Decision Making in a Decision Support Systems Environment:

An Evaluation of Spatial Ability and Task Structure

by

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(ABSTRACT)

Decision Support Systems (DSS) should increase the effectiveness of a decision and the efficiency of the decision making process. The success of DSSs has varied among individual users. One explanation for this variation is that individual's spatial ability has a moderating effect on performance. Another factor found to impact decision performance is the structure of the task.

The purpose of this study is to determine whether spatial ability factors have a moderating effect on decision making performance in a DSS environment under differing task structure. Three of the major factors of spatial ability (spatial scanning, spatial relations, and field independence) and two levels of task structure (moderately complex and complex) are considered in the study. Spatial scanning and field independence were assessed by the Kit Factor-Reference Cognitive Tests, Map Planning Test and Hidden Figures Test, respectively [Ekstrom et al., 1976]. Spatial relations was assessed by the Mental Rotations Test [Vanderberg & Kuse, 1978]. Model formulation and data analysis are two stages of decision making considered in the study. Decision making performance is assessed by time to complete the task, DSS features used, decision confidence, and decision accuracy. Computer experience is treated as a control variable.

Fifty Master level students in the School of Business attended three experimental sessions which involved completing several spatial ability tests, partic-

ipating in a ninety minute lecture on the software package, and completing four practice problems and two experimental cases. The software package employed in the experiment is IFPS, a DSS generator.

The results of the study indicate that spatial relations has a moderating effect on decision confidence during the data analysis stage of decision making. Furthermore, there is a significant moderating interaction effect between spatial relations and task complexity when performance is assessed by decision confidence. Spatial relations is found to be more significantly related to performance in the complex case than in the moderately complex case.

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This dissertation is dedicated with love to my mother, Barbara M. Ruf, who gave to me an appreciation for education that I will always treasure. Her love and unwavering belief in me has made this dissertation possible.

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Chapter 1

Background and Purpose of the Research

1.0 Introduction

To aid management in decision making, companies have made large investments in decision support systems (DSSs) [Pracht & Courtney, 1988]. The interest in DSSs has resulted from the inability of management information systems (MISs) to aid in solving semi-structured and ill-structured problems [Sprague, 1980]. Unlike other operational information systems that collect, manipulate, and distribute information, DSSs are designed to work with managers as they develop their decision strategy and arrive at a solution.

DSSs consist of databases, data models, and modeling procedures that allow users to analyze a wide range of problems and strategies [Keen & Scott Morton, 1978; Sprague & Carlson, 1982]. The goal of DSSs is to enable managers to access data and decision models to solve less well-structured problems.[1] For example, DSSs have been employed to support budgetary planning, cash flow projections, and strategic analyses [Boer, 1986]. An ideal DSS combines the management's judgment with the system's computational and data retrieval abilities to produce a flexible decision making system that rapidly adapts to new problems [Boer, 1986].

DSSs assist management in the decision making process by providing three basic features: 1) data query, 2) model formulation, and 3) data analysis. These

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1 Decision models refer to models that allow the user to manipulate the variables in a problem or to perform "what-if" types of analysis to arrive at an optimum solution.

features can be directly related to the decision making stages: 1) data collection, 2) problem structuring, and 3) analysis [Bonczek, Holsapple & Whinston, 1981]. A unique feature of a DSS is that users can interact with the system as they move through decision-making stages. Bonczek, Holsapple and Whinston [1979] refer to this interaction as the information processing bond, where the bond is strengthened "by increasing the computer's ability to recognize and carry out requests while simultaneously decreasing the decision maker's effort in specifying those requests [p. 268]." A goal of system designers and researchers is to minimize the bond between the user and the DSS. The focus of the present study is to develop a better understanding of the relationship between users' abilities and performance on DSSs. In addition, task structure is manipulated to investigate the effect that task structure has on decision making in a DSS environment.[2]

1.1 Definition of DSS

The term "Decision Support System" has been used by practitioners and researchers to describe a wide variety of computer applications. Sprague [1980] summarizes four characteristics of a DSS.

1. They tend to be aimed at the less well-structured, under-specified problems that upper level managers typically face.
2. They attempt to combine the use of models or analytic techniques with traditional data access and retrieval functions.

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[2] Generally, in the DSS literature, tasks have been characterized as structured, semi-structured, and ill-structured. Because of the difficulty in operationalizing these terms, task structure will be assessed in terms of task complexity in this paper. Task complexity will be defined as the number of distinct information cues that must be processed and the number of distinct acts that must be executed to perform the task and the relationship between the inputs, acts, and task outputs.

3. They specifically focus on features which make them easy to use by non-computer people in an interactive mode.
4. They emphasize flexibility and adaptability to accommodate changes in the environment and in the decision-making approach of the user.

These characteristics provide an abstract description of a DSS. A more extensive description is provided by Bailey, Hackenbrack, De and Dillard [1987].

Bailey et al. [1987] present a framework in which DSSs are defined as "any interactive computer application that helps a decision maker by providing access to large data banks or by implementing a decision model or both [p. 37]." Four basic characteristics that are normally associated with DSSs are identified.

1. The decision support system is a computer-based system enabling large amounts of data to be processed.
2. The decision support system provides an interactive user interface.
3. The decision support system provides access to large data banks, supporting retrieval, summarization, classification, and manipulation of data.
4. Many DSS applications suggest solutions to problems by using a decision model.

Based on the characteristics presented by Sprague [1980] and Bailey et al.[1987], a DSS will be defined in this study as a computer-delivered decision-aid system containing databases, model bases, and interactive interfaces that allow the decision maker to use and alter the data and model bases in real time to solve ill-structured problems.

1.2 Statement of the Problem and Objectives

Although a consensus may not be found on the exact definition of a DSS, researchers and practitioners agree that the major purpose of a DSS is to increase the effectiveness of a decision and/or the efficiency of the decision process [Bailey et al., 1987]. The extent to which DSS usage achieves this purpose varies among users. One reason for this variance is the influence of DSS users' individual characteristics [Reneau & Grabski, 1987; Sage, 1981; Zmud, 1979].

Prior research investigating the impact of individual differences on DSS usage has produced inconsistent findings [Reneau & Grabski, 1987]. One explanation given for these inconsistencies is that individual differences have been evaluated only in general terms of cognitive style [Huber, 1983]. Cognitive style identifies the dominant approach that decision makers employ to solve problems; however, the approach a decision maker employs may depend upon the task being performed [Sage, 1981]. Another explanation for these inconsistencies is related to the task characteristics [Jarvenpaa, Dickson & DeSanctis, 1985]. Although it is widely accepted that task characteristics are a major factor influencing decision-making, few studies have investigated the interaction effect of task structure and individual characteristics on decision making in a DSS environment [Jarvenpaa et al., 1985].[3] Other explanations for inconsistencies in the

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[3] Task structure and individual characteristics will be discussed in more detail in Sections 2.2 and 2.3, respectively.

findings have dealt with methodological problems and the type of DSS employed.[4]

Understanding how individual characteristics impact decision making when employing a DSS involves understanding how these characteristics influence both decision making and computer usage. Three of the individual characteristics identified in the literature as influencing the decision-making process and computer usage are spatial ability, experience, and age [Blaylock & Rees, 1984; DeSanctis, 1984; Egan, 1987; Pracht & Courtney, 1988].[5]

Spatial ability refers to an individual's ability to mentally manipulate and transform an image into other patterns, to perceive spatial patterns with respect to other objects, and to perceive an object in another perspective. The influence of spatial ability on decision making has been found in problem structuring [Pribyl & Bodner, 1987]. Problem solving requires a decision maker to manipulate the variables in the problem and structure the problem so that the best solution can be obtained. The structuring of a problem can be related to an individual's ability to perceive spatial patterns, while manipulation of the variables can relate to the mental manipulation of images. As a problem becomes more complex, it can be expected that spatial ability will play a more important role in problem solving [Pribyl & Bodner, 1987]. The influence of experience on decision making has been related to decision makers' ability to employ existing mental models in solving problems of similar structure [Sanford, 1985]. Age has been related to both the manner in which a decision is reached [Kirchner, 1958;

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[4] For further review see Aldag & Power, 1986; Courtney et al., 1983; Jarvenpaa et al., 1985; Sharda et al., 1988.

[5] User characteristics will be discussed further in Section 2.3.

Slovic, 1972] and the decision quality [Birren, 1964; Weir, 1964]. How spatial ability influences decision making in a DSS environment has yet to be investigated.

Spatial ability has also been found to be important in predicting user's performance on a computer [Egan, 1987]. Which factor(s) of spatial ability (spatial visualization, spatial scanning, spatial relations, and/or field independence) is(are) the most important in users' performance on computers has yet to be determined.[6] Age has mainly been found to be a predictor of users' performance when learning new applications [Gomez, Egan & Bowers, 1986; Cirella, Poon & Williams, 1980], whereas computer experience has been found to influence performance after the user has mastered a new application [Egan, 1987].

Individual characteristics have been found to influence both decision making and computer usage. The objective of this paper is to identify which spatial ability factors (spatial visualization, spatial scanning, spatial relations, and field independence) influence decision making in a DSS environment under differing task structures. The stages of decision making supported by DSSs of concern in the study are 1) data query, 2) model formulation, and 3) data analysis. However, the data query stage was eliminated from the study upon review of the pilot study (See Chapter 4).

An outline of the model employed in this study is presented in Figure 1. This model will be expanded in Chapter 3. Its components include the task structure, the features of a DSS, and user characteristics. The influence of user

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[6] Factors of spatial ability will be discussed in Section 2.3.1.

characteristics and task structure on stages of decision making in a DSS environment is postulated in the model.

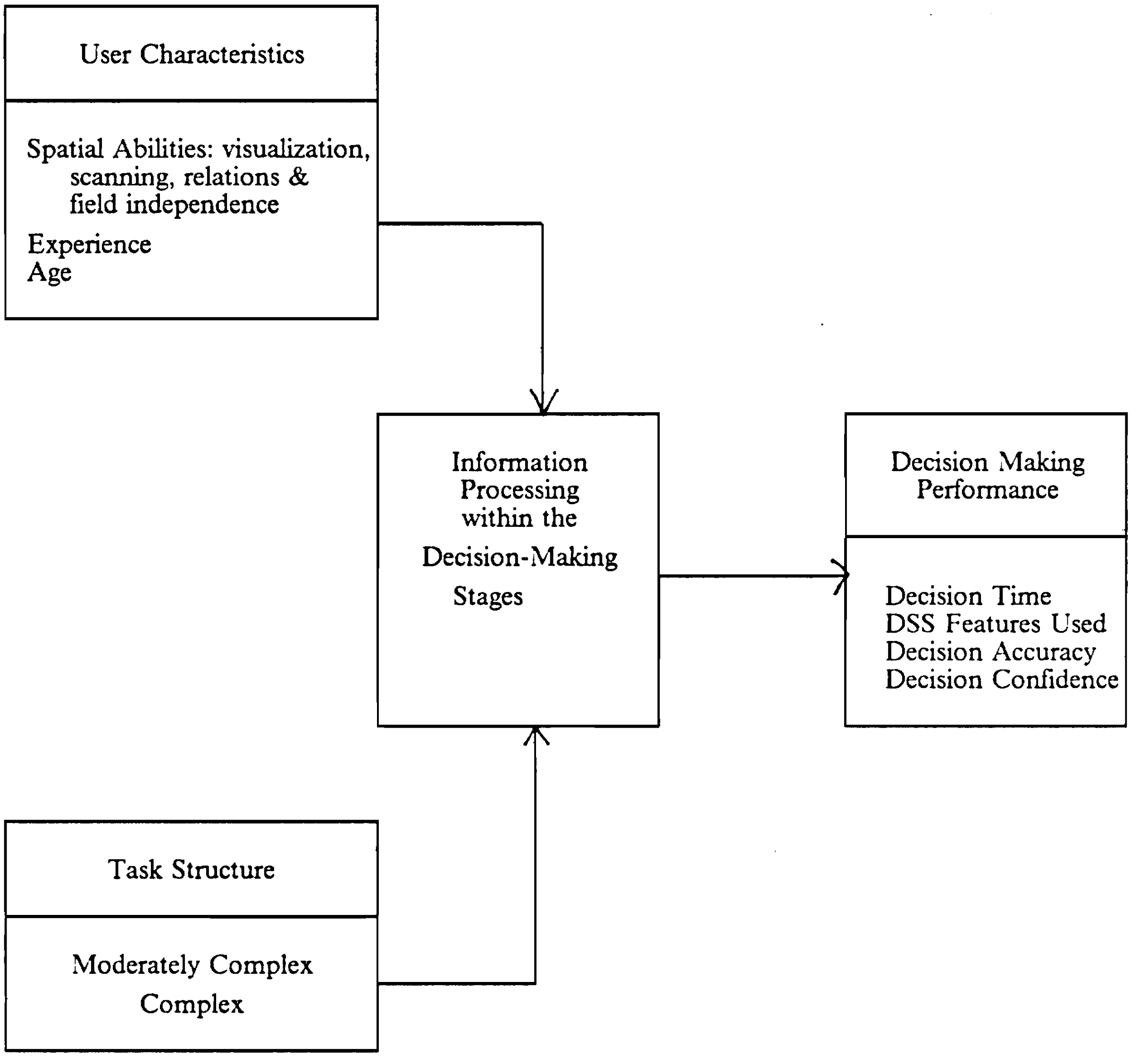

Figure 1. Factors Influencing the Decision-Making Process in a Decision Support System Environment.

1.3 Research Methods and Procedures

A laboratory study was conducted to test the hypothesized relationships expected in the research model. The dependent variables in the study were time to complete the task, DSS features used, decision confidence, and decision accuracy. The independent variable was task structure and the explanatory variables are measures representing the four major factors of spatial ability: spatial visualization, spatial scanning, spatial relations, and field independence. Other factors found to influence decision making in a DSS environment were controlled for such as age, computer experience, and decision-making experience. Interactive Financial Planning System (IFPS), a DSS generator, was employed in the study to develop a DSS. This software package contains model building and what-if analysis capabilities. Each individual received two cases differing in task structure. Half the group received a moderately complex case with a model and a complex case without a model. The other half of the subjects received the reverse: a moderately complex case without a model and a complex case with a model.

Because the pilot study's results revealed that the experiment would require more time than was available, the first stage of decision making, data query, was eliminated from the study since the DSS employed in the study provided the weakest support for this feature. Results of the study will be discussed primarily from the point of view of potential theoretical contributions to DSS literature.

1.4 Organization of the Dissertation

This dissertation is divided into seven chapters. Chapter 2 contains a review of relevant research findings from MIS, Psychology, Education, and Ergonomics. Literature on individual characteristics and decision making in a DSS environment is reviewed. The proposed conceptual model to be tested is then presented in Chapter 3. In Chapter 4, the research method and procedures used in the pilot studies are presented, followed by the results of the pilot studies. Chapter 5 provides a description of the research method and procedures used in the main study. This chapter includes research variables, sample selection, research instruments, and statistical methods. In Chapter 6, the results of the study and statistical analysis are presented. Implications of the findings, possible limitations of the study, and expected contributions are discussed in Chapter 7.

1.5 Chapter Summary

In this chapter a rationale was presented for investigating the influence of spatial ability and the interaction effect of spatial ability and task structure on decision-making performance in a DSS environment. A brief review of the DSS/MIS and Ergonomic literature reveals that spatial ability plays a role in computer usage and decision making. Furthermore, as the task becomes more complex, the influence of spatial ability on decision making increases. The purpose of this dissertation is to identify whether a relationship exist between spatial ability factors and decision making in a DSS environment and to empirically test these relationships. A secondary purpose is to identify the interaction effect that task structure and spatial ability have on decision making.

Chapter 2

Literature Review

2.0 Introduction

This chapter contains a review of prior literature pertinent to the present study. First, a brief description of research frameworks that have been proposed in the MIS and DSS literature will be presented to place the present study in relation to prior work. Next, research on task structure and decision making will be presented, followed by a review of three user characteristics: spatial ability, experience, and age. Finally, a review is presented of prior research on computer usage and spatial ability with respect to data query, model formulation, and data analysis, aspects of the decision-making process.

2.1 Decision Support System Research Model

The objective of this section is to provide a brief description of some of the major research frameworks that have been proposed in the MIS and DSS literature. Several MIS frameworks have been provided in the literature [Gorry & Scott-Morton, 1971; Chervany et al., 1971; Mason & Mitroff, 1973 and Lucas, 1973]. In a review of these frameworks, Ives et al. [1980] present a comprehensive framework which incorporates environmental and information system characteristics as well as process variables (See Figure 2). Their model consists of three information systems environments, three information system processes, and an information subsystem (ISS). These systems exist within an organization that has an external environment which, together with the organizational environment, contains factors that constrain or determine the operations of the information system. Three other environments that influence the information system (IS) are the user environment, IS development environment, and IS operations environment. The environment of focus in this paper is the user environment. The user environment depicts characteristics of the user and the user's task.

A second important factor of the model is the ISS. The ISS consists of three classes of variables: ISS content, presentation form, and time dimension. The dimension of the ISS content that is of concern in this paper is the availability of the decision models. The three processes that interact between the ISS and the environments are the use process, the development process, and the operations process. Of concern in this paper is the use process which involves the primary users' usage of the information system. This process is assessed in terms of the decision quality and productivity which results from use of the information system.

Ives et al. [1980] identified several types of research that can be conducted within their proposed framework: environment, process, ISS, or one or more variables from each category. Although they provide a comprehensive framework for identifying areas of research, a more detailed model is needed to generate hypotheses.

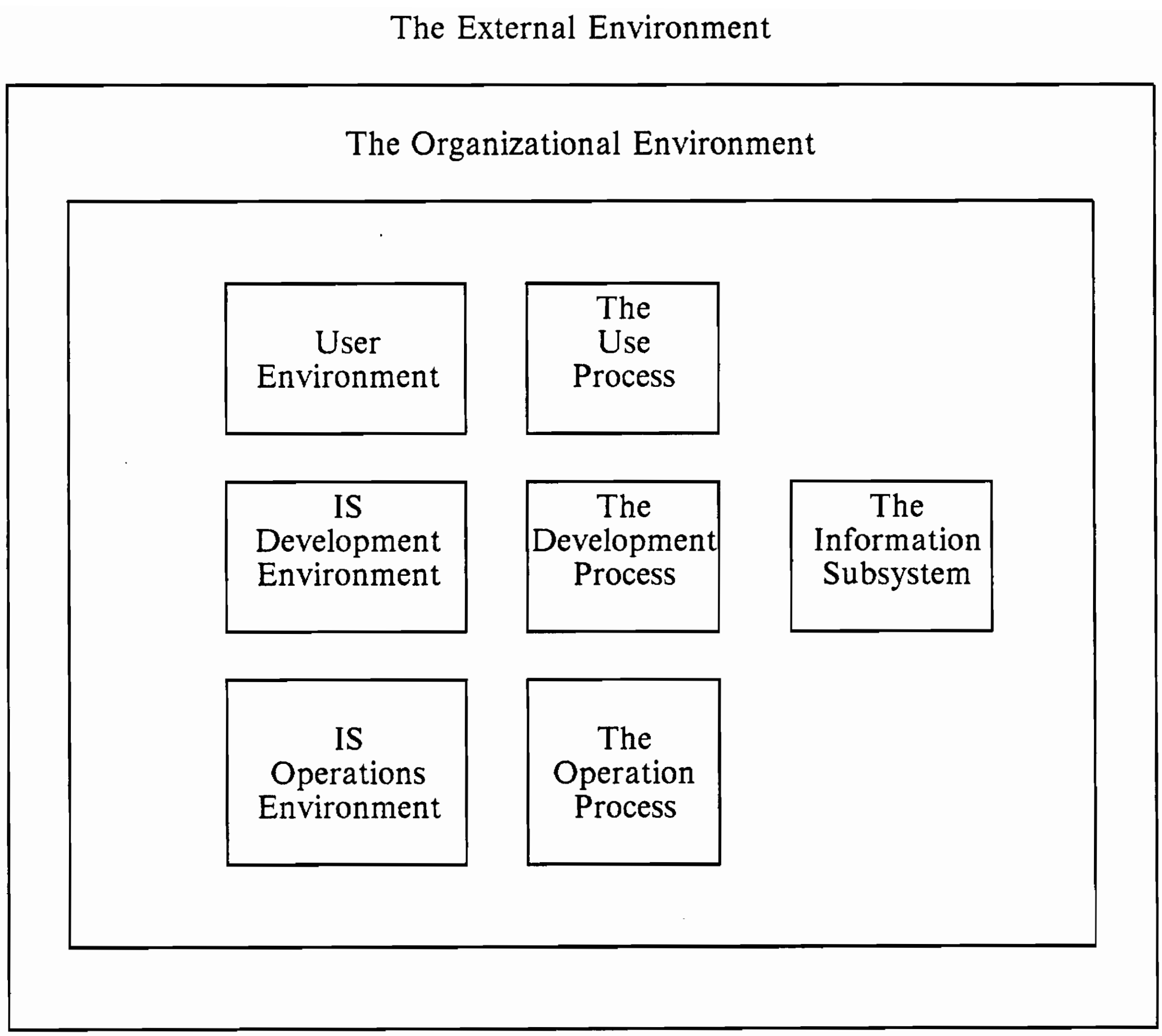

Figure 2: "A Framework for Research in Computer-Based Management Information Systems," from *Management Science*, Vol. 26 (9), by Ives, B., S. Hamilton and G. Davis, 1980, pp. 910-934.

