Using Smart-Stat in doing statistics would enable me to accomplish tasks more quickly.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

35. Learning to operate Smart-Stat would be easy for me.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

36. Using Smart-Stat would improve my performance in doing statistics.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

37. I would find it easy to get Smart-Stat to do what I want it to do.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

38. Using Smart-Stat in doing statistics would increase my productivity.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

39. My interaction with Smart-Stat would be clear and understandable.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

40. Using Smart-Stat would enhance my effectiveness in doing statistics.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

41. I would find Smart-Stat to be flexible to interact with.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

42. Using Smart-Stat would make it easier to do statistics.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

43. It would be easy for me to become skillful at using Smart-Stat.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

44. I would not find Smart-Stat useful in doing statistics.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

45. I would not find Smart-Stat easy to use.

extremely likely	quite likely	slightly likely	neither likely nor unlikely	slightly unlikely	quite unlikely	extremely unlikely

GLOSSARY AND TRADEMARKS

AI: See "artificial intelligence."

algorithm: A procedure for solving a problem in a finite number of steps.

ANOVA: Analysis of variance (ANOVE) tests hypotheses about differences in the mean values of one variable across two or more groups.

application generator: A type of fourth-generation language (4GL) that allows the user to enter data and specify how the data are to be manipulated and output.

artificial intelligence (AI): The study of how computing can be applied to perform tasks that involve intellectual, communication and sensory activities akin to those in human beings.

assembler: a language translator that converts assembly language into machine language.

assembly language: a low-level programming language, pioneered by Grace Hopper in the early 1950's, that allows instructions to be written in a mnemonic codes and then assembled into machine language.

atom: An individual or indivisible element. A proposition in logic that cannot be broken down into other propositions.

BASIC (Beginner's All-purpose Symbolic Instruction Code): A high-level language developed at Dartmouth College as an easy to learn and use language for beginning programmers.

binary system: The base 2 numbering system, uses the digits 0 and 1. Computer data and instructions can be represented using this numbering system.

BMDP (BioMedical Data Procedures): A computer system of software products for data analysis published by and a registered trademark of BMDP Statistical Software, Los Angeles, California.

byte: A measurement of computer storage roughly equivalent to one alphanumeric character.

C: A structured programming language created by Kernighan and Ritchie.

central processing unit (CPU): The computer unit that controls the actual operations of a computer system, consisting of primary storage, an arithmetic-logic unit, and a control unit.

COBOL (COmmon Business Oriented Language): A high-level, third generation computer language used in business data processing. It was specifically designed to manipulate large data files.

cognition: An intellectual process by which knowledge is gained about perceptions or ideas.

CPU: See "central processing unit."

data manager: The susbsytem(s) of a DSS capable of accessing, combining, adding, deleting and portraying logical data structures in user terms.

data support systems: Systems which extend data processing technology through providing information regardless of the use or the user.

data transformation: The process of applying mathematical operations to variables. Transformations involved arithmetic operations like addition and subtraction, exponential, trigonometric, and probabilistic functions; and other functions such as lagging or subsetting data cases.

database: An organized collection of data about some subject.

database management system (DBMS): A computer system for the storage and retrieval of information about some domain. The software which defines the data model, allowing the logical structure of the database to be define and the data to be accessed according to that structure.

decision support systems (DSS): A computer-based system composed of a language system, knowledge system, and problem processing system with the purpose of providing information and modelling aids to help users make decisions.

dependent variable: An unknown quantity or a variable which is predicted or explained based upon the value of other variables.

dialogue manager: The subsystem(s) of a DSS which serves as a user interface, receiving and responding to user commands and presenting data in a variety of formats.

domain: The problem area of interest.

DSS: See "decision support system."

Edu-Stat: A statistics software package developed by Clifford E. Young to take advantage of the power of microcomputers and to provide an instructive environment for students.

endless loop: See "loop, endless."

executive information systems (EIS): See "executive support systems."

executive support systems: Systems focused on a manager's or group of managers' information needs across a range of areas, focusing not on a single recurring type of decision, but incorporating in one system the data and analytic tools to provide information support for many managerial processes and problems. Current examples are often referred to as executive information systems, using powerful personal computers with software designed to retreive data from a mainframe and manipulate and display the data in a variety of ways, including graphically.

expert system: See "knowledge-based system."

fifth generation computer: A computer which uses inference to draw reasoned conclusions from a knowledge base, and interacts with its users via an intelligent user interface.

fifth generation language: An anticipated high-level computer language which uses natural language to communicate with the computer as human beings might communicate. See also "natural language processing."

first generation computer: A computer using vacuum tubes as its basic technology.

first generation language: computer instructions which are close to the binary logic level of the computer hardware, such as machine language.