For DSS research, several frameworks have been proposed. Sprague's [1980] framework presents a scheme for the development of a DSS which includes the user, the task, environmental factors, and three computer-based components (See Figure 3). The three basic components of the model are database management software (DBMS), model base management software (MBMS), and dialog generation and management software (DGMS). The DBMS enables access to external, transaction, and internal data. Some of the features related to the DBMS are data update, inquiry, retrieval, insertion, and deletion. Based on Anthony's taxonomy of managerial activities [1965] MBMS is divided into three levels of management: strategic, tactical, and operational. The model building process consists of a modeling language and a set of building blocks, similar to subroutines, which can be rapidly assembled to assist the modeler. The MBMS features involve creating models, model maintenance, and use or manipulation of the models.

The DGMS refers to the user-system interface. This component enables the user to communicate with the system and the system to communicate with the user. It consists of an action language, a presentation language, and the user's knowledge base or what the user needs to know in order to effectively use the DSS. The DGMS is an important component of the DSS, because it determines the usability of the functions provided by the DSS.

Sprague's (1980) framework for developing DSSs provides an implementational model that depicts the relationships between the features of a DSS and the user. This model, however, does not demonstrate how user differences influence the use of a DSS. In contrast to this model, Bonczek et al. [1981] present a more conceptual model that describes how the features of a DSS and the decision maker work together in reaching a decision.

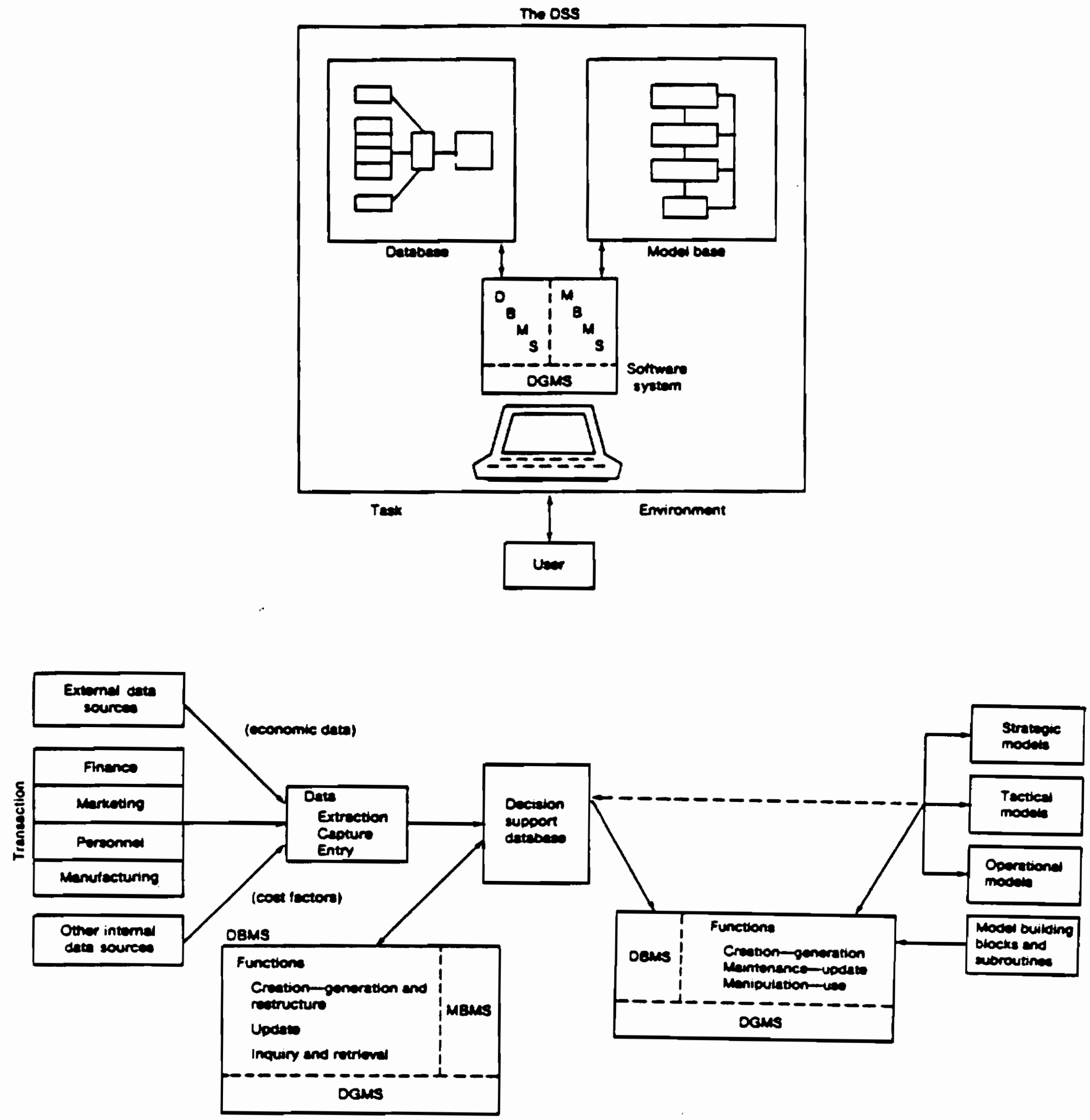

Figure 3: "A Framework for the Development of Decision Support Systems," MIS Quarterly, Vol. 4, No.4, 1980, pp. 1-26.

Bonczek et al.'s model [1981] consists of three subsystems: language subsystem, knowledge base, and problem-processing subsystem (See Figure 4). Language subsystem, similar to Sprague's DGMS, allows the user to communicate with the other two components of the DSS. Knowledge base contains all available knowledge independent of interaction with a user. The problem processor takes input from both the user and knowledge subsystems and produces information that supports decision making by emulating certain human cognitive activities: information collection, problem recognition, model formulation, and analysis. Bonczek et al.'s model presents a good general model; however, it does not include the effect of user differences in these abilities and how they might moderate performance.

Combining the behavioral factors presented in the MIS framework with the technical subsystems presented in the DSS framework, a new model is proposed as a base for this study (See Figure 5). From the MIS framework presented by Ives et al. [1980], the model includes factor groups related to user environment, use process, and the ISS. In the present study, the relationship between variables from all three groups is examined, i.e., the influence of individual differences (user environment) on the decision process (use process) in a DSS environment (ISS characteristics) is investigated. User environment includes user differences found to be related to DSS usage. DSS use process includes three major stages of the problem-solving process identified by Bonczek et al. [1981]: information collection, model formulation, and data analysis. Components of the information system, namely model base, database, and interface are based on Sprague's model.

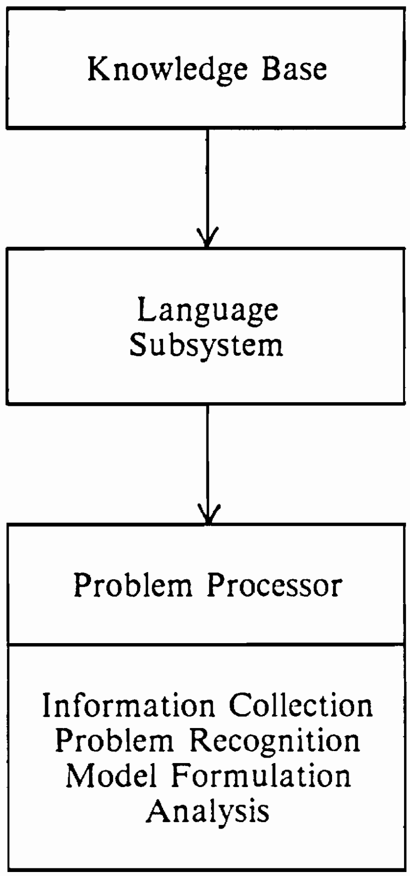

Figure 4. *Foundations of Decision Support Systems*, from New York: Academic Press, by Bonczek, R., C. Holsapple and A.B. Whinston, 1980.

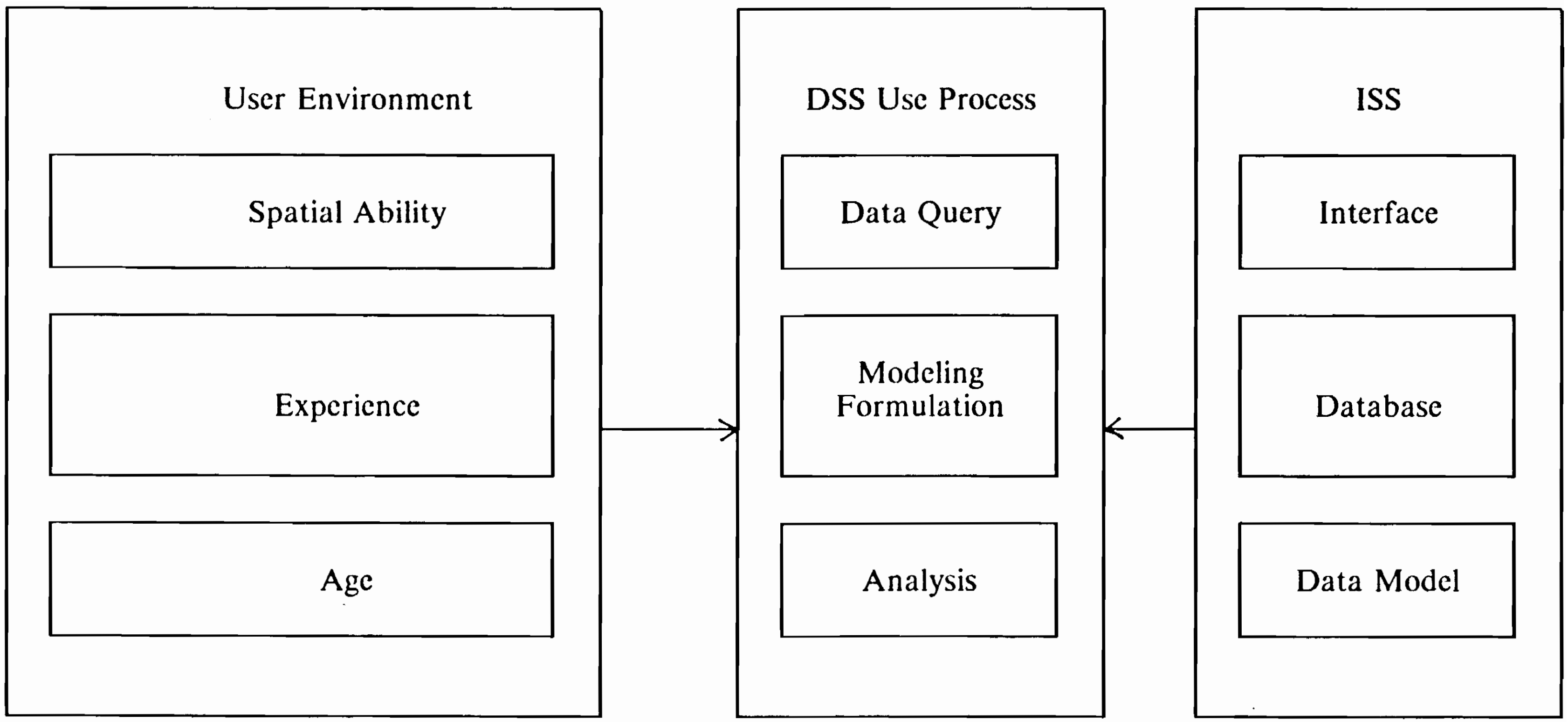

Figure 5. Decision Support System Research Model

2.2 Task Structure

A purpose of DSSs is to provide support for ill-structured decisions [Gorry & Scott-Morton, 1971; Sprague & Carlson, 1982]. In practice, however, DSSs have been found to be used to aid decision makers with moderate to well structured problems [Grochowsky & Walsh, 1984]. In this section, the assessment of task structure, and research findings on the impact of task structure on decision-making performance are presented and discussed.

Gorry and Scott-Morton [1971] provided a framework for evaluating decision making in an information systems context (See Figure 6). They employed Anthony's [1965] taxonomy of managerial activities: strategic planning, management control, and operational control. Based on Simon's [1960] classifications, decisions are categorized as structured, semi-structured, and ill-structured. They propose that an information system should support the decision making process and that the decision-making process differs depending on the activity level and the task structure. Structured decisions refer to decisions that are repetitive and routine in nature. Semi-structured decisions are stochastic in nature and can be estimated based on probabilities. For a decision that is unstructured "there is no cut-and-dry method of handling the problem because it hasn't arisen before or its precise nature and structure are elusive or complex, or because it is so important that it deserves a custom-tailored treatment [Simon, 1960], p. 125." The difference between semi-structured and ill-structured decisions is the amount of judgment, evaluation, and insight into a problem a decision maker must provide. Although Gorry and Scott-Morton's framework provides a general guideline for categorizing managerial decisions, the framework lacks a working definition for classifying tasks.

	Operational Control	Management Control	Strategic Planning
Structured	Accounts Receivable	Budget Analysis - Engineered Costs	Tanker Fleet Mix
	Order Entry	Short-term Forecasting	Warehouse and Factory Location
	Inventory Control		
Semi-Structured	Production Scheduling	Variance Analysis - Overall Budget	Mergers and Acquisitions
	Cash Management	Budget Preparation	New Product Planning
Unstructured	PERT/COST Systems	Sales and Production	R&D Planning

Figure 6. "A Framework for Management Information System," from Sloan Management Review, by Gorry and Scott-Morton, Vol. 13 (1), 1971, pp. 55-70.

Other classifications of tasks are complexity, task content, task difficulty, and task attributes. The most common way to classify tasks is by complexity. Complexity level has been assessed by the number of attributes presented, the number of alternatives available, non-linear relationships between information dimensions, etc. [Wood, 1986].

In an attempt to combine the numerous definitions used to assess complexity, Wood [1986] presented a theoretical model of task complexity. He identified three dimensions of complexity that determine the total complexity of a task: component complexity, coordinate complexity, and dynamic complexity. Component complexity refers to "the number of distinct acts that need to be executed in the performance of the task and the number of distinct information cues that must be processed in the performance of those acts [p. 66]." As the number of information cues decreases and/or the number of acts decreases, the skill requirements for a task will decrease. Redundant information cues will also reduce component complexity. Coordinate complexity refers to the form and strength of the relationship between task inputs, acts, and task products. The more complex these relationships are, the greater an individual's ability must be to accomplish the task. The third dimension of complexity, dynamic complexity, refers to tasks where the inputs and outputs are non-stationary over time. Examples of dynamic complex tasks are probability learning and multi-stage decision making.

Wood's model of complexity can be used to categorize a wide range of tasks. Because dynamic complexity is irrelevant to the types of tasks employed in the present study, component complexity and coordinate complexity will be used to identify complexity levels.

Much of the research on task complexity has been in the area of choice strategy. The research findings indicate that based on the task complexity level, individuals will select a strategy to reduce cognitive strain [Olshavsky, 1979] and individuals who select a reduced processing strategy for complex decision tasks perform better [Paquette & Kida, 1988]. Although choice strategy research is not the focus of the present study, the findings provide support for the notion that task complexity is an important research variable when examining decision-making performance.

In the DSS literature, few studies have considered the effect of task complexity on DSS performance. Research findings on the impact of graphics on decision making indicate that the type of task may be more important in determining performance than the presentation mode [Jarvenpaa et al., 1989]. In a 1985 study, Mykytyn (1985) examined the impact of cognitive style (as measured by the Myers-Briggs Type Indicator) and task structure (as assessed by Gorry & Scott-Morton's 1971 framework) on DSS performance. He found that task structure affected the frequency of DSS feature usage and that the interaction effect of cognitive style and task structure affected decision confidence.

Whether a problem is complex may depend upon an individual's knowledge of the relevant information and familiarity with the solution path. Sanford [1985] argues that the initial mental model of a problem will influence the problem solving outcome and that the degree or richness of mapping may determine the feeling of familiarity with the problem. The degree to which an individual has prior knowledge of a problem and his/her mapping ability may influence whether a problem is considered complex or not.

2.3 User Characteristics

Three characteristics identified in the literature as impacting upon the decision-making process and computer usage are spatial ability, experience, and age. In this section, research findings on these three characteristics are presented.

2.3.1 Spatial Ability

Identifying that there is a distinct difference between verbal ability and spatial ability is important in supporting the motivation of the present study. In this section, literature on the processing of spatial information is used to provide a theoretical explanation of how spatial ability might impact decision making. This is followed by a review of the major factors of spatial ability identified in the literature.

2.3.1.1 Spatial Information Processing

In numerous studies, spatial ability has been identified as being distinct from verbal ability [Cattell, 1971; Vernon, 1965]. Lohman [1979] suggests that intelligence may be split into verbal and spatial factors. Furthermore, research findings have demonstrated that spatial processing appears to be fundamentally different from verbal-symbolic-sequential processing [Cooper & Shephard, 1973].

McGee's [1979] review of spatial ability research states that there are at least two spatial factors: spatial visualization and spatial orientation. Spatial visualization refers to "the ability to mentally rotate, twist, or invert a pictorially presented stimulus object" (p. 893). Spatial orientation refers to the ability to picture an object in another perspective, while remaining unconfused about the changing orientation. A more indepth review of spatial ability studies, Lohman [1979] delineates three distinct components of spatial ability: spatial visualization, spatial orientation, and spatial relations. Lohman is in agreement with McGee's description of spatial orientation; however, he makes a distinction between spatial visualization and spatial relations. Spatial relations refers to the ability to mentally rotate a stimulus object rapidly, whereas spatial visualization refers to twisting or inverting a stimulus object.

Two other spatial factors identified in the literature are spatial scanning [Guilford et al., 1952] and field independence [Witkin et al., 1971]. Spatial scanning refers to the ability to scan a field quickly, identify paths, and reject false leads [Ekstrom et al., 1976]. Field independence refers to the ability to hold in one's mind a particular configuration, and find it embedded in distracting material. Although field independence has been a commonly used measure of cognitive style in DSS/MIS research, numerous psychologists have argued that it is a cognitive ability as opposed to a style [Cronbach & Snow, 1977; Macleod & Jackson, 1986; Mckenna, 1984].

A large body of research has related the efficiency of processing different kinds of information to the two hemispheres of the brain [Farah, 1988]. Although both hemispheres of the brain share the potential of many functions in a normal person, the two hemispheres do tend to specialize to some extent. The left hemisphere (in right handed individuals) has been associated with the processing of verbal information and involves analytical and logical thinking that involves processing of information sequentially. The right hemisphere has been associated with the processing of spatial information. This hemisphere processes information more diffusely and can process more inputs in parallel than does the left hemisphere [Robertson, 1985]. It has been hypothesized that the left hemispere generates the visual images and the right hemisphere maintains and manipulates it [Farah, 1988].

Several researchers investigating verbal versus spatial representation in searching for the optimal form of presenting material have come to a similar conclusion, namely that preference for material and style of thinking may be dependent upon individuals' differences in verbal and spatial abilities [Shneiderman, 1980; Yallow, 1980; and Wickens, 1984]. Research on how information is stored and processed provides additional support for individual differences in spatial ability as well as explaining how spatial information may be processed. Three theoretical propositions concerning how information is stored or coded have been put forth: the radical-imagery hypothesis, the conceptual propositional hypothesis, and the dual-coding hypothesis.[7] The radical-imagery hypothesis [Podgorny & Shepard, 1978] suggests that information is converted into visual images and stored. In contrast, the conceptual-propositional hypothesis [Anderson & Bower, 1973; Pylyshyn, 1973] holds that visual and verbal information are represented in the some form of abstract propositions about objects and their relationships. The dual-coding hypothesis [Paivio, 1986] purports that there are two separate, but interacting coding and storage systems, verbal and imaginal, and that information may be coded and stored in either or both. In support of the dual-code hypothesis, Paivio discusses two forms of processing: synchronous and sequential processing. Visual images have been inferred to be organized in a hierarchical manner, whereas verbal systems have been described in terms of symbolic representation that are organized in a sequential or serial

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[7] For further review of the propositional-imagery debate see Kieras, 1978; Kosslyn & Pomerantz, 1977; Paivio, 1977.

fashion. Anderson [1978] argues that there is insufficient behavioral data to establish whether information is stored in pictures or propositions. Which hypothesis is correct is not the issue here. There is support for both forms of internal representation, pictorial and propositional, and individuals may vary in the degree to which they employ propositional and visual representation.

A model developed by Baddeley and Hitch, 1974 (see also Baddeley, 1990), provides an explanation of how verbal and spatial information is processed in short-term memory. In their model, short term memory has three components: the central executive system and two slave systems. The central executive system is comprised of a general work space and an attentional mechanism that allocates resources between the two slave systems. The two slave systems are called the articulatory loop and the visual-spatial scratch pad. The articulatory loop processes verbal information while the visual-spatial scratch pad is where images are retained and manipulated. When solving a problem, relationships of the elements in the problem will be etched on the visual scratch pad and manipulation of these relationships can occur to arrive at an optimal solution. Note that this is an interactive process; when verbal information is needed for the problem, the executive system shifts some of the resources to the articulatory system.

2.3.1.2 Spatial Ability and Decision Making

Imagery research provides further understanding of the relationship between spatial ability and problem solving. The ability to obtain and the facility to use visual spatial imagery has been hypothesized as being required for solving problems [Koussy, 1935; Smith, 1964]. Imagery ability has typically been measured in terms of two qualities: vividness and control. Imagery control refers to one's ability to manipulate or rearrange an image. Vividness refers to one's ability to retain a detailed image of an object. Research investigating individual differences in processing spatial information suggests that imagery control is important in performing spatial tasks [Kosslyn, 1981; Paivio, 1978; Pelligrino & Kail, 1986; Poltrock & Brown, 1984]. In a review of imagery and spatial ability studies, Poltrock and Agnoli [1986] conclude that particular components of imagery ability, such as quality of images, efficiency of image rotation, and the efficiency of image search or image integration, contribute to spatial test performance. They suggest that spatial visualization ability requires two dimensions of image quality, accuracy and capacity, and that spatial relations ability requires the efficiency of an image rotation process. Vividness of imagery appears not to be as important in spatial ability.

Combining cognitive theory and mental imagery theory with problem solving, Greeno [1973] identifies two phases of the problem-solving process. The first phase, problem structuring, involves gaining an understanding of the problem and developing "a structural network that represents the main relationships among the elements of the problem [p. 106]." Based on a review of empirical work in problem solving, he suggests that human problem solvers sometimes draw pictures and use imaginal processes to depict the relationships of the elements of a problem. The second phase, problem solving, involves "transforming the initial situation or given variables into the desired situation or unknown variables [p. 107]."

Imagery has been shown to be important for problem formulation and important for novel problem-solving tasks [Paivio, 1986; Richardson, 1983; Sanford, 1985]. This suggests that an individual's ability to use and control images may influence the decision outcome. Because imagery control and performance on spatial tasks are related, individual differences in decision making, specifically problem structuring, may be explained by an individual's spatial ability.

2.3.2 Experience

Experience has been found to influence decision making and computer usage. Research findings on the impact of experience is reported in this section.

The impact of experience on decision making can be theoretically explained by Greeno's [1973] problem solving model. According to Greeno, problem solving requires information, techniques, and ideas that decision makers know and remember from previous experience. Information is transferred from semantic memory (long-term) to working memory (short-term), where it is processed with new information perceived. Greeno's model postulates that a decision maker with prior experience in decision making need only retrieve information and problem-solving techniques employed before, and combine it with new facts, to reach a solution. Less experienced users need to develop techniques for solving the problem. In support of this model, Taylor [1975] found that the years of experience managers had were positively associated with decision accuracy and negatively associated with time required to reach a decision. Furthermore, experience in the type of decision was related to the evaluation of information but not to the appropriateness of the strategy selected.

Several studies have found that prior computer experience will not influence the use of a system or performance until the user has acquired some experience with the new system [Egan & Gomez, 1985; Egan, 1987; and Fenichel, 1981] and that prior experience may initially hamper performance [Gomez et al., 1983]. Research investigating users' performance on database query systems indicates that there is a greater variance in information search behavior [Greene et al., 1986] and that the time taken to query a system may improve with system experience. Furthermore, experience on a DSS may reduce the number of queries made during decision making [Kasper, 1983]. DSS research findings related to individual performance on model formulation tasks suggest that prior experience may influence the decision outcome [Benbasat et al., 1981]. Transfer of users' knowledge from one system to another, i.e., when knowledge of one system can be applied to understanding another system, has not been directly examined.

2.3.3 Age

DSS research findings on age and decision making suggest that older individuals may require more time to reach a decision, may have some difficulty integrating information for accurate decision choices, and may be less confident in their decision [Taylor, 1975]. Studies investigating the influence of age on computer usage suggest that age can be a powerful predictor of the difficulty users have in learning to use a complex computer system [Egan, 1987]. Greene et al.'s study [1986] on database query performance found that age made a substantial contribution to predicting errors in information search. The study utilized four forms of interface conditions and found that the correlation between age and errors was .57 and older subjects performed worse than younger subjects. These findings were consistent with Egan and Gomez's [1985] study on text editing utilizing SEQUEL which found the correlation between age and errors was .70.

One reason that age appears appears to be positively correlated with learning a computer system (i.e., the older an individual is the longer it takes them to learn) may be that the task requires spatial skills. Horn and Cattell [1966] found that individuals reach a peak in spatial ability in their late 20's and early 30's and then decline, the cause of which is unknown. These findings may explain why older individuals may have greater difficulty learning a spatially oriented task. In support of this statement, Roberts and Moran [1983] found that novice users learned to perform text editing tasks quicker when they used screen editors as compared to line editors. They suggest that because screen editors provide users with a full screen of text, users do not need to maintain an internal representation of the target text and the demand for spatial ability is reduced. Additionally, full-screen editors don't require users to remember all the text before and after the line to be changed - that frees up a lot of mental energy for learning the editor. This feature may also reduce the reliance on spatial ability.

2.4 Computer Usage and Spatial Ability

This section contains a review of research on spatial ability in relation to decision making and the three features of DSS that are addressed in this study: data query, model formulation, and data analysis. Research findings on each of these stages are presented separately.

2.4.1 Data Query

Research on query performance indicates that spatial visualization and computer experience may explain individual differences in query performance. Spatial visualization involves the manipulation of spatial patterns into other arrangements. Retrieving information from a database involves visualizing where the information is located in the database and visually imagining the path through which the information must be retrieved.

Variance in data query performance has been observed in several studies. Dumais and Wright [1986] examined how novice users retrieve stories they had filed using some combination of names and screen locations. They found that the slowest performer took ten times longer retrieving the information than the fastest performer. Greene et al.'s [1986] study employing SEQUEL found that the slowest performer took only three times longer. One reason for the difference between these studies is whether they performed the search until they found the target. Subjects in Greene et al.'s study were allowed only one search, whereas in Dumais and Wright's study subjects were allowed to search the database until the target was found.

In an attempt to understand the large variance in information search behavior, Vincente et al. [1987] investigated the impact of spatial ability and verbal ability as moderators of information retrieval of a hierarchical database. They found that spatial visualization (as measured by Kit Factor-Reference Cognitive Tests: Paper Folding Part 1 & 2) was the best predictor of performance. Subjects with low spatial visualization ability took twice as long to perform the task as subjects with high ability. Their data suggests that low visuospatial users were getting lost in the file system. Vincente and Williges [1988] performed a similar study changing the interface to include a partial map of the hierarchy and an analog indicator of current file position. Their results were consistent with their prior study except the new interface reduced the within-group variablity in performance.

Kasper [1983] examined database usage patterns with DSS. Ninety-six graduate students participated in the study. Subjects were asked to pretend that they were general managers of a firm and required to make eight sets of operational control and management control decisions over a eight week period. Several studies have found that as users' experience on DSS increased, the number of data items and occurrences per item retrieved decreased; however, these trends were not consistent. Furthermore, subjects who developed their own batch mode applications (Specific DSS) did no better in forecasting the results of their decisions than those who did not develop Specific DSS. Performance, assessed in terms of time and decision setting understanding, did significantly improve by the use of Specific DSS.

2.4.2 Model Formulation

Research on model formulation indicates that spatial scanning, field independence, and prior experience may help explain individual differences in model formulation performance. Spatial scanning refers to the ability to scan a visual field, identify a path, and be able to quickly reject false leads. In model formulation, an individual must identify the relationship between the variables of interest in the problem and determine a path or approach to solve the problem. Field independence refers to the ability to maintain a configuration in one's mind and find it embedded in distracting material. Similarly in model formulation, an individual must identify the important variables in a problem and work through the details of a problem without becoming confused by other irrelevant facts.

Kasper [1985] evaluated the impact of forecasting decision models on decision making when the models were developed by the user. The experiment was held over an eight week period involving eight forecasting decisions. Forty graduate business students participated in the study. The modeling group was allowed to store their model and modify it as they went along, while the non-modeling group were not able to store their model. The modeling group was found to perform significantly better than the non-modeling group. Although the time spent on decision making by each group was not recorded for each week, the number of queries performed was recorded, and the difference in the number of queries between the modeling group and non-modeling group was found to be insignificant. This implies that the time spent on model formulation was not significantly different between the two groups. The implications of these findings may be that data manipulation does not have an impact on time spent on the task.

Dos Santos and Bariff [1988] conducted a similar study on the effect of user versus system-guided model manipulation in a laboratory setting. Forty-six undergraduate business students were given twelve hypothetical scenarios that managers generally face.[8] The subjects were required to identify and prioritize the problems for each case. Cognitive style assessed by the Group Embedded Field Test [Witkin, 1971] was controlled. They found that the system-guided model group performed significantly better on both problem finding and problem prioritizing. A reason for better decision performance in the system-guided group may be that students did not have prior experience in developing models for solving these problems; therefore, they relied on the computer to direct them. More experienced decision makers, such as the graduate students used by Kasper(1985), may prefer developing their own model, hence perform better.

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[8] The authors did not indicate exactly what type of decision was examined.

Programming has been stated as being similar to other problem solving tasks that require hypothesis testing [Irons, 1982]. In programming, similar to model formulation, an individual must manipulate the data and decision models until an optimal solution is arrived at. Identifying the problem area has been found to require spatial scanning ability.

Irons [1982] investigated the impact of novice programmers' cognitive ability on programming sub-tasks. Irons hypothesized that since novice programmers lack the conceptual knowledge of programming tasks in large segments, programming is similar to other problem solving tasks that require hypotheses testing. Forty-three students from an introductory FORTRAN course were tested on their ability to compose, comprehend, and debug a program. Spatial scanning (measured by Kit of Reference Tests of Cognitive Factors - Map planning) predicted debugging proficiency. Similar findings were produced by Testa's [1973] in which subjects' performance on the Group Embedded Figures Test was significantly correlated to class grades in an introductory COBOL course.

Pracht and Courtney (1988) studied the relationship between decision makers' characteristics and the use of a problem-structuring aid by examining the impact of graphics-based DSS on decision problem understanding. Eighty-four subjects were divided into two groups, one with access to a DSS and the other without such access. They found that individuals with high analytic ability (field independent) were able to use the DSS effectively to formulate the correct problem structure, whereas those with low analytic ability (field dependent) were ineffective.[9] Furthermore, field independents performed better when the DSS was

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[9] The managerial and information system literature uses the term high/low analysts, as opposed to the psychology literature which utilizes the term field independent/dependent. The terms are interchangeable.

employed than when not employed. Field dependents performed about the same with or without the use of a DSS.

2.4.3 Data Analysis

Based on the research findings on field independence and decision-making performance, it can be concluded that field independents' decision performance is better than that of field dependents. Field independents are better able to summarize disaggregated data to arrive at a solution than field dependents. Field dependents may improve their decision performance by employing a decision aid to summarize the data for them; however, when this information is summarized into a spatial format such as graphics, they have difficulty arriving at a solution. This does not hold true for field independents; graphics enhance their ability to understand the problem.

Benbasat and Dexter [1979] investigated the influence of cognitive style and different types of accounting information systems on decision-making performance. Subjects were categorized as field independent (high analysts) or field dependents (low analysts). Subjects consisted of 24 accounting majors, 20 faculty members, and 4 professional accountants. Each subject operated a computer-simulated plant by making decisions about purchases and production levels of each of 15 periods. Half of the subjects had access to a database of disaggregated data while the other half had aggregated information. Decision performance was measured in terms of profit. They found that subjects classified as field independents had higher profit performance and took less time to make decisions than subjects classified as field dependents. Additionally, there was no significant difference in the number of reports requested by each group.

In another study by Benbasat and Dexter [1982], they investigated whether decision aids could improve decision performance of subjects classified as field dependents in a task environment unsuitable for their cognitive style. The task environment consisted of a relatively structured inventory control/production scheduling system. The simulation model in the study had been used in several prior studies [Schroeder & Benbasat, 1975; Benbasat & Schroeder, 1977]. Sixty-one students enrolled in an advanced logistics course were employed in the study. The experimental game was divided into 10 decision periods in which three decisions had to be made: set order point, set order quantity, and set the daily production figure.

They found that field dependents with access to a decision aid out-performed field dependents with no decision aid. Furthermore, there was no decision time difference between field dependents with or without decision aids. Subjects classified as field independent were found to perform no differently and to take more time when they utilized a decision aid than field independents without a decision aid. These findings differ from Benbasat and Dexter's 1979 study in that difference in the time required to make the decision was the same for field independents and field dependents in the 1979 work.

In a 1981 study, Benbasat et al. investigated whether computer interface and user characteristics affect decision performance effectiveness and behavior. User characteristics were experience and cognitive style (assessed in terms of field independence). Interface characteristics were dialog type (user guided versus system guided) and language characteristics (length of commands and default types). Performance was evaluated in terms of the task completion, average profit, and decision making time. Fifty participants played a computer game in groups of three over the course of one week. The task involved selecting a price-quantity combination that maximized profit. The results revealed that high analytics (field independents) completed the task more often than low analytics (field dependents). Furthermore, high analytic subjects requested more graphs than low analytic subjects.

2.5 Chapter Summary

In this chapter DSS/MIS research models were described, and research on factors influencing decision-making performance was presented. Task structure and user characteristics were two factors discussed that influenced decision-making performance. A review of literature on computer usage and spatial abilities pertinent to the three stages of decision making was also undertaken.

To understand where the present study fits in with prior research, several DSS/MIS research models were described. Based on Ives et al.'s [1980], Bonczek et al.'s [1981], and Sprague's [1980] models, a proposed research framework was presented. The model depicts the three major decision-making stages or uses of a DSS and two influential factors on performance: user environment (user characteristics) and the information sub-system.

Four major factors discussed that influence decision-making performance were task structure, spatial ability, experience, and age. Based on Wood's [1986] model of task complexity, task structure was defined as the number of distinct information cues that must be processed and the number of distinct acts that must be executed to perform the task, and the relationship between the task inputs, acts, and task outputs. Literature on task structure suggests that task structure is important in determining decision-making performance and that experience with the task may reduce perceived complexity.

The review of the spatial ability literature provides support for the distinct differences between verbal and spatial ability. Baddeley and Hitch's [1974; Baddeley, 1990] model on short-term memory provides a visual representation of the processing of spatial information and verbal information during decision making. Additionally, imagery research was discussed to explain how spatial ability plays a role in decision making.

Next, research on the impact of experience and age revealed that these factors influence both decision making and computer usage. Experience was shown to influence decision making and computer experience in terms of accuracy and time to arrive at a solution. Because age is correlated with both experience and spatial ability, there is a potential problem with employing age as a research variable.

In the last section, research on the moderating effect of spatial ability on the decision-making stages was presented. The research findings suggest that spatial visualization and computer experience contribute greatly to subsequent performance differences. With respect to model formulation, spatial scanning, field independence, and experience may impact decision-making performance. Based on review of data analysis tasks, field independence was found to influence decision-making performance.

Chapter 3

Research Questions and Model

3.0 Introduction

The primary purpose of the present study is to investigate whether spatial ability moderates decision-making performance in a DSS environment. A secondary purpose is to examine whether the role that spatial ability plays in decision making is more important when the task structure is complex as opposed to moderately complex. In this chapter, the DSS research framework presented in Chapter 2 will be reviewed, followed by the proposed research model. The research model is presented to provide a theoretical base for this experiment. A summary of the research findings supporting this model will be presented, followed by the research questions.

3.1 DSS Research Framework

In this section, the DSS research framework is discussed (See Figure 7). This framework is provided to place the present study in relation to prior work. The model is composed of three factor groups: user environment, DSS use process, and information subsystem (ISS) as presented by Ives et al.[1980].

The user environment includes user characteristics found to be related to DSS usage. Because the results of prior studies employing cognitive style as an user characteristic have been so inconsistent, some researchers have suggested abandoning cognitive style as a research variable and have suggested that cognitive ability (spatial ability) is the research variable that should be investigated

[Reneau & Grabski, 1987; DeSanctis, 1984; and Pracht & Courtney, 1988]. Research interest in spatial ability has historically been related to mechanical aptitude [Smith, 1964; and Stenguist, 1922] and practical ability [Alexander, 1935; and McFarlane, 1925]. Recent research has suggested that computer skills and problem-solving skills are dependent upon spatial abilities [Egan, 1987; Pracht & Courtney, 1988; and Vincente et al., 1987]. Other characteristics that have been found to influence decision making consistently are experience and age. These characteristics will be discussed in more detail in Section 3.2.

The DSS use process contains three basic features of a DSS: 1) data query, 2) model formulation, and 3) data analysis. These factors can be directly related to the decision-making stages: 1) data collection, 2) problem structuring, and 3) data analysis [Bonczek et al., 1981]. Because performance in each stage may be influenced by different abilities, the present study assesses decision-making performance separately for each stage.

The three components of the ISS are interface, database, and data models. In the present study, the DSS employed contains an interactive interface that is user friendly, a database, and a data model. Because there is little research on spatial ability in the DSS literature, the present study is concerned with showing that spatial ability is an important user characteristic. The impact that spatial ability has on decision-making performance when different types of interfaces, databases, and data models are employed will be left for future research.

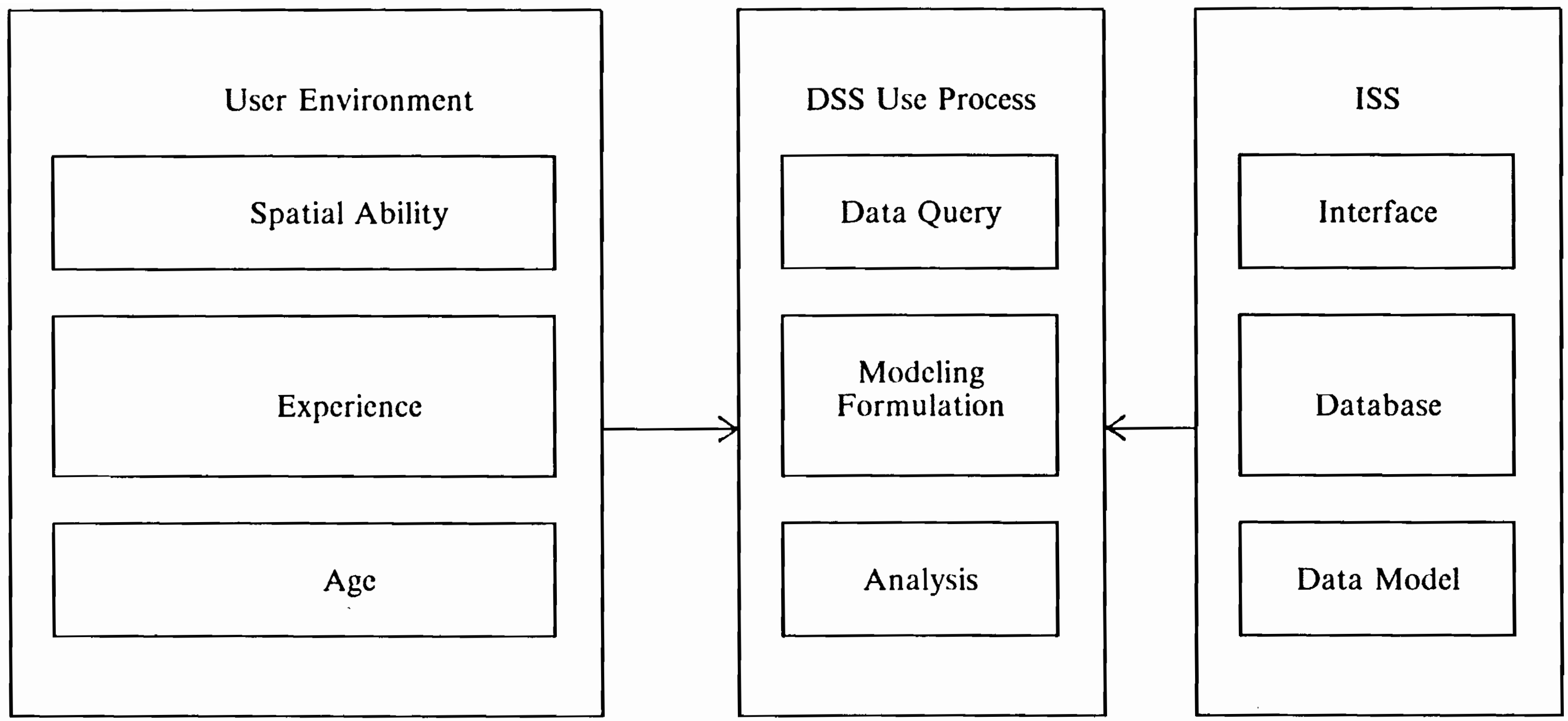

Figure 7. Decision Support System Research Model

3.2 Proposed Research Model

The proposed research model components include user characteristics, task structure, and features of a DSS (See Figure 8). The model indicates that user characteristics and task structure have a moderating effect on decision making performance in a DSS environment. The influence of experience and age on decision making will be controlled. The following sections provide a summary of the research findings that support these relationships.