FORTRAN (FORmula TRANslation): A high-level, third generation language designed for scientists, engineers, and mathematicians to solve complex numerical problems.

fourth generation computer: A computer using microprocessors and large scale integration chips as its basic technology.

fourth generation language (4GL): an easy to use, easy to learn, high productivity applications language.

frame: A knowledge representation of an object in terms of slots where there is one slot for each of the objects characteristics, or attributes. A particular insance of an object consists of a value for each of the frame's slots. The value may be assigned or determined by a procedure attached to the slot. A frame may also be one node in a knowledge representation network, related to other frames through inheritance slots.

front-end: A system which removes some of the processing load from a central computer, typically handling communications coordination functions before the data are sent to the central system for processing.

fuzzy logic: Ways of reasoning that can cope with uncertain or partial information; characteristic of human thinking and many expert systems.

fuzzy set: A generalization of set theory that allows for various degrees of set membership rather than none or all.

general problem solver (GPS): The first problem solver to separate its problem solving methods from knowledge of the specific task being considered. The GPS problem solving approach employed "means-ends analysis."

grammar: The scheme for specifying the sentences allowed in a language.

hardware: The physical components of a computer system.

heuristic: A "rule-of-thumb," or empirical knowledge used to help guide a problem solution. The rules in a rule set may be thought of as being heuristics.

hierarchy: A system of things ranked one above the other.

high-level language: third generation, procedural-oriented computer programming languages which use instructions that closely resemble human language and mathematical notation, such as BASIC, COBOL, FORTRAN, PL/I, Pascal, and APL.

Horn clause: A set of statements joined by logical ANDS which has at most only one conclusion.

IBM: a registered trademark of International Business Machines, Inc.

IFPS (Interactive Financial Planning System): A computer software modeling system published by and a registered trademark of Execucom Systems Corporation of Austin, Texas.: See "Interactive Financial Planning System."

inference: The process of reaching a conclusion based on an initial set of propositions, the truths of which are known or assumed.

inference engine: Software which accepts a problem statement from the user, and uses reasoning knowledge about the problem area to attempt to derive a solution. Needed problem-specific information (e.g. from the user) in the course of reasoning, with explanation for the need for added information. The solution is presented along with an interpretation of the line of reasoning used in reaching the solution.

inheritance: The process by which a slot in an object frame of a frame-based knowledge network representation receives its value from a superclass frame associated with the object frame.

instantiation: Replacing a variable by, or binding or assigning the value of a variable to, an instance (an individual) that satisfies the system (or satisfies the statement in which that variable appears).

intelligence: The degree to which an individual can successfully respond to new situations or problems, based upon the individual's knowledge level and the ability to appropriately manipulate and reformulate that knowledge and incoming data as required by the situation.

interface: The system by which the user interacts with the computer.

iterative: A process requiring the repetition of a series of steps until a desired state is reached.

JIPDEC (Japan Information Processing Development Center): Organizers of the October, 1981, International Fifth Generation Computer Conference.

K: An abbreviation for kilobyte.

KBS: See "knowledge-based system."

kilobyte: A measurement of computer storage equivalent to two to the tenth power, or 1024 bytes.

kludge: A computer system which is made up of components which that are poorly matched or were originally intended for some other use.

knowledge engineering: The AI approach focusing on the use of knowledge to solve problems.

knowledge processing system (KPS): The subsystem of a computerized support system in which all application-specific knowledge is represented for use by the problem processing system. Also see "data manager."

knowledge representation (KR): A data structure used to organized knowledge required for problem solving. Examples of knowledge representations include scripts, semantic networks, and frames.

knowledge-base: Along with the inference engine, one of two main parts of a knowledge-based system. The knowledge base holds the knowledge about a particular topic in the form of facts.

knowledge-based system (KBS): A computer-based system composed of a user interface, an inference engine, and stored expertise (i.e., a rule set, a "knowledge base", or an entire knowledge system). Its purpose is to offer advice or solutions for problems in a particular area. The advice is comparable to that which would be offered by a human expert in that problem area because the system is programmed to follow the "human reasoning" used by an expert to deduce certain findings as reached through judgment based on experience. In order to avoid overstating its capabilities, the term "knowledge-based system" is preferred to the more commercial term "expert system."

KPS: See "knowledge processing system."

KR: See "knowledge representation."

language processing system (LPS): The subsytem of a computerized support system that consists of all acceptable commands (problem statements, or input to the system) and all possible presentations (results, or output from the system). Also see "dialogue manager."

LEXIS: A computer database of legal references, established in 1973 by and a registered trademark of Mead Data Corporation, accessible at a fee for searching legal citations and case law.

loop, endless: See "endless loop"

LOTUS 1-2-3: A microcomputer software package which provides a modeling language in the form of a spreadsheet, offering the opportunity to insert labels or formulae into cells which occur at the intersection of rows and columns.

low-level language: first and second generation computer languages, such as machine or assembly, which requires the programmer to have detailed knowledge of the internal binary level of computer hardware instructions.