3.2.1 User Characteristics

Prior research on the impact of individual characteristics on decision-making performance in a DSS environment has been criticized for lacking a developed theory to explain variances in performance. Supported by Baddeley and Hitch's 1974 model on short-term memory, spatial ability was selected as the research variable of interest. Baddeley and Hitch's model explains how information is processed in short term memory, hence, where problem solving occurs. In their model, the two slave systems to the central executive system are the visual-spatial scratch pad, where images are retained and manipulated, and the articulatory loop where verbal information processing takes place.

Based on the knowledge that an individual's ability to process verbal information is distinct from the ability to process spatial information, the first research question to be addressed in this study is as follows:

> Does an individual's spatial ability influence decision making in a DSS environment when controlling for age and experience ?

Four factors of spatial ability, identified in Chapter 2, were found to be distinct from each other: spatial visualization, spatial scanning, spatial relations, and field independence. Prior studies on computer usage and spatial ability, however, have not examined all four factors. The present study will investigate only the relationships that have been supported by prior literature. A summary of the relationships between factors of spatial ability and decision-making performance in a DSS environment is presented in Figure 8.

The first stage of decision making shown in the model is data query. Several studies that investigated the impact of individual differences on query performance have found that spatial visualization is a significant predictor of users' performance [Vincente et al., 1987; Greene et al., 1986]. Spatial visualization involves the manipulation of spatial patterns into other arrangements. Similarly, retrieving information from a database involves visualizing where the information is located in the database and visually imaging the path over which the information must be retrieved. Because the pilot study results revealed that the experiment required more time than was available, this stage of decision making was eliminated from the study. (See section 4.12.)

In the second stage of decision making, model formulation, spatial scanning and field independence have been found to be associated with structuring a problem [Irons, 1982; Pracht & Courtney, 1988; and Testa, 1973]. Spatial scanning refers to the ability to scan a visual field, identify a path, and quickly reject false leads. In model formulation, an individual must identify the relationship between the variables of interest in the problem and determine a path or approach to solve the problem. Field independence refers to the ability to maintain a configuration in one's mind and find it embedded in distracting material. Similarly in model formulation, an individual must identify the important variables in a problem and work through the details of a problem without becoming confused by other irrelevant facts.

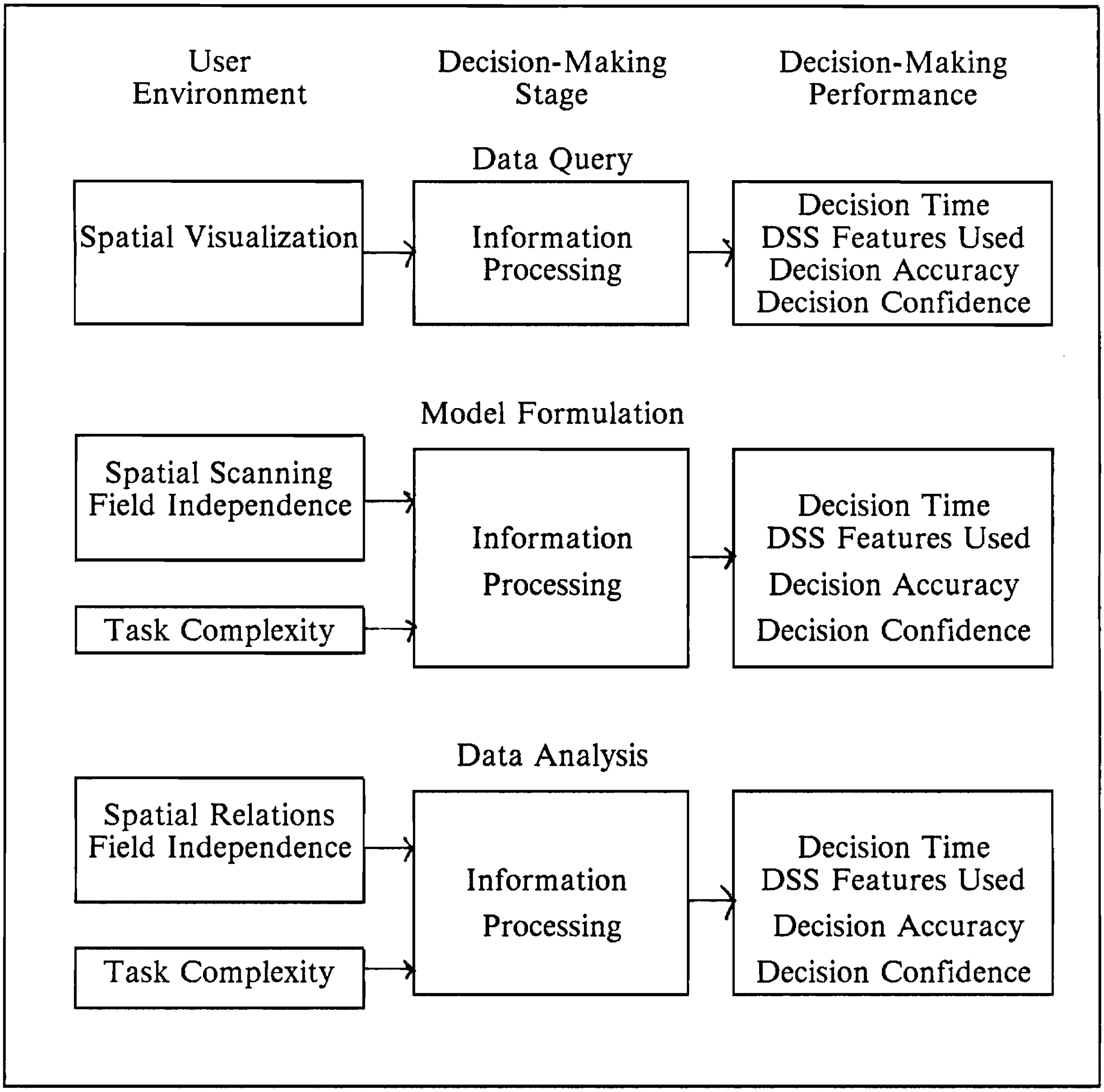

Figure 8: Proposed Research Model

In the third stage of decision making, data analysis, two spatial factors are identified as influencing decision making: spatial relations and field independence. Prior research on the influence of spatial relations has only dealt with performance on computer software games; a logical argument can be stated that spatial relations is important for data analysis. Data analysis requires an individual to choose between competing alternatives. Similarly, spatial relations requires an individual to compare similar stimuli from differing perspectives. Research findings on the influence of individual differences on decision making employing a decision model have found that field independence is associated with decision-making performance [Benbasat & Dexter, 1979, 1982].

3.2.2 Task Structure

Task structure has been found to influence decision-making performance [Jarvenpaa et al., 1985; Paquette & Kida, 1988]. Few studies in the DSS literature, however, have investigated this effect. Consequently, this study addresses the following research question:

> Is spatial ability more important to decision-making performance when the task structure is complex than when it is moderately complex?

Research findings indicate that, when rote memory or simple algorithms are sufficient for solving tasks, spatial ability does not play an influential role in decision making. When the task is complex and requires problem-solving skills, spatial scanning becomes more important as a moderator of performance [Pribyl & Bodner, 1987; Sanford, 1985]. This suggests that spatial scanning ability will play a major role in model formulation for complex decisions, whereas for moderately complex decisions spatial scanning ability may play a less important role.

3.3 Chapter Summary

In this chapter, a DSS research framework based on Ives et al.'s [1980], Sprague's [1980], and Bonczek et al.'s [1981] work in which this study will be conducted was presented. In addition, the proposed research model was presented and supported by research findings. The model identified which factors of spatial ability are associated with decision-making performance in the three stages of decision making: data query, model formulationm, and data analysis. Decision making was assessed by decision time, DSS features used, decision accuracy, and decision confidence.

Chapter 4

Pilot Studies

4.1 Introduction

This chapter contains the methodology and results of four pilot studies. The first two pilot studies were designed to investigate the moderating effect of spatial ability on performance in accounting tasks. The second two pilot studies were designed to establish time requirements for the experimental session and to test the instruments employed in the experimental session.

4.2 Pilot Study One

Prior research has identified spatial ability as an influential factor in predicting decision-making performance [Richardson, 1983; Sanford, 1985]. However, this relationship has not been examined with accounting tasks. The first pilot study was undertaken to investigate the influence of spatial ability on performance in intermediate accounting and cost accounting classes. Three spatial ability factors examined in the study were: spatial visualization, spatial scanning, and spatial relations. Performance was assessed by the final grade received in the courses.

4.2.1 Subjects

The subjects were selected from undergraduate students enrolled in intermediate accounting and cost accounting classes at Virginia Polytechnic Institute and State University (VPI&SU). The subjects were in their third year in the accounting program. The instructor of each class requested that the students volunteer to participate in the study. Twenty-nine subjects participated in the cost accounting class and 26 in the intermediate accounting class.

4.2.2 Materials

Three major factors of spatial ability commmonly identified in the literature are spatial visualization, spatial scanning, and spatial relations [Lohman, 1979]. To assess spatial visualization the following tests were employed from the Kit Factor-Reference Cognitive Tests: Paper Folding Test, Part 1 and Part 2 [Ekstrom et al., 1976]. The Paper Folding Tests require an individual to visualize where a whole punched through a folded piece of paper will appear after the paper has been unfolded. To assess spatial scanning the following tests were employed from the Kit Factor-Reference Cognitive Tests: Map Planning Test, Part 1 and Part 2 [Ekstrom, et al., 1976]. The Map Planning Test requires an individual to identify the shortest route between two points on a map representing streets. The Map Planning Test and the Paper Folding Test were selected because they have been found to be an accurate measure of spatial ability [Dupree & Wickens, 1982]. To assess spatial relations the Mental Rotations Test [Vandenberg & Kuse, 1978] was employed. The Mental Rotations Test requires an individual to match a three dimensional object with two identical objects rotated in different positions. Test-retest of this measure has been found to be reliable [Kuse, 1977].

Performance was measured by the final grade received in the accounting courses. SAT scores were collected as a surrogate measure of general verbal and math ability. Subjects provided self reports of their verbal and math SAT scores.

4.2.3 Procedures

During the first week of classes, the experimenter attended the accounting classes. Subjects were briefed on the purpose of the study, a consent form was completed, demographic information was collected, and spatial ability tests were administered (see Table 1 for descriptive statistics). A grade release form was also completed giving the class instructor permission to release the students' final grades to the experimenter.

To remove effects of general math and verbal ability on class performance, a regression model was run with final grade as the dependent variable and SAT score as the independent variable. The residual scores from the regression model were then correlated with the spatial ability scores.

4.2.4 Results and Discussion

When the cost accounting class performance scores were correlated with the spatial ability factors spatial relations was found to be significantly related at the alpha level = .05 (see Table 2). When general math and verbal ability was treated as a covariate spatial scanning had a correlation coefficient of .51 at p value = .01. For spatial relations the correlation coefficient was .26 when general math and verbal ability was not controlled at p value = .06. When intermediate accounting class performance scores were correlated with the spatial ability scores none of the spatial ability factors were significantly related to class performance.

These results identified (1) which spatial factors were important in problem solving in cost accounting and (2) that the influence of spatial ability on problem solving is task dependent. In financial accounting where memorizing rules and applying those rules is dominant, spatial ability was not found to be related. In contrast, problems in cost accounting are not as well defined and numerous approaches can be used to solve a problem.

Table 1
Descriptive Statistics on Spatial Ability Scores and Class Performance[10]

Studies	Spatial Visualization	Spatial Scanning	Spatial Relations	Course Grade
Cost Class (n = 29)				
Mean Score	12.16	26.40	17.21	78.43*
Standard Dev.	3.24	6.15	8.26	7.57
Intermediate Class (n = 26)				
Mean Score	11.00	24.94	14.90	79.94*
Standard Dev.	3.13	4.91	7.01	9.22
PC Class (n = 23)				
Mean Score	12.71	24.05	21.15	52.14*
Standard Dev.	3.25	6.02	7.96	22.27

Statistics were run on the computer on SAS release No. 5.18 at VPI&SU.

* Mean score was based on 100 posible points.

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10 Spatial visualization and spatial scanning were measured by the Paper Folding Test and Map Planning Test, respectively [Ekstrom et al., 1976]. Spatial relations was measured by the Mental Rotations Test. Spatial visualization and Paper Folding Test; spatial scanning and Map Planning Test; and Spatial relations and Mental Rotation Test are used interchangeably throughout the dissertation.

Table 2
Correlation Coefficients for Spatial Ability and Performance

Studies	Spatial Visualization		Spatial Scanning		Spatial Relations	
Cost Class	R*	P	R*	P	R*	P
(n = 29)						
Raw Score	.06	.72	.19	.28	.36	.04
Factoring SAT Score	.03	.21	.51	.01	.26	.06
Intermediate Class						
(n = 26)						
Raw Score	-.19	.34	.25	.21	-.01	.93
Factoring SAT Score	.18	.42	.31	.18	.06	.79
PC Class						
(n = 23)						
Raw Score	.42	.03	.16	.43	.30	.14
Factoring SAT Score	.43	.03	.12	.15	.33	.12

* Correlation Coefficients

Statistics were run on the computer on SAS release No. 5.18 at VPI&SU.

4.3 Pilot Study Two

The relationship between spatial ability and performance on LOTUS 1-2-3 was investigated in the second study. This study was undertaken to identify spatial ability factors that moderate performance on a computer. LOTUS was selected because it has been considered a DSS generator [Asim, 1986]. Three spatial ability factors examined in the study were: spatial visualization, spatial scanning, and spatial relations. Performance was evaluated by the grade received on the final exam which was given on the computer.

4.3.1 Subjects

All students enrolled in a Personal Computer (PC) course in business at VPI&SU were subjects in the study. The students were undergraduates learning how to use LOTUS LOTUS 123. Twenty-three students were in the PC class. The subjects were third or fourth year accounting students. Students worked with LOTUS 123 for at least 45 minutes each day during the course. The course was held for 5 days a week for 6 weeks.

4.3.2 Materials

Three major factors of spatial ability identified in the literature were examined: spatial visualization, spatial scanning, and spatial relations [Lohman, 1979]. To assess spatial visualization the following tests were employed from the Kit Factor-Reference Cognitive Tests: Paper Folding Test, Part 1 and Part 2 [Ekstrom et al., 1976]. The Paper Folding Test requires an individual to visualize where a whole punched through a piece of paper will appear after the paper has been unfolded. To assess spatial scanning the following tests were employed from the Kit Factor-Reference Cognitive Tests: Map Planning Test, Part 1 and Part 2 [Ekstrom, et al., 1976]. The Map Planning Test requires an individual to identify the shortest route between two points on a map representing streets. The Map Planning Test and the Paper Folding Test were selected because they have been found to be an accurate measure of spatial ability [Dupree & Wickens, 1982]. To assess spatial relations the Mental Rotations Test [Vanderberg & Kuse, 1978] was employed. The Mental Rotations Test requires an individual to match a three dimensional object with two identical object rotated in different positions. Test-retest of this measure has been found to be reliable [Kuse, 1977].

Performance was measured by the final exam grade. The exam was given on the computer. SAT scores were collected as a surrogate measure of general intelligence. Subjects provided self reports of their verbal and math SAT scores.

4.3.3 Procedures

Prior to the final exam, the experimenter explained the purpose of the study, handed out a consent form and demographic questionnaire, and administered the spatial ability tests. A grade release form was also completed giving the class instructor permission to release the students' final grades to the experimenter. The final exam was given on the computer. Subjects had two hours to complete 6 problems. Each problem required the subjects to develop a LOTUS 123 template.

To remove effects of general intelligence on performance, a regression model was run with final grade as the dependent variable and SAT score as the independent variable. The residual scores from the regression model were then correlated with the spatial ability score.

4.3.4 Results

When correlations of performance on the final exam and spatial ability factors were run, spatial visualization was found to be significantly related to performance at p value = .03. The correlation coefficient when general intelligence was not treated as a covariate and with general intelligence as a covariate was .42 and .43, respectively. These findings suggest that subjects with high spatial visualization ability performed better using a hierarchical command language than subjects with low ability.

4.4 Pilot Study 3

Prior to running the experimental study, a pilot study was conducted to establish time requirements and to identify any problems with the training handouts, experimental cases, and the training session.

4.4.1 Subjects

Subjects selected in the study were from undergraduate students enrolled in a senior level information system class at VPI&SU. Twenty subjects participating in the study received extra credit in their information systems class. They received the full percentage of the extra credit if they cooperated in all parts of the study.

4.4.2 Interactive Financial Planning System

A commercially available software package, Interactive Financial Planning System (IFPS) was employed in the study. The criteria set for a DSS in Chapter 1 are met with IFPS. i.e., it contains databases, model bases, and an interactive interface that allows the decision maker to use and alter data and model bases in real time to solve less structured problems. IFPS is an interactive menu driven system in which a model can be coded in near-natural language. View, model, and "what if" are some of the options available to the user for analyzing data.

The view option lists a stored data file or decision model. Users can develop a decision model to solve problems with the model option. The "what-if" option is used to manipulate model parameters in a developed model. Additionally, IFPS maintains a log file of all transactions.

4.4.3 Decision Task

The decision-making stages, data query, model formulation, and data analysis are of concern in the study. In the data query stage, the task requires the subjects to produce six reports on financial information stored in three different files.

Two tasks are employed with differing structure: moderately complex and complex in the model formulation stage.[11] The moderately complex task required subjects to determine the amount of additional shares of stock that can be issued given that the price/earnings ratio does not fall below a specific criterion. Subjects had to develop a decision model in which the additional share issued and the market price per share could be manipulated. A one-page summary on background information and financial data on the company was provided.[12] Requirements for the complex task were to determine the market average debt/equity ratio, and the company's debt/equity ratio and price/earnings ratio. Subjects had to develop a decision model in which the bonds issued and the number of common stock issued could be manipulated. The task contains a one-page summary on background information and financial data of the company, along with a list

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[11] To assess the complexity level of these cases, Wood's [1986] model of task complexity was employed. Component complexity was assessed by the number of distinct information cues required to complete the task. This was determined by the researcher reviewing the cases. See Section 5.7 for further discussion.

[12] A revised version of this case is in Appendix A.

of variable names contained in the data file.[13] The only difference between the tasks in the data analysis stage and model formulation stage is that a decision model is provided for the subjects to aid them in arriving at a solution.

4.4.4 Performance Measures

Four measures of the decision maker's performance were: 1) time required to complete the task, 2) the number of DSS features used, 3) decision accuracy, and 4) decision confidence. Time to reach a decision is operationally defined as the number of minutes elapsed from starting the case to completion of the case. The start time was written on the test. The completion time was determined by the time recorded on the saved log. The number of DSS is assessed by the number of IFPS commands executed. Information on DSS features used was determined from the log file maintained by IFPS.

For the data query task, decision accuracy is defined as querying the correct information. Subjects receive one point for each correct query. Decision accuracy for the moderately complex task is defined as reaching a correct solution, right or wrong. The complex task required subjects to determine the debt/equity ratio, price/earnings ratio, and the market average debt/equity ratio when capital is raised by borrowing money or issuing common stock. Subjects received up to 10 points, two points for each correct answer. Subjects' confidence in their decision was measured by the response to a posttask question on a seven-point Likert scale.

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[13] A modified version of this case is presented in Appendix B.

4.4.5 Explanatory Variables

Several of the major factors of spatial ability identified in the literature are spatial visualization, spatial scanning, and spatial relations [Lohman, 1979] and field independence [Mckenna, 1984]. To assess spatial visualization, the following tests were employed from the Kit Factor-Reference Cognitive Tests: Paper Folding Test, Part 1 and Part 2 [Ekstrom et al., 1976]. To assess spatial scanning the following tests were employed from the Kit Factor-Reference Cognitive Tests: Map Planning Test Parts 1 and 2 [Ekstrom, et al., 1976]. To assess field independence, the Hidden Figures Test I (Part 1) was employed from the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]. The Map Planning Tests, Paper Folding Tests, and Hidden Figures Test were selected because they have been found to be an accurate measure of spatial ability [Dupree & Wickens, 1982]. The test-retest reliability scores of the Paper Folding Tests, Map Planning Tests, and Hidden Figures Test are .75, .80, .82, respectively [Ekstrom et al., 1976]. Spatial relations ability was assessed by the Mental Rotations Test (MRT) [Vanderberg & Kuse, 1978]. Test-retest of this measure has found this test to be reliable [Kuse, 1977].

4.4.6 Control Variables

Age, computer experience, and decision-making experience were treated as covariates. Information on these variables was collected on a background questionnaire administered to the subjects during the first session of the study.

Decision-making experience was assessed by the number of months the subjects had had with making decisions in a work environment. Prior studies have found that decision makers' ability to select the appropriate strategy for solving a problem is dependent upon their decision-making experience in general rather than the type of decision [Taylor, 1975]. Hence, the present study is not concerned with the type of decision-making experience, and is focused only on the amount of experience. The score subjects received were transformed into a logarithmic scale to represent the diminishing effect of decision-making experience on performance. Computer experience was determined by the number of software packages the subjects were familiar with and the number of months spent using the software. To represent the diminishing effect of computer experience on performance, the subjects scores were transformed into a logarithmic scale.

4.4.7 Procedures

Subjects attended one four hour session. In the beginning of the session, subjects were briefed on the purpose of the study, demographic information was collected, and spatial ability tests were administered. Next, the instructor gave a two hour lecture on how IFPS works. To follow along with the lecture, subjects were provided with a handout on IFPS. After the lecture, subjects were required to complete three practice problems. Upon completion of these problems subjects had three cases to complete.

4.4.8 Results

Several problems were revealed from the study. First, the training session took longer than expected resulting in subjects having time to complete only one case. To correct for this, 1) the data query task was eliminated and 2) the material in the training session was reduced to include only information necessary to complete the cases. Second, subjects had difficulty understanding how to solve the cases. This problem was partly due to the subjects' lack of accounting background and partly due to how the case material was presented. The cases were revised and simplified.

4.5 Pilot Study 4

After implementing changes from the third pilot study, another pilot study was run. The major purpose of the fourth pilot study was to identify any problems with the revised training handout, experimental cases, and training session.

4.5.1 Subjects

The subjects were selected from graduate students enrolled in Management Information Systems classes at VPI&SU. Twenty-four students participated in the study. Subjects received credit totaling ten percent of their course grade for participating in the study. They received full points if they cooperated in all parts of the study. Subjects were eliminated from the study if they had prior experience on IFPS.

4.5.2 Measures

The decision-making stages that are of concern in the study are model formulation and data analysis. IFPS was the software package employed (see Section 4.4.2 for description). Although the cases were revised for clarity, the requirements of the cases are the same as described in Section 4.4.3. Decision-making performance was assessed by 1) time, 2) DSS features, 3)confidence, and 4) decision accuracy (see Section 4.4.4 for description). The explanatory variables were spatial scanning, spatial relations, and field independence (see Section 4.4.5). The control variables were age, computer experience, and decision-making experience (see Section 4.4.6).

4.5.3 Procedures

Prior to the experimental sessions subjects were briefed on the purpose of the study, a consent form was completed, demographic information was collected, and spatial ability tests were administered. Due to the limited availability of computers, two sessions were run. In the first group, fifteen subjects attended three seventy-minute sessions. In the second group, nine subjects attended two sessions of two hours in length.

All subjects completed ninety minutes of lecture and thirty minutes of practice problems. Each subject was seated at a computer. Subjects were provided with a handout on IFPS on which they took notes and which they returned to during the sessions. The information in the IFPS handout was organized in the same format as the presentation.

In the first part of the lecture, a brief overview of IFPS was provided. During the remaining part of the lecture, the subjects were taught to create a model, activate a model, view a model, view a data file, and perform what-if analyses. Mathematical functions employed on IFPS were also reviewed. As each area was discussed, the subjects performed the tasks on the computer. Upon completion of the lecture, three practice problems were performed. The subjects were required to show the correct answer to the instructor, before continuing on to the next problem.

The practice problems were designed to increase the understanding of how IFPS works. The first problem was designed to make the subjects familiar with what-if analysis. Subjects were required to make up a case in which the number of units sold was manipulated. The second problem was designed to increase the subjects' knowledge of developing models and using a data file with their developed model. The third problem reinforced the subjects' ability to develop a model and use a data file with the model, and ensured that the subjects knew how to use the mean function.

After completing practice problem three, the subjects completed experimental cases. Before the cases were handed out, the subjects were taught to develop a log file. Upon completion of each case, the subjects raised their hand, the instructor saved their log file, and the subjects completed a postcase questionnaire on the understandability of the cases and the complexity of the cases. The next case was then given to them. When the subjects had finished the cases, they completed a postexperiment questionnaire.

4.5.4 Results

Several factors were revealed as a result of this preliminary process:

1. When the subjects were provided a model to solve the case, several subjects complained that they were not aware that the model was already developed. To correct for this, the wording in the cases was changed to clearly specify that a model had been developed for them to use to perform the analysis.

2. Based on the postexperiment questionnaire responses to the question regarding the training session, several changes were implemented. Because the smaller group whose session ran for two hour blocks of time indicated that the training session was more sufficient than did the larger group, a limit of 10 to 12 subjects per group was set and the time length for each session was set at two hours. Additionally, an assistant was added to the training session to ensure that the subjects did not fall behind during the training session.

3. Based on responses to the task complexity question, there was only a slight perceived difference between the cases; therefore, the less structured case was simplified.

4. Four individuals could not complete the moderately complex case and two could not complete the complex case. Because the moderately complex case was administered first and there was a larger number of subjects that could not complete the case, a learning effect may have occurred. To eliminate any learning effect, the order in which the cases were administered was randomized. In addition to randomizing the order of the cases, an additional practice case was developed.

5. Several individuals had to be dropped from the study because they had locked up the software package, hence losing the log file. To reduce this problem, a review of common errors that occur when using IFPS was added and reviewed during both sessions.

6. In the postcase questionnaire, the question on time to complete the task was eliminated because subjects were given unlimited time to complete each case. Additionally, the case complexity question was eliminated from the posttask questionnaire because it was already asked in the postcase questionnaire and did not provide any additional information.

4.6 Conclusion

This chapter contains a discussion on the methodology and results of several pilot studies that were conducted. The results of the first study indicate that spatial scanning and spatial relations are related to performance in cost accounting classes. Thus, spatial scanning and spatial relations are related apparently to problem solving efficiency. From these results, spatial scanning and spatial relations were selected as variables of interest in the present study. The second study identified spatial visualization as a significant factor influencing performance on LOTUS. These findings suggest that spatial visualization was hypothesized to be related to data query performance. However, due to time constraints this stage of decision making was dropped from the study; hence, eliminating spatial visualization as a variable of interest in the present study. To test instruments and procedures for the experimental study, several pilot studies were run. The time length of the experimental session was established based on Pilot study 3. In addition, the wording of the cases was improved. Pilot study 4 helped further refine the experimental sessions. As a result of this study, the training session was improved by adding an assistant, reducing the number of subjects per session, and adding a review of typical errors. The only changes made to the cases were to clarify whether a model were available to use or one had to be developed.

Chapter 5

Research Methodology

5.1 Introduction

This chapter contains the methodology for a laboratory study designed to test hypotheses related to research questions presented in Chapter 3. First, an overview of the research design, participants in the study, the software employed, and decision task are discussed. Next, the dependent variables, independent variable, explanatory variables, and control variables are defined. This is followed by the research hypotheses and statistical models employed to analyze the data.

5.2 Overview of the Experiment

A laboratory study was conducted to assess which factors of spatial ability influence decision makers' performance in various decision-making stages under differing task structure. Based on Bonczek et al.'s model [1981] of the problem processes, the decision-making stages of interest in the present study were model formulation and data analysis.[14] In order to investigate these stages, four performance measures were considered: (1) time to complete the task, (2) DSS features used, (3) decision accuracy, and (4) decision confidence. The relationship

[14] The data query stage of decision making was eliminated from the study based on a time constraint problem identified during the pilot study. See Section 4.4.8.

between spatial ability and performance is examined separately for each performance measure.[15]

The independent variables in the study were levels of task structure. Task structure is a discrete variable consisting of two levels: moderately complex and complex. The explanatory variables were three major factors of spatial ability: spatial relations, spatial scanning, and field independence. These spatial ability factors were treated as continuous variables. Because the background of the subjects was diverse, differences found in computer experience could potentially impact the dependent variables and therefore, experience was treated as a covariate to remove any effect on the dependent variables.[16]

5.3 Subjects

Subjects were selected from students working towards a Master's degree in accountancy or business administration. Students were enrolled in graduate accounting courses at Virginia Polytechnic Institute and State University (VPI&SU). Five classes participated in the study. Subjects received credit totaling five to ten percent of their grade for participation in the study. They received the full percentage if they cooperated in all parts of the study. Subjects were expected to have an educational background that would ensure their understanding of the subject matter in each case and to have completed an introductory finance course. Prerequisites for the masters program at VPI&SU

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[15] The performance measures are evaluated independently because that is how they are treated when evaluating an information system. When changes in an information system are made, one or more of these performance measures maybe improved and not necessarily a combination of the measures.

[16] Two covariates, age and decision-making experience were eliminated because they were found not to be related to performance in the present study. See Appendix V for statistical results when age and decision-making experience are in the models.

ensured this knowledge level. Subjects were eliminated from the final analysis if they had had prior experience on IFPS.

Sixty-six subjects took part at the onset of the study. Two subjects were dropped because they had missing spatial scores, ten were because they could not complete the cases, and four were dropped because of extreme performance scores.[17] Descriptive statistics for the fifty subjects are presented in Table 3.[18] The subject's average age was 27 with the range from 21 to 43. Twenty-one of the subjects were women and 29 were men. Twenty-three subjects were in the master of accountancy program and 27 in the master of business administration program at VPI&SU. Computer experience level of the subjects ranged from 2 months to 235 months of experience with an average of 48 months of experience.[19]

Spatial visualization scores ranged from 0 to 20 with an average of 12.03.[20] The average spatial scanning score was 23.13 with a range from 5.2 to 39.[21] The average score on the field independence test was 7.32 with a range from 0 to 16. The scores were the same as the average reported in Ekstrom et al. [1976] Test Bank. The average spatial relations scores was 16.80 with a range from 1.5 to 37.[22] See Table 3 for spatial scores.

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17 The elimination of the four outliers and 10 drop outs. are discussed in Section 6.4.

18 Differences in the sample size are due to non-response.

19 Computer experience was measured as the number of months of experience on each software package plus the number of software packages known.

20 The average score for college students as reported by Ekstrom et al. [1976] is 13.8.

21 The average score for college students as reported by Ekstrom et al. [1976] is 25.

22 The average score for college students as reported by Vanderberg & Kuse [1978] is 22.7.

Table 3: Demographic Information on the Subjects

Gender	Frequency	Percent
Female	21	42
Male	29	58
Concentration		
Masters of Accountancy	23	46
Masters of Business Administration	27	54

	N	Mean	Std Dev.	Min.	Max.	Median
Age	44	27	6	21	43	25
Experience:						
Computer Experience	50	50	50	2	235	27
Decision Making	50	27	40	1	180	2
Spatial Ability Scores:*						
Spatial Visualization	50	12.03	4.22	0	20	11.6
Spatial Scanning	50	23.13	7.00	5.2	39	22.6
Spatial Relations	50	16.80	8.23	1.5	37	16.0
Field Independence	50	7.32	4.04	0	16	7.0
GMAT Scores	43	559	67.14	410	750	550

* The spatial ability names, spatial visualization, spatial scanning, spatial relations, field independence, are used interchangeablly with Paper Folding Test, Map Planning Test, Mental Rotations Test, and Hidden Figures Test, respectively.

5.4 Interactive Financial Planning System

The present study employed a commercially available software package, Interactive Financial Planning System (IFPS), that has been widely used in businesses and universities [Sharda, et al., 1988]. IFPS meets the criteria set for a DSS in Chapter 1, i.e., it contains databases, model bases, and an interactive interface that allows the decision maker to use and alter data and model bases in real time to solve less structured problems. IFPS is a hierarchical menu driven system that allows users to code their model in near-natural language; once a model is developed, the model may be used on any data file. IFPS is an interactive system that employs a spreadsheet format. Some of the options available to the user for analyzing data are view, model, and "what if". The view option lists a stored data file or decision model. The model option allows users to develop a decision model to solve problems. Employing a developed model, the "what-if" option can be used to manipulate model parameters, allowing one to immediately see the effects. IFPS is designed to maintain a log of all transactions.

5.5 Decision Task

The decision-making stages of concern in the study were model formulation and data analysis. In the model formulation stage, two tasks were employed with differing structure: moderately complex and complex.[23] The King case was employed as the moderately complex task (see Appendix A). This case requires the subjects to determine the amount of additional shares of stock that can be issued given that the price/earnings ratio does not fall below a specific criterion. In this

[23] See Section 5.7 for discussion on determination of task complexity.

task, subjects must develop a decision model in which the additional share issued and the market price per share can be manipulated. The task contains a one-page summary on background information and financial data on the company. The Delta case was employed as the complex task (see Appendix B). This case requires subjects to determine the market average debt/equity ratio, and the company's debt/equity ratio and price/earnings ratio. In this task, the subjects must develop a decision model in which the bonds issued and the number of common stock issued can be manipulated. A one-page summary on background information and financial data of the company was provided along with a list of variable names contained in the data file.

Tasks in the data analysis stage are the same as the moderately complex task and complex task described above. The only difference between the tasks is that a decision model is provided for the subjects to aid them in arriving at a solution. For the moderately complex case (Appendix C), the model provided is shown in Appendix D. For the complex case (Appendix E), the subjects received the model presented in Appendix F.

5.6 Dependent Variables

The dependent variables consisted of four measures of the decision maker's performance: 1) time required to complete the task, 2) the number of DSS features used, 3) decision accuracy, and 4) decision confidence. Decision makers' performance can be assessed in terms of the efficiency of the decision process and the effectiveness of a decision. The efficiency of the decision process was presumed to be measurable by the time required to complete a task and the number of DSS features used. Time to reach a decision has been used in many DSS/MIS studies [Benbasat & Dexter, 1979, 1982 & 1985; Goslar et al., 1986; and Green & Hughes, 1986]. In the present study, time to reach a decision is operationally defined as the number of minutes from starting the case to completion of the case. The starting point was written down on the top of the test by the instructor. After the subjects completed the case, they were instructed to save the log of their session. The completion time was recorded on the saved log.

The second variable, number of DSS features used, has been employed in DSS/MIS studies [Green & Hughes, 1986; and Mykytyn, 1985]. The number of DSS features is evaluated by the number of features used by the subject. The DSS features that were counted are all IFPS commands executed, such as view, what-if, and solve. Information on DSS features used was determined from the log file maintained by IFPS. See Appendix G, for an example of a log file.

Decision effectiveness is evaluated in terms of decision accuracy. Decision accuracy for the moderately complex task is defined as reaching a correct solution. The answer to the moderately complex task is rated as either right or wrong. The complex task required subjects to determine the debt/equity ratio and price/earnings ratio under differing conditions and the market average debt/equity ratio. Subjects received up to 10 points, two points for each correct answer.

The fourth dependent variable, confidence in the decision, also has been employed as a variable in DSS/MIS studies [Cats-Baril & Hughes, 1987; Goslar et al., 1986]. There are several reasons why confidence is an important variable. First, for users to continue employing a DSS, they must be confident in the decision they reach when using the system. Second, decision makers will have trouble convincing other members of the organization that they have arrived at an appropriate solution to a problem if they are not confident that their decision is correct. Subjects' confidence in their decision was measured by the response to a postcase question on a seven-point Likert scale (see Question 1 in Appendix H).

5.7 Independent Variable - Task Structure

Two levels of task complexity were employed to assess task structure: moderately complex and complex. The King case was employed as the moderately complex task (see Appendix A) and the Delta case was employed as the complex case (see Appendix B). To assess the complexity level of these cases, Wood's [1986] model of task complexity was employed. Because one component of Wood's model, dynamic complexity, was irrelevant to these cases, only component complexity and coordinate complexity were considered.

Component complexity is assessed by the number of distinct acts and the number of distinct information cues required to complete the task. Based on component complexity, the King case has five information cues and a minimum of eight acts. The Delta case has a minimum of eleven information cues and requires at least sixteen acts. This was determined by the researcher reviewing the cases. Coordinate complexity refers to the form and strength of the relationship between tasks input, acts, and outputs. With respect to coordinate complexity in the King case, once the subjects have set up the equation for the new earnings per share number and price/earnings ratio, the number of new shares issued and the market price of common stock need only be manipulated. The decision model is shown in Appendix D. In the Delta case, when bonds are issued, the bond amount, the bond rate, tax rate, and market price of common stock must be manipulated. When additional stocks are issued, additional shares must be calculated and the market price must be given. The decision model is shown in Appendix F.

Providing a model to the subjects clearly reduces the number of distinct acts required to complete the King case to 3 and the Delta case to 10. However, it does not reduce the number of distinct information cues required to complete the task or the form of the relationships between the inputs, acts, and outputs. For example, in the Delta case, whether the subjects receive a model or not, they must remember to change the market price of the stock when issuing debt and stock.

To ensure that subjects' prior experience with the task does not interfere with their perception of the tasks as moderately complex or complex, a postcase questionnaire was administered to determine whether the different complexity levels were achieved (see Question 5, Appendix H). Note that whether subjects were in agreement that the Delta case is complex is not of concern in this study, rather that the subjects agree that the Delta case is more complex than the King case.

5.8 Explanatory Variables - Spatial Ability

Two factors of spatial ability identified in the literature are spatial scanning and spatial relations [Lohman, 1979]. Another spatial ability factor that has been identified is field independence [Mckenna, 1984]. To assess spatial scanning the following tests were employed from the Kit Factor-Reference Cognitive Tests: Map Planning Test, Parts 1 and 2 [Ekstrom et al., 1976]. The Map Planning Test requires an individual to identify the shortest route between two points on a map which represent streets. A demonstration problem and several practice problems are provided with this test. The score on the test was the number of correct answers.

To assess field independence, the Hidden Figures Test I (Part 1) was employed from the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]. This test requires an individual to identify a shape within a maze of shapes. This test contains only demonstration problems. The scores on the tests were calculated by the number of correct responses minus one-fifth of the number of wrong responses. A fraction of the number wrong was subtracted to control for guessing. The Map Planning Test and Hidden Figures Test were selected because they have been found to be an accurate measure of spatial ability [Dupree & Wickens, 1982]. The reliability scores of the Map Planning Tests and Hidden Figures Test are .80 and .82, respectively [Ekstrom et al., 1976].

Spatial relations ability was assessed by the Mental Rotations Test (MRT) [Vanderberg & Kuse, 1978]. The MRT requires an individual to match a three dimensional object with two identical objects rotated in different positions. This test contains an example of what is required along with several practice problems. The scores on the tests were calculated by the number of correct responses minus one-half of the number of wrong responses. A fraction of the number wrong was subtracted to control for guessing. Test-retest of this measure has found this test to be reliable [Kuse, 1977].[24]

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[24] The researcher manually graded each spatial ability test from an answer key provided in the test bank. To reduce possible grading errors, the researcher regraded the tests after several weeks had passed from the first grading. This resulted in correction of approximately 10 tests.

5.9 Control Variable

Computer experience was treated as a covariate. Information on this variable was collected by a background questionnaire (Appendix I) administered to the subjects during the first session of the study. As noted previously in the chapter, age and decision-making experience were dropped from the model because they were found to be insignificant factors.

Because one could argue that a person with knowledge of two software packages has more general knowledge of computers than a person with knowledge of only one software package, subjects were asked to list the software packages they had used and to indicate the number of months they had used the software. Subjects received one point for each software they listed and one point for each month spent using the software. Although this assessment of computer experience is somewhat crude, it acknowledges the more exposure subjects have to computers, the more general computer knowledge the subject possesses. According to Egan [1987] computer experience influences performance on a software package after the user becomes familiar with the package. The scores subjects received were transformed into a logarithmic scale to represent the diminishing effect of computer experience on performance.