LPS: See "language processing system."

management support system (MSS): An information technology based system which supports management at the operational, strategic, and tactical levels.

means-end analysis: A problem solving approach (used by GPS) in which problem-solving operators are chosen in an iterative fashion to reduce the difference between the current problem solving state and the goal state.

model manager: The subsystem(s) of a DSS capable of incorporating, cataloguing and maintaining a wide range of models supporting all levels of management and interrelating these models with linkages to the data.

MS: a trademark of Microsoft Corporation.

MS-DOS: MicroSoft Disk Operating System, also licensed to IBM as PC-DOS, or Personal Computer Disk Operating System.

MSS: See "management support system"

natural language processing (NLP): A kind of user-interface, sometimes called natural language understanding (NLU), which allows the user to carry on a conversation with a computer-based system in much the same way as he or she would converse with another human. In its more ideal configurations (which may be described as natural language understanding), the system is able to learn new terms, understand new requests in the context of prior requests, overlook grammatical errors, and carry out actions implied by the conversation.

NLP: See "natural language processing."

NLU: See "natural language processing."

natural language understanding: See "natural language processing."

Pascal: A high-level, third generation language originally designed to teach structured-programming concepts, suited for both file processing and mathematical applications.

PC: Personal computer, generally referring to the class of IBM-PC computers consisting of an Intel 8088 or 8086 central processing unit, capable of addressing a maximum of 640 kilobytes or random access memory.

power users: Users who are more sophisticated in their computer experience than the average user.

PPS: See "problem processing system."

pragmatics: The study of the use of language in context.

problem processing system (PPS): the subsytem of a computerized support system which accepts problems stated in terms of the language system and draws upon the knowledge system in an effort to produce solutions.

Prolog (PROgramming in LOGic): A logic programming language, oriented toward processing Horn clause axioms by a resolution theorem prover using the principle of unification.

query: A formal request for data from a database.

RAM: See "random-access memory".

random-access memory (RAM): Often referred to as internal or main memory, used for dynamic storage of programs and data.

rule-based system: A knowledge-based system using production rules to represent knowledge.

SAS (Statistical Analysis System): A computer system of software products for data analysis published by and a registered trademark of SAS Institute Inc., Cary, North Carolina.

script: A framelike knowledge representation containing sequences of events.

second generation computer: Computer using discrete transistors as its basic technology.

second generation language: a low-level programming language which uses tokens rather than binary instructions, such as assembly language.

semantic network: A knowledge representation for describing the properties and relations of objects, events, concepts, situations, or actions by a directed graph consisting of nodes and arcs (labeled edges connecting nodes.

semantics: The study of the meaning of words.

slot: An attribute or characteristic of an object represented by a frame in a frame-based knowledge representation. A slot may be filled with a designated value about the particular object or situation represented by the frame, may receive its value from a procedure or rule attached to it or may inherit its value by default or from another frame which is related to the object frame in a hierarchical frame network.

software: The programs which control the operation of a computer system.

SPSS (Statistical Package for the Social Sciences): A computer system of software products for data analysis published by and a registered trademark of SPSS, Inc., Chicago, Illinois.

syntax: The study of the structure of phrases and sentences.

system: A set of interrelated entities that work together for a common purpose in such a synergistic way that it may appear that "the whole is greater than the sum of its parts."

third generation computer: Computer having integrated circuits (but not microprocessors) as its basic technology.

third generation language: procedural-oriented computer programming languages such as BASIC, COBOL, FORTRAN, PL/I, Pascal, and APL, which use commands which operate on constructs at a higher level of logic more meaningful to humans than. Also known as "high-level languages."

Turbo Pascal: A microcomputer implementation of the Pascal language by and a registered trademark of Borland International, Inc.

Turbo Prolog: A microcomputer implementation of the Prolog language by Borland International, Inc.

unification: The procedure for carrying out instantiations, attempting to find substitutions for variables that will make two atoms identical.

very large scale integration (VLSI): Very Large Scale Integration of transistors and other electronic components on microelectronic chips.

Visicalc: An early (1978) microcomputer software package which provides a modeling language in the form of a spreadsheet, offering the opportunity to insert labels or formulae into cells which occur at the intersection of rows and columns.

VLSI: See "very large scale integration."

WESLAW: A database of legal references, established in competition with LEXIS by and a registered trademark of West Publishing Company, accessible at a fee for searching legal citations and case law.

VITA

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Doctor of Philosophy

Thesis: A PROTOTYPE MANAGEMENT SUPPORT SYSTEM: DESIGN, IMPLEMENTATION, AND EMPIRICAL TESTING OF A NATURAL LANGUAGE-LIKE KNOWLEDGE-BASED INTERFACE BETWEEN AN END USER AND A STATISTICAL PROBLEM PROCESSING PACKAGE FOR MICROCOMPUTERS

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