5.10 Procedures

Five groups of subjects participated in the study. All subjects attended three experimental sessions. The first experimental session took place in a classroom and was held for one hour. For the remaining two experimental sessions, the subjects were divided into nine experimental groups. Each experimental group attended two-hour sessions in a computer lab for two consecutive evenings.[25] The subjects initially chose the experimental group based on their availability. Once the subjects had selected the experimental group, they were not allowed to switch groups.

During the first session, the subjects were briefed on the purpose of the study and informed that they were required to attend two-hour evening sessions for two consecutive nights to receive credit in the course they were attending. The subjects then completed a consent form (Appendix J), a background questionnaire (Appendix I), and three spatial ability tests. Two tests from the Kit Factor-Reference Cognition Tests [Ekstrom et al., 1976] were given: Map Planning Test (Parts 1 & 2) and Hidden Figures Test I (Part 1). The instructions for each test are provided on the front page of the test booklets. The instructor read the directions to the subjects and asked if everyone understood what was required of them. Only a few instances occurred where the instructions had to be clarified.

For the Map Planning Test, practice problems are included in the test booklets. The subjects were given one and half minutes to work on the practice problems. The instructor went over the answers to the practice problems and inquired whether everyone understood the directions. There were no questions asked. Each part of the Map Planning Test took three minutes.

The time limit for the Hidden Figures Test is ten minutes. There are no practice problems for this test. The final spatial ability test that was administered the Mental Rotations Test by Vanderberg and Kuse [1978.] This test contains several practice problems in which the subjects had one and an half minutes to

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[25] Based on the evaluation of the pilot study, it was determined that the experimental sessions held in the computer lab would not exceed fourteen subjects. Therefore, the original 5 groups were divided into 9 groups.

work. The instructor reviewed the answers and inquired whether there were any questions. The questions asked were to confirm that the subjects were doing the tasks correctly. The Mental Rotations Test has two parts in which the subjects had three minutes to complete each part. After the spatial ability tests were completed and the material collected, the subjects picked one of the nine experimental groups.

During the second session, a lecture on IFPS was given for ninety minutes. The instructor followed a set of notes to ensure that each experimental group heard the same presentation (see Appendix K). The subjects worked along on IFPS as each IFPS feature was discussed. They were also provided with a handout on IFPS which followed the lecture notes (see Appendix L). Upon completion of the lecture, the subjects completed three practice problems (Appendix M). The instructor and an assistant went around the room answering questions.[26] Typical problems encountered were activating the model and activating the databases.[27] Before the subjects were allowed to start the next practice problem, they were required to have the instructor or assistant check their answers. If the subjects did not have the correct solution, they were told what was wrong. They were required to fix the errors before they could continue. This was done as a check on the individual's ability to use IFPS and to solve the problems.

In the beginning of the third session, the subjects were given ten minutes to read through the training handout to refresh their memory of IFPS. Upon com-

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[26] Based on the results of the pilot study, it was determined that an assistant would participate in the training session. The assistant was a male PhD student who had knowledge of IFPS and had completed each practice problem prior to assisting in the sessions.

[27] After a model is created with IFPS, the model must be activated and every time the model is edited the database must be activated to run the model. At the onset of using IFPS, this is confusing to the subjects.

pletion of the practice problems, the two common errors made when operating IFPS were reviewed. The common errors are not specifying the time period of the model and not entering a file specification. Based on pilot study four's results, these common errors were found to lock up the system. Reviewing these errors with the subjects eliminated any problems with the system locking up. These errors were reviewed to make sure the subjects were aware of them and to show the subjects how to correct them. Any questions that the subjects had were then addressed. Approximately three questions were asked by each experimental group. The last practice problem was then completed in approximately 10 minutes. Upon completion of the practice problem, the subjects were taught to set up a log file. The log file recorded all IFPS commands used by the subjects.

The subjects were then told that they had unlimited time to complete the cases and that they were to refer to the IFPS handout for any problems encountered during the remaining session. Based on pilot study four's results, the moderately complex case took an average of 15 minutes and the complex case took an average of 50 minutes to complete. Because of the large time differences in the cases, the subjects were informed that the time length of the cases differed and that the person next to them would not have the same case. The cases were handed to each subject so that no two subjects sitting next to each other received the same case. Upon completion of the first case, the subjects raised their hand and the instructor saved their log file. After the postcase questionnaire was completed, the instructor set up a new log file and gave the subjects the second case. The same procedure was used after the second case, except that the subjects received the postexperiment questionnaire.

5.11 Research Hypotheses

This study investigated only the relationships and the interaction effects that are supported by prior literature. Several general hypotheses were generated to answer the research question advanced in Chapter 3. The hypotheses (stated in the null form) were tested for each of the decision-making stages.

<u>Model Formulation</u>

H_1 The spatial scanning ability and field independence of the subject will have no moderating effect on 1) time to complete the task, 2) DSS features employed, 3) decision accuracy, or 4) decision confidence in the model formulation tasks.

H_2 There will be no moderating interaction effect between spatial scanning ability and task structure on 1) time to complete task, 2) DSS features employed, or 3) decision confidence in the model formulation tasks.

The first and second hypotheses are concerned with users' performance on the model formulation tasks. Hypothesis 1 deals with the influence of spatial scanning and field independence on model formulation performance. This hypothesis was tested for the moderately complex task and the complex task separately. As stated in Chapter 3, spatial scanning and field independence have been found to be associated with structuring a problem [Irons, 1982; Pracht & Courtney, 1988; and Testa, 1973]. It was expected that subjects scoring high in spatial scanning ability or field independence will require less time, use fewer DSS features, make more accurate decisions, and be more confident in their decision than low ability subjects. Failure to reject this hypothesis for either factor of spatial ability and any dependent variable would indicate that these factors of spatial ability may not be important for decision making in the DSS environment under investigation. Mixed results will identify which factors of spatial ability are important and which performance measures are influenced by the specific spatial factors.

Hypothesis 2 deals with the influence of spatial ability on model formulation tasks of differing structure. Spatial scanning has been identified as influencing decision making when the task is complex [Pribyl & Bodner, 1987; and Sanford, 1985]. It is expected that when the task is complex, individuals low in spatial scanning will require more time, use more DSS features, and be less confident than when the task is moderately complex. Performance differences in tasks of differing structure are expected to be larger for low ability subjects than for high ability subjects.

Data Analysis

H_3 The spatial relations ability and the field independence of the subject will have no moderating affect on 1) time to complete the task, 2) DSS features employed, 3) decision accuracy, or 4) decision confidence in the data analysis tasks.

H_4 There will be no moderating interaction effect between spatial relations ability and task structure in terms of 1) time to complete the task, 2)

DSS features employed, or 3) decision confidence in the data analysis tasks.

The third and fourth hypotheses are concerned with users' performance on the data analysis tasks. Hypothesis 3 deals with the influence of spatial relations ability and field independence on data analysis performance. This hypothesis will be tested for both the moderately complex task and the complex task. As stated in Chapter 3, data analysis requires an individual to choose between competing alternatives. Similarly, spatial relations requires an individual to compare similar stimuli from differing perspectives. Additionally, field independence has been found to be associated with decision-making performance when a decision model is employed [Benbasat & Dexter, 1982]. It is expected that subjects scoring high in spatial relations ability or field independence will require less time, use fewer DSS features, make more accurate decisions, and be more confident in their decision than low ability subjects. Failure to reject this hypothesis for either factor of spatial ability and any dependent variable would indicate these factors of spatial ability may not be important for decision making in the DSS environment under investigation. Mixed results will identify which factors of spatial ability are important and which performance measures are influenced by the specific spatial factors.

The fourth hypothesis deals with the influence of spatial relations on solving tasks of differing structure. When the task is complex, it is expected that individuals low in spatial relations will require more time, use more DSS features, and be less confident than when the task is moderately complex. Larger performance differences are expected in tasks of differing structure for low ability subjects than for high ability subjects.

A summary of the hypotheses tested for each stage of decision making is presented in Table 4.

Table 4

Test of the Hypotheses

Dependent Variable	Model Formulation Tasks					Data Analysis Tasks				
	Mod. Comp.		Complex			Mod. Comp.		Complex		
	S	F	S	F	S*T	R	F	R	F	R*T
Time	H_1	H_1	H_1	H_1	H_2	H_3	H_3	H_3	H_3	H_4
DSS Features	H_1	H_1	H_1	H_1	H_2	H_3	H_3	H_3	H_3	H_4
Decision Confidence	H_1	H_1	H_1	H_1	H_2	H_3	H_3	H_3	H_3	H_4
Decision Accuracy	H_1	H_1	H_1	H_1	**	H_3	H_3	H_3	H_3	**

S = Spatial Scanning
F = Field Independence
T = Task Complexity
R = Spatial Relations

** Decision accuracy is a discrete variable for the moderately complex task and a continuous variable for the complex task; therefore, the interaction effect of task structure and the spatial ability factors cannot be evaluated.

5.12 Statistical Model

Four types of regression models were employed in the study to analyze the data.[28] The models include only hypothesized relationships. Tests were performed to check for multicollinearity problems (See Appendix U). Due to a small sample size two covariates, age and decision making experience were dropped from the study. These factors were chosen because they were not significant in any of the regression models (See Appendix V).[29] Each model will be discussed separately along with the corresponding hypothesis.[30]

The influence of spatial scanning and field independence on the model formulation tasks are of concern in the first hypothesis. To test Hypothesis 1, Model 1 was run on the following dependent variables: time, DSS features, decision confidence, and decision accuracy. The data was analyzed separately for the moderately complex case and the complex case. Because decision accuracy is a discrete variable in the moderately complex task, Model 1 was run employing logistic regression.[31] For the results of decision accuracy in the complex task, Model 1 was run employing multiple regression. Model 1 is as follows:

$$Y_i = \alpha + \beta_1 C_i + \beta_2 S_i + \beta_3 F_i + \varepsilon_i$$

where
Y_i either represents time, DSS features, decision accuracy, or decision confidence.

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28 Multiple regression analysis is considered the appropriate method of analysis when the independent variables are both continuous and categorical [Kerlinger & Pedhazur, 1982].

29 One change resulted due to dropping these variables, in the moderately complex case when the decision making stage was data analysis field independence was found to be significantly related to decision confidence.

30 A significant regression coefficient will indicate that the variable or interaction is related to the dependent variable. The betas were tested by a t test. The significance level was .05 which is typical for research in this area [Cohen & Cohen, 1983.]

31 Logistic regression is often used when the dependent variable is dichotomous [Cohen & Cohen, 1983]

C_i is computer skill level of the ith subject; a continuous variable measured in terms of the number of months of experience.

S_i is spatial scanning of the ith subject; a continuous variable measured by the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]

F_i is field independence of the ith subject; a continuous variable measured by the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]

The second hypothesis is concerned with the interaction effect of spatial scanning and task structure on the model formulation task. Model 2 was run for the following dependent variables: time, DSS features, and decision confidence.[32] Model 2 is as follows:

$$Y_{ij} = \alpha + \beta_1 C_i + \beta_2 S_i + \beta_3 F_i + \beta_4 T_j + \beta_5 S_i T_i + \varepsilon_i$$

where
Y_i either represents time, DSS features, or decision confidence.

C_i is computer skill level of the ith subject; a continuous variable measured in terms of the number of months of experience.

S_i is spatial scanning of the ith subject; a continuous variable measured by the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]

F_i is field independence of the ith subject; a continuous variable measured by the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]

T_j is task structure (j = 1,2), where 1 = moderately complex and 2 = complex.

The first hypothesis is stated as $\beta_2 = 0$ and $\beta_3 = 0$. Hypothesis 2 is stated as $\beta_5 = 0$.

Hypothesis 3 is concerned with the influence of spatial relations and field independence on data analysis performance. Model 3 was run on the following dependent variables: time, DSS features, decision confidence, and decision accuracy. Model 3 was run employing logistic regression for the results of decision

[32] Becuase field independence has been identified as having a potential impact on decision making performance, it is treated as a control variable.

accuracy in the moderately complex task and run employing multiple regression for the complex task. Model 3 is as follows:

$$Y_i = \alpha + \beta_1 C_i + \beta_2 F_i + \beta_3 R_i + \varepsilon_i$$

where
Y_i either represents time, DSS features, decision accuracy, or decision confidence.

C_i is computer skill level of the ith subject; a continuous variable measured in terms of the number of months of experience.

F_i is field independence of the ith subject; a continuous variable measured by the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]

R_i is spatial relations of the ith subject; a continuous variable measured by the Mental Rotation Test [Vanderberg & Kuse, 1978]

Hypothesis 4 is concerned with the interaction effect of spatial relations ability and task structure. Model 4 was run on the following dependent variables: time, DSS features, and decision confidence. Model 4 is as follows:

$$Y_{ij} = \alpha + \beta_1 C_i + \beta_2 F_i + \beta_3 R_i + \beta_4 T_i + \beta_5 T_j R_i + \varepsilon_i$$

where
Y_i either represents time, DSS features, or decision confidence.

C_i is computer skill level of the ith subject; a continuous variable measured in terms of the number of months of experience.

F_i is field independence of the ith subject; a continuous variable measured by the Kit Factor-Reference Cognitive Tests [Ekstrom et al., 1976]

R_i is spatial relations of the ith subject; a continuous variable measured by the Mental Rotation Test [Vanderberg & Kuse, 1978]

T_j is task structure (j = 1,2), where 1 = moderately complex and 2 = complex.

Hypothesis 3 is stated as $\beta_2 = 0$ and $\beta_3 = 0$. Hypothesis 4 is stated as $\beta_5 = 0$. A summary of these analyses is provided in Table 5.

Prior to running the statistical model, some preliminary analysis of the data was performed. First, due to seating limitations, all subjects did not go through the experiment at the same time. To ensure that differences in the experimental setting do not influence the results, an ANOVA was employed to test that performance scores did not significantly differ between the groups. Second, several manipulation checks were performed to assess the cases employed in the study and the experimental settings. Third, Pearson product moment coefficient of correlations was computed for the independent and dependent variables. The correlations between the independent variables were analyzed to ensure that there is not a problem of multicollinearity.[33]

[33] According to the statistical literature, correlations of .60 or greater may indicate a multicollinearity problem. Based on the results of some preliminary work presented in Section 4.5, only two spatial tests were significantly correlated: spatial relations and spatial scanning ($r = .31$, $p = .02$); and spatial relations and field independence ($r = .26$, $p = .06$).

Table 5

Data Analysis Models

Dependent Variable	Model Formulation Tasks					Data Analysis Tasks				
	Mod. Comp.		Complex			Mod. Comp.		Complex		
	S	F	S	F	S*T	R	F	R	F	R*T
Time	M=1	M=1	M=1	M=1	M=2	M=3	M=3	M=3	M=3	M=4
DSS Features	M=1	M=1	M=1	M=1	M=2	M=3	M=3	M=3	M=3	M=4
Decision Confidence	M=1	M=1	M=1	M=1	M=2	M=3	M=3	M=3	M=3	M=4
Decision Accuracy	M=1*	M=1*	M=1	M=1		M=3*	M=3*	M=3	M=3	

M = Model
S = Spatial Scanning
F = Field Independence
T = Task Complexity
S = Spatial Relations

*Logistic regression was employed on these models.

5.13 Conclusion

This chapter contains a discussion of the methodology for the experimental study that was conducted. The software packages, subjects, visuospatial tests and decision tasks employed in the study were presented first. This was followed by definitions of the dependent variables (time, DSS features, decision confidence, and decision accuracy), independent variable (task structure), explanatory variables (spatial ability factors), and the control variable (computer experience). The research hypotheses were then developed. The hypotheses were tested for the decision-making stages model formulation and data analysis. The statistical models employed to analyze the results were than presented.

Chapter 6

Statistical Results

6.0 Introduction

This chapter contains the results of the laboratory study described in Chapter 5. Manipulation checks, descriptive statistics, and test of the hypotheses are presented.[34] The analysis of hypotheses relating to the model formulation tasks will be presented first, followed by the analysis of hypotheses relating to the data analysis tasks.

As discussed in Chapter 5, regression models were employed to identify existing relationships between spatial ability factors decision-making performance in various decision-making stages. The decision-making stages in the study were model formulation and data analysis. Fifty subjects took part in the study. Twenty-eight subjects were in the model formulation group when the case was moderately complex and in the data analysis group when the case was complex. Twenty-two subjects were in the model formulation group when the case was complex and in the data analysis group when the case was moderately complex (see Table 6).[35]

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[34] For all statistics run on the computer, the statistical package employed was SAS, release No. 5.18 at VPI&SU. The SAS program was used to run the logistic regression model; the subroutine to run logistics is supported by F. Harrell and B. Peterson from Duke University Medical Center.

[35] Ten subjects who could not complete both cases and four subjects identified as outliers were dropped from the study, and are not included in the statistics. See section 6.4 for further discussion.

Table 6

Number of Subjects Participating in Each Stage of Decision Making

Dependent Variable	Model Formulation Tasks					Data Analysis Tasks				
	Mod. Comp.		Complex			Mod. Comp.		Complex		
	S	F	S	F	S*T	R	F	R	F	R*T
Time	28	28	22	22	50	22	22	28	28	50
DSS Features	28	28	22	22	50	22	22	28	28	50
Decision Confidence	28	28	22	22	50	22	22	28	28	50
Decision Accuracy	28	28	22	22		22	22	28	28	

S = Spatial Scanning
F = Field Independence
T = Task Complexity
R = Spatial Relations

6.1 Manipulation Checks

In this section manipulation checks on group differences are presented first, followed by a discussion on how the information in each case was perceived by the subjects. Although wording of the cases was the same for subjects formulating a model and subjects employing a predefined model, their responses are reviewed separately because inherently subjects receiving a model were provided with more information than subjects developing their own model.

Two checks were performed to determine whether the experimental sessions differed. Because the first experimental session involved five groups of subjects, the spatial ability tests were administered to each group at different times. Analysis of variance was run to detect any group differences in spatial ability. As is shown in Appendix O, there were no significant differences between the 5 groups on spatial scanning, spatial relations, and field independence. Thus, randomization of subjects was insured.

A second test was performed on the 9 experimental groups to assess whether the experimental sessions differed and whether the training session was adequate for the subjects to complete the cases. Responses to questions 2 and 3 on the posttask questionnaire (Appendix N) are presented (see Appendix P). An ANOVA was performed on the mean responses to these questions to identify any group differences. As is shown in Appendix P, there were no significant differences between the experimental groups on the effectiveness of employing IFPS and the adequacy of the training session. Because the groups did not differ, it was assumed that the experimental sessions were similar and hence, the groups could be combined for further analysis. Eighty-five percent felt that employing

IFPS enhanced their ability to solve the cases, and ninety-six percent felt that the training session was sufficient (see Appendix P).

In the study, each subject received two experimental cases. Twenty-nine subjects solved a moderately complex case without a model and a complex case with a predefined model (Appendix F); twenty-three subjects received a moderately complex case with a predefined model (Appendix D) and a complex case without a model. Questions 2 and 3 in the postcase questionnaire (Appendix H) were asked to assess whether the information in the cases was sufficient for solving the problem and whether the presentation of the information was easy to comprehend. Question 4 in the postcase questionnaire (Appendix H) was asked to assess whether the predefined model was effective in solving the case. Responses to these questions are provided in Appendix Q and Appendix R.

Ninety-three percent of the subjects without a model and 95% of the subjects employing the predefined model agreed that the information was sufficient. Ninety percent of the subjects formulating a model and 87% of the subjects employing a predefined model agreed that the presentation of the information was easy to understand.

Among the subjects completing the complex case, perceptions on the adequacy of the information and the ease of understandability of the information were not as consistent as in the moderately complex case. Sixty-eight percent of the individuals with no model and 72% of the individuals with a predefined model felt the information was sufficient. An additional 13% of the individuals with no model felt the information was neither inadequate nor sufficient. With respect to the ease of understandability of the information presentation, 52% of the individuals without a model and 58% of the individuals with a model felt the information was not difficult to understand of which 26% and 14% respectively, felt it was neither easy nor difficult.

The lack of agreement in the responses to the complex case may have implications for interpreting the results. One possible explanation for the disagreement in the responses is that the presentation of the information in the complex case was perceived as complex, confounding the responses to the sufficiency and understandability of the information. This point is particularly pertinent to Question 3 on whether the presentation of the information is easy or difficult to understand. Because of the wording of this question, some individuals may have evaluated the information as being difficult to understand when the case is complex and the reverse when the case is moderately complex.

Another possible reason for disagreement among the responses may be that familiarity with this type of problem may influence how subjects perceived the cases. This would be particularly true for the responses to Question 2. Individuals with less familiarity with this type of problem may have felt the information was less adequate than individuals with more familiarity. Because data was only collected on general decision-making experience, an evaluation cannot be performed on this possibility.

The lack of agreement in the responses to Question 2 may possibly affect the performance measures of time, confidence, and accuracy. Individuals who felt the information was inadequate probably wanted additional information. Because these individuals had trouble identifying the information in the case that was needed to solve the problem, they may have taken longer to solve the problem, been less confident in their decision, and have been more apt to arrive at the wrong answer than the individuals who felt the information was sufficient. To check for this, the performance scores of those individuals who assessed the information as inadequate were compared to the average performance scores of the group. Out of 12 subjects, the number of subjects that were below the average performance scores for confidence and accuracy were 7 and 6, respectively. Eight out of 12 subjects were above the average time required to complete the task. If the perceived inadequacy of the information had an effect on performance, it would be expected that more of the subjects' performance scores would be below the average score for confidence and accuracy and above for time. This was found only when time was the measure of performance.

To assess whether the predefined decision model had been useful in solving the cases, Question 4 in the postcase questionnaire (Appendix H) was asked. For the moderately complex case, 96% of the subjects agreed that the model enhanced their decision effectiveness. For the complex case, 72% of the subjects agreed that the model improved their decision effectiveness. When the performance scores of individuals reporting the model had a negative effect on their decision effectiveness were compared with the average scores of the group, there was no difference found. Hence, it may be assumed that the subjects' perception of the models effectiveness had no effect on performance.

Question 5 in the postcase questionnaire (Appendix H) was asked in order to assess whether task complexity was achieved. Responses to this question are found in Appendix S. A *t* test was run on the mean responses to task complexity level of the moderately complex case and the complex case. The results indicate that the perceived complexity levels of the moderately complex case and the complex case were different at the significance level .05 (p value = .001) (see Appendix S).

6.2 Descriptive Statistics

In this section, performance scores are presented and discussed. Performance scores for the moderately complex case and complex case are presented in Table 7. As expected, the time required to complete the cases and the number of DSS features employed were less for the moderately complex task than for the complex task. When the subjects were not provided a model to solve the cases, the average performance scores for time and DSS features for the complex case were almost twice the average scores in the moderately complex case. In the moderately complex case, the average time was 16.28 and the average number of DSS features employed was 25.21, whereas in the complex case, the average time was 48.54 and the number of DSS features employed was 52.13. When the subjects were provided a predefined model, the average performance scores for time and DSS features were 12.45 and 25.00 for the moderately complex case, and 34.14 and 34.96 for the complex case. Furthermore, the confidence level of the subjects was, as expected, less for the complex case than for the moderately complex case. The subjects' confidence level was approximately two levels lower for the complex case than for the moderately complex case when a model was not provided and when a predefined model was provided to solve the cases.

The subjects' performance when they employed a predefined model and when they developed their own model were as expected. For the moderately complex case, subjects employing the predefined model took less time, used approximately the same number of DSS features, and were more confident than subjects developing their own model. On average, when a predefined model was provided, the subjects took approximately 5 minutes less, used approximately one less DSS feature, and were one confidence level higher than the subjects without a model. For the complex case, the subjects took less time, used more DSS features, and were more confident when employing the predefined model. When the subjects were provided with a model, on average they took 14 minutes less time, employed 20 less DSS features, and were one confidence level higher than when the subjects were not provided with a model. This suggests that the performance measures were in line with what they should have been.

Table 7: Comparison Between Moderately Complex and Complex Case Experimental Groups on Performance Measures

Model Formulation

Moderately Complex Case

Dependent Variables	N	Mean	Std Dev.	Min.	Max.
Time - minutes	28	16.28	5.57	7	31
DSS Features (0 to #)	28	25.21	13.50	9	51
Confidence (1 to 7)	28	5.35	1.87	1	7

	N	Frequency	Percent
Answer - correct	28	25	90

Complex Case

Dependent Variables	N	Mean	Std Dev.	Min.	Max.
Time	22	48.54	15.65	15	82
DSS Features (0 to #)	22	52.13	27.45	18	116
Confidence (1 to 7)	22	3.81	1.53	1	6
Answer (0 to 10)	22	6.00	2.04	2	10

Data Analysis

Moderately Complex Case

Dependent Variables	N	Mean	Std Dev.	Min.	Max.
Time	22	12.45	6.82	5	28
DSS Features (0 to #)	22	25.00	10.65	13	50
Confidence (1 to 7)	22	6.22	0.81	5	7

	N	Frequency	Percent
Answer - correct	22	19	87

Complex Case

Dependent Variables	N	Mean	Std Dev.	Min.	Max.
Time	28	35.14	11.15	19	57
DSS Features (0 to #)	28	34.96	16.77	13	71
Confidence (1 to 7)	28	4.21	1.57	1	7
Answer (0 to 10)	28	8.14	2.10	4	10

6.3 Statistical Test of the Hypotheses

The following sections contain the statistical results of the regression models run on each dependent variable: 1) time, 2) DSS features, 3) confidence, and 4) decision accuracy. The significance level of .05 was chosen to test the hypotheses. The SAS program used to run the data is in Appendix T.[36]

6.3.1 Hypothesis 1 : The spatial scanning ability and field independence of the subjects will have no effect on 1) time to complete the task, 2) DSS features employed, 3) confidence, and 4) decision accuracy in the model formulation tasks.

The purpose of the first hypothesis is to investigate whether spatial scanning ability and field independence ability explains performance on model formulation tasks. Performance was assessed in terms of time to complete the task, DSS features employed, confidence in the decision, and decision accuracy. Regression model 1 was run for each dependent variable on the moderately complex case and the complex case.

When performance was assessed in terms of time, neither spatial scanning (measured by Map Planning Test) nor field independence (measured by Hidden Figures Test) were found to be significantly related to performance (see Table 8). The results were the same for both the moderately complex case and the complex case. Spatial scanning and field independence were not found to be significantly related to performance when performance was assessed in terms of the number of DSS features employed for both the moderately complex case and the complex case (see Table 9). Confidence in one's decision and decision accuracy were also not found to be related to spatial scanning nor to field independence for both the

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[36] A test run on the program was performed with dummy data to ensure the program was working properly.

moderately complex case and the complex case (see Table 10 and Table 11). Thus, hypothesis 1 cannot be rejected when performance is assessed by time, DSS features employed, confidence, and decision accuracy.

Table 8: Model Formulation - Regression with Time as a Performance Measure

Dependent Variable: Time

Moderately Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	199.735	66.578	2.497	0.0840
Error	24	639.978	26.665		
Corrected total	27	839.714		**R-Square**	0.2379

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	22.923	4.363	5.253	.0001
Computer Experience	1	-2.656	0.973	-2.731	.0117
Spatial Scanning	1	0.138	0.158	0.874	.3909
Field Independence	1	-0.132	0.251	-0.527	.6030

Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	551.708	183.902	0.721	0.5525
Error	18	4591.746	255.097		
Corrected total	21	5143.454		**R-Square**	0.1073

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	68.989	15.726	4.387	.0004
Computer Experience	1	-4.500	3.458	-1.301	.2095
Spatial Scanning	1	-0.009	0.498	-0.019	.9851
Field Independence	1	-0.575	0.908	-0.634	.5342

Table 9: Model Formulation - Regression with DSS Features as a Performance Measure

Dependent Variable: DSS Features

Moderately Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	140.888	46.962	0.236	0.8706
Error	24	4781.825	199.242		
Corrected total	27	4922.714		**R-Square**	0.0286

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	32.404	11.928	2.717	.0120
Computer Experience	1	-1.913	2.659	-0.719	.4789
Spatial Scanning	1	-0.054	0.432	-0.126	.9010
Field Independence	1	0.082	0.686	0.120	.9053

Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	17.989	5.996	0.007	0.9992
Error	18	15814.601	878.588		
Corrected total	21	15832.590		**R-Square**	0.0011

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	53.402	29.185	1.830	.0839
Computer Experience	1	-0.767	6.41	-0.120	.9061
Spatial Scanning	1	0.095	0.924	0.103	.9191
Field Independence	1	-0.097	1.685	-0.058	.9543

Table 10: Model Formulation - Regression with Confidence as the Performance Measure

Dependent Variable: Confidence

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	3	7.993	2.664	0.740	0.5387
Error	24	86.435	3.601		
Corrected total	27	94.428		**R-Square**	0.0847

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	4.396	1.603	2.742	.0114
Computer Experience	1	-0.172	0.357	-0.482	.6345
Spatial Scanning	1	0.083	0.058	1.432	.1650
Field Independence	1	-0.060	0.090	-0.653	.5201

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	3	3.155	1.051	0.411	0.7474
Error	18	46.117	2.562		
Corrected total	21	49.272		**R-Square**	0.0640

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	5.141	1.576	3.262	.0043
Computer Experience	1	-0.311	0.346	-0.898	.3809
Spatial Scanning	1	0.013	0.049	0.272	.7890
Field Independence	1	-0.068	0.091	-0.752	.4617

Table 11: Model Formulation - Regression with Decision Accuracy as the Performance Measure

Dependent Variable: Decision Accuracy

Moderately Complex Case

	DF	**Chi-Square**	**Probability**
Model	3	1.89	.5952

Variable	**Beta**	**Std Error**	**Chi-Square**	**Probability**
Intercept	5.617	4.010	1.96	0.1610
Computer Experience	-0.868	0.792	1.20	0.2730
Spatial Scanning	-0.018	0.101	0.03	0.8590
Field Independence	0.026	0.193	0.02	0.8920

Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	15.846	5.282	1.318	0.2995
Error	18	72.153	4.008		
Corrected total	21	88.000		**R-Square**	0.1801

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	2.436	1.971	1.236	.2324
Computer Experience	1	0.281	0.433	0.649	.5244
Spatial Scanning	1	0.071	0.062	1.139	.2695
Field Independence	1	0.117	0.113	1.031	.3163

6.3.2 Hypothesis 2: There is no interaction effect between spatial scanning ability and task structure on 1) time to complete the task, 2) DSS features employed, and 3) decision confidence in the model formulation tasks.

The second hypothesis was concerned with the interaction effect between spatial scanning (measured by Map Planning Test) and task structure (complexity) on performance in model formulation tasks. Performance was assessed by time to complete a task, DSS features employed, and confidence in the decision. When time and DSS features were employed to assess performance, there was no significant interaction effect between spatial scanning and task structure (complexity) (see Table 12). When performance was assessed by confidence there was not a significant interaction effect between spatial scanning and task complexity (see Table 13). Therefore, the second hypothesis cannot be rejected for the performance measures: time, DSS features, and confidence.

Table 12: Model Formulation - Interaction Effects of Spatial Ability and Task Complexity Level when Performance is Assessed by Time and DSS features

Dependent Variable: Time

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	13505.348	2701.069	22.42	0.0001
Error	44	5299.131	120.434		
Corrected total	49	18804.480		R-Square	0.7182

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	590.42	4.90	0.0320
Complexity	1	1578.94	12.00	0.0008
Spatial Scanning	1	28.37	0.24	0.6298
Field Independence	1	75.35	0.63	0.4332
Spatial Scanning * Complexity	1	44.35	0.37	0.5470

Dependent Variable: DSS Features

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	9063.644	1812.728	3.87	0.0054
Error	44	20621.175	468.663		
Corrected total	49	29684.820		R-Square	0.3053

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	99.938	0.21	0.6465
Complexity	1	533.549	1.14	0.2918
Spatial Scanning	1	18.921	0.45	0.8417
Field Independence	1	0.037	0.00	0.9929
Spatial Scanning * Complexity	1	19.265	0.04	0.8403

* Because of unequal group sizes, Type III Sums of Squares are reported.

Table 13: Model Formulation - Interaction Effects of Spatial Ability and Task Complexity Level when Performance is Assessed by Confidence

Dependent Variable: Confidence

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	40.092	6.682	2.66	0.0349
Error	44	132.787	3.017		
Corrected total	49	172.880		**R-Square**	0.2319

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	2.667	0.88	0.3522
Complexity	1	0.136	0.05	0.8527
Spatial Scanning	1	1.024	0.34	0.5632
Field Independence	1	2.981	0.99	0.3257
Spatial Scanning * Complexity	1	3.494	1.16	0.2878

* Because of unequal group sizes, Type III Sums of Squares are reported.

6.3.3 Hypothesis 3: The spatial relations ability and field independence of the subjects will have no effect on 1) time to complete the task, 2) DSS features employed, 3) confidence, and 4) decision accuracy in the data analysis tasks.

The purpose of the third hypothesis was to investigate whether spatial relations ability (as measured by MRT) and field independence ability (as measured by Hidden Figures Test) are predictors of performance in data analysis tasks. Performance was assessed in terms of time to complete the task, DSS features employed, confidence in the decision, and decision accuracy. A regression model was run for each dependent variable and for each task complexity level.

When subjects were provided with a decision model, spatial relations ability and field independence ability were not found to be significantly related to time (see Table 14). Thus, when performance is assessed by time hypothesis 3 cannot be rejected. Field independence was found to be significantly related to the number of DSS features employed at the .05 significance level in the moderately complex case (see Table 15). This relationship did not hold in the complex case.

For the moderately complex case, field independence was found to be significantly related to confidence in the decision with a T statistic = 2.286 and p value = .03 (see Table 16). Thus, when performance is measured in terms of confidence and the task structure is moderately complex, the third hypothesis is rejected at the significance level of .05. For the complex case, spatial relations was found to be significantly related to confidence with a T statistic = 2.844 and p value = .009 (see Table 16). Therefore, the third hypothesis is rejected when performance is assessed in terms of confidence in the complex case.

For the moderately complex case and the complex case, spatial relations and field independence were not found to be related to decision accuracy (see Table

17). Thus at alpha =.05, the null form of hypothesis 3 cannot be rejected when decision accuracy is the measure of performance.

Table 14: Data Analysis - Regression with Time as a Performance Measure

Dependent Variable: Time

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	3	366.102	122.034	3.581	0.0344
Error	18	613.352	34.075		
Corrected total	21	979.454		**R-Square**	0.3738

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	27.032	5.327	5.074	.0001
Computer Experience	1	-4.092	1.264	-3.237	.0046
Spatial Relations	1	0.102	0.170	0.603	.5537
Field Independence	1	-0.279	0.341	-0.818	.4240

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	3	223.591	74.530	0.570	0.6401
Error	24	3137.836	130.743		
Corrected total	27	3361.428		**R-Square**	0.0665

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	43.225	8.888	4.863	.0001
Computer Experience	1	-1.514	2.021	-0.749	.4610
Spatial Relations	1	-0.272	0.269	-1.008	.3234
Field Independence	1	0.214	0.560	0.383	.7048

Table 15: Data Analysis - Regression with DSS Features as a Performance Measure

Dependent Variable: DSS Features

Moderately Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	692.275	230.758	2.458	0.0960
Error	18	1689.724	93.873		
Corrected total	21	2382.000		**R-Square**	0.2906

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	45.173	8.842	5.108	.0001
Computer Experience	1	-4.358	2.098	-2.077	.0524
Spatial Relations	1	0.242	0.282	0.858	.4022
Field Independence	1	-1.149	0.566	-2.027	.0577

Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	645.954	215.318	0.743	0.5367
Error	24	6951.010	289.625		
Corrected total	27	7596.964		**R-Square**	0.0850

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	28.582	13.228	2.161	.0409
Computer Experience	1	-0.215	3.008	-0.072	.9434
Spatial Relations	1	-0.063	0.401	-0.158	.8757
Field Independence	1	1.227	0.834	1.471	.1543

Table 16: Data Analysis - Regression with Confidence as the Performance Measure

Dependent Variable: Confidence

Moderately Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	3.709	1.236	2.192	0.1243
Error	18	10.154	0.564		
Corrected total	21	13.863		**R-Square**	0.2675

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	6.107	0.685	8.909	.0001
Computer Experience	1	-0.020	0.162	-0.129	.8992
Spatial Relations	1	-0.035	0.021	-1.637	.1190
Field Independence	1	0.100	0.043	2.286	.0346

Complex Case

Source	**DF**	**Sum of Square**	**Mean Square**	**F Statistic**	**Probability**
Model	3	17.844	5.948	2.921	0.0546
Error	24	48.869	2.036		
Corrected total	27	66.714		**R-Square**	0.2675

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**T Statistic**	**Probability**
Intercept	1	2.353	1.109	2.122	.0443
Computer Experience	1	0.080	0.252	0.321	.7513
Spatial Relations	1	0.095	0.033	2.844	.0090
Field Independence	1	0.006	0.069	0.092	.9273

Table 17: Data Analysis - Regression with Decision Accuracy as the Performance Measure

Dependent Variable: Decision Accuracy

Moderately Complex Case

	DF	Chi-Square	Probability
Model	3	3.34	.3418

Variable	Beta	Std Error	Chi-Square	Probability
Intercept	1.202	4.338	0.08	0.7818
Computer experience	-0.667	0.820	0.66	0.4159
Spatial Relations	1.139	0.178	0.61	0.4342
Field Independence	1.790	0.247	0.52	0.4690

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	3	10.116	3.372	0.740	0.5384
Error	24	109.312	4.554		
Corrected total	27	119.428		**R-Square**	0.0847

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	8.921	1.658	5.378	.0001
Computer Experience	1	-0.140	0.377	-0.373	.7124
Spatial Relations	1	0.040	0.050	0.803	.4300
Field Independence	1	-0.144	0.104	-1.377	.1812

6.3.4 Hypothesis 4: There is no interaction effect between spatial relations ability and task structure on 1) time to complete the task, 2) DSS features employed, and 3) decision confidence in the data analysis tasks.

The fourth hypothesis of the dissertation was concerned with the interaction effect between spatial relations (as measured by MRT) and task structure (complexity) on performance in data analysis tasks. Performance was assessed by time to complete a task, DSS features employed, and confidence in the decision. When time was employed to assess performance, there were no significant interaction effects between spatial relations and task structure (see Table 18). Thus, the null form of hypothesis 4 cannot be rejected when performance is assessed by time to complete the task.

When performance was assessed by DSS features employed, there were no interaction effects between spatial relations and task structure (see Table 18). Therefore, at the .05 alpha level, the fourth hypothesis cannot be rejected when DSS features is employed as the measure of performance. When performance was assessed by confidence, an interaction effect exists with a F statistic = 8.43 and p value = .005 (see Table 19). Individuals with high spatial relations ability are to be more confident in their decisions than individuals low in spatial relations ability. This relationship between spatial relations ability and confidence is stronger in the complex case than in the moderately complex case. Therefore, at the alpha level .05, the fourth hypothesis is rejected for the performance measure confidence.

Table 18: Data Analysis - Interaction Effects of Spatial Ability and Task Complexity Level when Performance is Assessed by Time and DSS features

Dependent Variable: Time

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	6817.928	1363.585	15.52	0.0001
Error	44	3864.791	87.836		
Corrected total	49	10682.791		**R-Square**	0.6382

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	340.033	3.87	0.0554
Complexity	1	1611.224	18.34	0.0001
Spatial Relation	1	20.629	0.23	0.6303
Field Independence	1	0.314	0.00	0.9526
Spatial Relation * Complexity	1	53.122	0.60	0.4409

Dependent Variable: DSS Features

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	1472.202	294.440	1.33	0.2687
Error	44	9729.977	221.135		
Corrected total	49	11202.180		**R-Square**	0.1314

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	164.830	0.75	0.3926
Complexity	1	171.510	0.78	0.3833
Spatial Relation	1	5.612	0.03	0.8742
Field Independence	1	47.913	0.22	0.6439
Spatial Relation * Complexity	1	6.514	0.03	0.8645

* Because of unequal group sizes, Type III Sums of Squares are reported.

Table 19: Data Analysis - Interaction Effects of Spatial Ability and Task Complexity Level when Performance is Assessed by Confidence

Dependent Variable: Confidence

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	69.683	13.936	10.08	0.0001
Error	44	60.816	1.382		
Corrected total	49	130.500		**R-Square**	0.5339

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	0.066	0.05	0.8280
Complexity	1	34.890	25.24	0.0001
Spatial Relation	1	6.448	4.67	0.0363
Field Independence	1	1.489	1.08	0.3049
Spatial Relation * Complexity	1	11.647	8.43	0.0058

* Because of unequal group sizes, Type III Sums of Squares are reported.

6.4 Outliers and Drop-outs

Prior to running the statistical tests of the hypotheses, several tests were run on the data to check for outliers. Influence diagnostics proposed by Belshley, Kuh, and Welsch (1980) were run to measure the influence of each observation on the estimates. These diagnostics provide a student residual which indicates for each observation whether it lies extremely above or below the sample population. The student residual or standardized residual is the residuals divided by their standard deviation. A student residual greater than 3 is reasonably considered an outlier [Cohen and Cohen, 1983.] Any observation greater than 3 was considered an outlier and dropped from the database. There were four observations dropped, two from the group receiving the moderately complex case with a model and the complex case without a model and two from the group receiving the opposite. The student residuals for these observations ranged from 3.5 to 6.7.

The outliers' spatial ability scores were compared to the remaining group to identify whether spatial ability was the reason for large differences in performance. The mean score for spatial scanning (24.25) was slightly larger than the group's mean score (23.13). The average score on the spatial relations test was 14.87; the groups was 17.15. For field independence, the average was 5.5 compared to the groups, 7.3. Except for spatial scanning ability, the outliers' scores were slightly lower than the group's average. However, these differences do not appear to be great. This suggest that spatial ability was not the reason for large differences in performance scores of the outliers.

Ten subjects who could not complete both cases were dropped from the study. To test whether an individual's spatial ability level was a reason for their inability to complete the cases, a *t* test was run on the spatial ability scores of the subjects not completing the case and those completing the case. All spatial ability scores were significantly different at the .01 alpha level except for field independence. The *t* values for spatial scanning and spatial relations were 7.08 and 2.94, respectively. Drop-out subjects had an average score on the spatial scanning test of 16.61, whereas the experimental group's average was 23.13. On the Spatial Relations test drop-out subjects had an average score of 14.26 in comparison to the experimental group's 17.15 average. For field independence there were no significant differences found with a *t* value of .868. The average scores were 6.68 for the drop-out subjects and 7.32 for the experimental grouup. Although a significant difference was not found with field independence, the experimental group's average was higher.

The outliers had on average a lower ability in spatial relations and field independence than did the experimental group. Drop-out subjects had on average a lower ability in spatial relations, spatial scanning, and field independence than did the experimental group. This indicates that an individual's level of spatial ability may have influenced whether they were able to learn how to employ IFPS and/or solve the experimental cases. Additionally, subjects remaining in the experimental group possess a level of spatial ability which may have implications when interpreting the results or be a limitation of the study.

6.5 Summary of Results

In the model formulation stage of decision making, there were no significant relationships found between performance and spatial scanning or field independence when performance was measured by time, DSS features, confidence, and decision accuracy. In the data analysis stage of decision making, field independence was found to be related to DSS features employed in the moderately complex case. However, when age and decision experience were controlled, this relationship was not significant. When performance was measured by confidence level in the moderately complex case, field independence was found to be significantly related, and in the complex case spatial relations ability was significant. See Table 20 for a summary of these results. Interaction effects were found between spatial relations and task complexity when performance was measured by confidence level (see Table 20).

Table 20

Summary of T Statistics for Significant Hypothesized Relationships

Dependent Variable	Model Formulation Tasks					Data Analysis Tasks				
	Mod. Comp.		Complex			Mod. Comp.		Complex		
	S	F	S	F	S*T	R	F	R	F	R*T
Time										
DSS Features							-2.03*			
Decision Confidence							2.28*	2.84**		8.4**
Decision Accuracy										

M = Model
S = Spatial Scanning
F = Field Independence
T = Task Complexity
R = Spatial Relations

* .05 significance level
** .001 significance level

6.6 Ex Post Facto Analysis

As mentioned in Chapter 5, only those relationships that were supported by prior research were to be examined in the present study. A problem with this approach was that all four spatial factors identified in the literature have not been examined together in the decision-making stages model formulation and data analysis.[37] Therefore, ex post facto analysis was performed employing step-wise regression to identify which spatial ability factors were related to decision-making performance. Although conclusions cannot be made on ex post facto analysis, statistically significant relationships between spatial ability factors and decision-making performance can be identified [Kerlinger, 1982]. This analysis was not performed on the model formulation stage of decision making due to performance measurement problems identified with this stage (see Section 7.1.1 for measurement problem reasons).

Stepwise regression was run on each dependent variable: time, DSS features employed, confidence, and decision accuracy. Stepwise regression was only run for the complex case when the performance was decision accuracy.[38] Computer experience was treated as a control variable and entered into the model prior to entering the spatial factors.

For the moderately complex task, there were no significant spatial ability factors identified when performance was assessed by time. When DSS features was the performance measure, field independence and spatial scanning were significantly related to performance. The F value was 5.09 for field independence

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[37] Spatial visualization was assessed by the Paper Folding Test Part 1 and Part 2 from the Kit Factor-Refernece Cognitive Tests [Ekstrom et al., 1976].

[38] Stepwise could not be run when the case was moderately complex because the variable was discrete.

at p value = .03 and 2.42 for spatial scanning at p value = .13. Field independence and spatial relations were significantly related to performance when confidence was the performance measure. For field independence and spatial relations, the F value was 5.23 and 2.68 at p value .03 and .11, respectively.

Analysis of the complex case revealed relationships between spatial ability and decision-making performance for all performance measures except, decision accuracy. When performance was assessed by time, spatial visualization was a significant variable with a F value of 3.44 at p value .07. Spatial visualization and field independence were found to be significantly related to DSS featured employed. The F value was 4.59 for field independence at p value = .04 and 2.59 for spatial visualization at p value = .12. Finally, when confidence is the performance measure spatial relations was significantly related with an F value of 8.95 at p value = .006.

Although the hypothesized relationships did not provide support that spatial ability is related to decision-making performance in a DSS environment, the ex post facto analysis provided some support for the influence of spatial ability on performance. Furthermore, this analysis identified which spatial factors were important to the various performance measures.

Table 21
Summary of F Statistics for StepWise Regression
Data Analysis Tasks

Moderately Complex Case				
	Spatial Ability Factors			
Dependent Variable	Spatial Visualization	Spatial Scanning	Spatial Relations	Field Independence
Time				
DSS Features		2.42 .13		5.09 .03
Confidence			2.68 .11	5.23 .03
Complex Case				
	Spatial Ability Factors			
Dependent Variable	Spatial Visualization	Spatial Scanning	Spatial Relations	Field Independence
Accuracy				
Time	3.44 .07			
DSS Features	2.59 .12			4.59 .04
Confidence			8.95 .006	

6.6 Chapter Summary

The results of the laboratory study have been presented in this chapter, including manipulation checks and descriptive statistics. As a result of the manipulation checks, two problems were identified with the complex case. The subjects were not in agreement that the information was sufficient for solving the cases and that the presentation of the information was easy to understand. Two explanations were proposed for the disagreement among the responses to the complex case: 1) inherently the presentation of the information was complex, and 2) experience with this type of task may influence subjects' perception of the case.

Although few of the hypothesized relationships were found in the data, other relationships that were not hypothesized did exist among the variables. Furthermore, analysis of the subject's spatial ability scores that were dropped from the study, indicate that the relationship between spatial ability and performance may not be linear. Further discussion on the results and on the lack of significance results will be provided in Chapter 7.

Chapter 7

Conclusions, Limitations, and Extensions

7.0 Introduction

The primary purpose of this study was to identify which factors of spatial ability moderate decision making in a DSS environment. The secondary goal was to determine the effect that task complexity has on the influence of spatial ability and decision-making performance in a DSS environment. Two stages of decision making were investigated: model formulation and data analysis. To accomplish these goals a controlled laboratory study was conducted. Fifty subjects completed two cases: 1)formulating a model to solve the case, and 2)employing a predefined model to solve the case. Furthermore, each subject received a moderately complex case and a complex case. This chapter contains discussion on the conclusions of the results, limitations of the study, and directions for future research.

7.1 Conclusions

This section contains a discussion on the results of the study with respect to the research questions presented in Chapter 3. An overall interpretation of the results of this study could be that spatial ability has no impact on information processing performance of individuals in a DSS environment. This observation is based on the fact that only 4 of the 38 hypotheses tested supported the proposed research model which postulated that spatial ability was a moderating factor on information processing.

As mentioned early, few studies have been performed that have examined all four spatial ability factors. Additionally, in the DSS literature, field independence is the only factor of spatial ability that has been examined. The present study examines only the relationships and interaction effects that have been supported in prior research. Other relationships and interaction effects between performance and spatial ability factors not hypothesized were presented in Section 6.6. Conclusions cannot be reached with respect to these results; however, non-hypothesized relationships present among the variables were identified. These statistically significant relationships are of interest for future research. In the remaining sections of the chapter, the research questions will be discussed in relation to the decision-making stages: model formulation and data analysis.

7.1.1 Model Formulation

In this section the first research question is addressed with respect to the model formulation stage of decision making. The first question was stated as follows:

> Does an individual's spatial ability (spatial scanning and field independence) influence decision making in a DSS environment when controlling for computer experience?

Based on Baddeley and Hitch's [1974] model of how information is processed in short-term memory, a distinction is made between two systems in which verbal processing and spatial processing take place. Their model suggests that spatial ability is a distinct ability required in problem solving. In the DSS literature field independence ability has been associated with problem structuring. Research on programming indicates that spatial scanning is related to problem structuring. This study did not find support for either of these spatial ability factors in the decision-making stage model formulation.

One possible explanation for differences found between the results of the present study and prior studies is that the decision tasks differed to a large extent, hence not requiring the same abilities. In Pracht and Courtney's 1988 study field independence was found to be associated with problem structuring. The decision task was to determine the price, quality, and volume of a product for a company over a time period with the goal of maximizing long-term profit. Three differences in the tasks of Pracht & Courtney's study and the present study are as follows:

1. more relationships existed between the variables in the task employed in Pracht and Courtney's study;
2. the DSS employed in Pracht and Courtney's study used a graphical depiction of the relationships among the variables; and
3. decisions were assessed over several time periods, rather than just one period.

These differences between the tasks administered in the studies may explain why the findings were inconsistent.

Because research on spatial ability in the DSS literature has focused only on field independence, research in the educational literature was reviewed to identify relationships between spatial ability factors and model formulation performance. An assumption was made that programming was similar to model formulation, i.e., individuals in both tasks must manipulate the data and decision models until an optimal solution is found. Iron's [1982] identified spatial scanning ability as being related to identifying the problem area. This assumption may not be valid.

Other possible reasons for insignificant findings with regard to spatial scanning ability and field independence will be discussed in relation to the performance measures: time, DSS features, and decision accuracy. Unlike the spatial ability tests where subjects were given a time limit to complete the tests, subjects were given an unlimited time to complete each case. This may have resulted in some individuals completing the task more slowerly than they could.

In observing the raw data, a variation in the number of DSS features employed by the subjects appeared to be dependent on how they developed their model. Some individuals developed a model that provided answers under various conditions. These subjects used a small number of DSS features. Other individuals developed a model in which 'what-if' analysis was performed on the model to arrive at the answers for the various conditions. When the individuals solved the cases by performing "what-if" analysis, they used more DSS features. Hence, the approach the individual employed to solve the task may have determined the number of DSS features employed, rather than spatial ability.

Decision accuracy was measured on different scales for the moderately complex case and the complex case. For the moderately complex case decision accuracy was assessed as either right or wrong. Two problems arose in analyzing the data. First, a large sample size is required in logistic regression which was not obtained in the present study. Second, a majority of the subjects arrived at the correct solution (25 out of 28), resulting in little variation in the responses.

In conclusion, spatial scanning and field independence were not found to be related to performance in the decision-making stage model formulation. This suggest that the processing of information is similar for low spatial ability individuals and high spatial ability individuals. One plausible reason that these findings differed from prior studies is that the decision tasks were significantly different from each other, hence requiring different abilities. The lack of research on spatial ability factors in the model formulation decision-making stage contributed to the problem of identifying which spatial ability factors influenced decision-making performance. Several problems were discussed with respect to the measures of performance. Based on these measurement problems, a conclusive statement can not be made with respect to spatial scanning and field independence, and their relationships with decision-making performance.

7.1.2 Interaction Effects - Model Formulation

The second research question dealt with the interaction effects between spatial ability factors and task complexity. It was expected that the association between spatial scanning and performance would be stronger when the task complexity level was greater. The research results do not support this expectation, hence in the model formulation stage there appears to be no relationship between performance and task complexity under differing task structures. To ensure that manipulation of task complexity was achieved, a *t* test was run on the perceived complexity rating for moderately complex case and the complex case. The cases were perceived to be significantly different at the P value = .001. Although the task complexity was manipulated successfully, potential problems with the measurement of decision-making performance discussed in the previous section may be a plausible reason for insignificant findings.

7.1.3 Data Analysis

In this section, the results on the data analysis stage of decision making are discussed with respect to the first research question. The first research question was stated as follows:

> Does an individual's spatial ability (spatial relations and field independence) influence decision making in a DSS environment when controlling for computer experience?

The most widely studied spatial ability factor in the DSS literature, field independence, has been found to be related to decision-making performance in the data analysis phase of decision making. Another spatial factor identified in this paper as relating to decision performance was spatial relations. Although this factor has not been directly associated with decision making performance in the literature, spatial relations ability may be related to performance on data analysis tasks because data analysis tasks and test of an individual's spatial relations ability require an individual to compare similar stimuli from differing perspectives and choose between competing alternatives.

The findings in the present study did not provide support for most of the hypothesized relationships. In the moderately complex case, field independence was found to be significantly related to confidence in the decision and weakly related to DSS features employed. Unlike the model formulation stage, where the number of DSS features employed maybe related to the decision-making approach, in the data analysis stage all subjects were given a model in which they performed "what-if" analysis to arrive at a solution. The finding that field independence is associated with confidence supports prior findings in the psychology literature that suggests that high visualizers are more confident in the decisions than low visualizers, i.e., individuals that can retain a vivid image of an object are more confident. The field independence test requires an individual to retain an image of an object and find that image in a complex arrangement.

In the complex case, spatial relations was found to be associated with confidence in the decision. Again, these findings are in agreement with the psychology literature. Individuals who are good at retaining a vivid image are more confident in their decision. Tests on spatial relations ability requires the individual to visualize an image in a rotated position. One possible reason that spatial relations was related to confidence in the complex case and field independence in the moderately complex case is the difference in the difficulty levels of the two tasks. The complex case had more relationships among the variable that needed to be manipulated than the moderately complex case. Similarly, the test on spatial relations was three- dimensional as compared to the two-dimension figures in the field independence test, and it required the subjects to rotate the image as compared to not rotating the image in the field independence test.

Reasons for the lack of support for the relationships between field independence and the dependent variables time and decision accuracy may be similar to problems identified in the model formulation stage of decision making. First, tasks in the prior studies differed in that they employed simulation models in which subjects were required to determine a production schedule or select a price-quantity combination. This task is different from the present study that employed a debt/equity problem.

Another potential problem is that the subjects were given as much time as needed to solve the cases. The time taken by individuals to complete the cases may have been shorter for some individuals had there been a time constraint. Finally, because logistic regression requires a large sample size and a large sample size was not obtained in the present study, the analysis of the results are weak for the performance measure decision accuracy. Additionally, there was little variance in the responses making it diffucult to identify any relationships.

In conclusion, field independence was found to be associated with DSS features employed in the moderately complex case. Although this relationship was significant with a p value = .05, field independence was not found to be related to DSS features employed in the complex case. Because of these inconsistent results, the relationship found between DSS features and field independence in the moderately complex case is questionable.

With respect to the performance measure confidence, field independence was identified as a significant variable when the task was moderately complex and spatial relation was identified a significant variable when the task was complex. These findings support prior research in psychology literature that high visualizers are more confident in their decisions. Finally, reasons for insignificant results for performance measures time and decision accuracy were put forth.

7.1.4 Interaction Effects - Data Analysis

The second research question is addressed with respect to the data analysis stage of decision making in this section. The second research question was stated as follows:

> Is spatial ability more important to decision-making performance when the task structure is complex than when it is moderately complex?

Although it is recognized that task complexity influences decision performance few studies in the DSS literature have examined this variable. A t test was run on the perceived complexity rating for the moderately complex case and the complex case to check if task complexity differences were percieved (see Appendix S). In the present study, an interaction effect was found between spatial relation and task complexity when performance was assessed as decision confidence. Individuals with high spatial relations ability tended to be more confident in their decisions than individuals with low spatial relations ability. A larger confidence difference was found when the case was complex as compared to the moderately complex case. This suggest that when the tasks are complex a large within group difference is found on spatial relations ability than when the task is moderately complex.

7.2 Limitations

As in all laboratory studies controlling for confounding variables is an important and difficult task. In the present study, self reports were collected on computer experience. The accuracy of these reports determines the explanatory information they provide. Because some subjects may have reported use of a software package for numerous months but actually had little knowledge of how to use it, the operationalization of this measure may not have been precise. Additionally, lack of variability in the age and decision making experience measures may have reduced the explanatory power of the control measures. Lack of variability was due to a small sample size and a homogeneous group of subjects.

Eliminating outliers and drop-outs also reduced the variability of spatial ability among the subjects in the experiment. On average the spatial ability scores of these subjects were below the experimental groups, hence eliminating lower spatial ability individuals and reducing the generalizability of the results. Self selection occurred as a result of high spatial ability subjects being able to complete the cases. Had an upper limit been set on the number of DSS features employed and the amount of time spent on the case, the results may have differed.

Another potential problem with the study involved the cases employed. The lack of agreement among the subjects with respect to the sufficiency and presentation of the information in the complex case suggests that performance may have been affected by the case presentation. Developing cases which all individuals could complete was difficult without a homogenous group of decision makers. Although in this study graduate level students were employed, their backgrounds were diverse with respect to courses taken and work experience. A solution to this problem would be to have a population of individuals with similar knowledge or experience.

As in many studies that employ software packages, a problem with decision-making performance is that the individual must master the software package before an assessment of decision making can be made. In the present study, individuals that could not complete the task were eliminated from the study to control for this problem. This was done based on the assumption that these individuals did not have enough knowledge to solve the case or that they did not acquire enough computer skills to solve the case. Although ninety-six percent of the subjects who completed the cases felt that the training session was sufficient, either extending the study to include more practice problems or testing the subjects on their knowledge of the system may have eliminated any computer usage problems. Furthermore, individuals that had trouble completing the cases also had significant lower scores than individuals completing the case. This may indicate that a certain level of spatial ability was necessary to understand how to use the system in the allotted time period or to complete the cases.

7.3 Future Research

As mentioned earlier, studies in the DSS literature have examined only one factor of spatial ability, field independence. Further research is needed to increase the understanding of the relationship between spatial ability factors and decision making in a DSS environment. Several research directions are described in this section.

The present study examined whether spatial ability was associated with decision-making performance in a DSS environment. In interpreting the results, it is difficult sometimes to assess whether decision performance is a result of the individual's ability to solve the case or the individual's ability to use the software. Because of the complexity of this research environment and the lack of prior research in this area, there are two major directions for research to be undertaken. The first direction of research focuses on decision making when a computer is not present. This direction of research can be divided into several areas.

1. Because stages of decision making contain rather distinct processes, initially it is important to investigate each stage separately. Therefore, the three stages of decision making in which spatial ability should be investigated are : 1) problem identification, 2) problem structuring, and 3) data analysis.
2. In a business environment numerous types of decisions are made; all requiring different abilities. Further research is needed to identify which type of problems require spatial ability. By categorizing decisions requiring verbal and spatial abilities, the quality of future research can be improved.

3. As pointed out in earlier chapters, task complexity level is an important factor when assessing performance. Further research is needed on assessing complexity levels of a task and on identifying at what point task complexity influences an individual's ability to solve a problem.
4. The last area of research deals with the decision-making experience level of the subjects. In the present study decision-making experience was measured by self reports. Because of the diverse background of the subjects it is questionable whether this is a good measure. Future research is needed employing individuals that have the same level of decision-making experience.

The second major direction for future research should be to examine which factors of spatial ability influence computer usage. There are several areas of research that can be performed.

1. Numerous studies have identified that spatial ability influences computer usage; however, not all factors identified in this study have been examined, except for one study on data query. Further research is needed on manipulation of data and creating and manipulating decision models.
2. Another area of research on the relationship between spatial ability factors and computer usage should focus on the different types of interfaces, such as traditional-language driven systems, menu driven systems and icon-based systems.
3. Although several studies have found that spatial ability is related to learning how to use a text editor, more research is needed in the area on learning how

to use DSS. In addition, research is needed to address whether spatial ability cease to predict performance when individuals go from novice to experts.

Support for two distinct types of information processing verbal information processing and spatial information processing, is well founded in the psychology literature. Research, however, is lacking in identifying which factors of spatial ability are important for specific tasks. By combining the results from the two directions of research discussed above and by repeatedly examining all four spatial ability factors, a more comprehensive research model can be provided for future DSS research.

The focus of this research was on the relationship between spatial ability and decision making performance on a DSS. The results indicate that spatial ability factors did not explain variances in performance on DSS with respect to decision time, DSS features employed, and decision accuracy. Spatial ability did however, explain some of the variance in decision confidence in the data analysis stage of decision making. Given measurement problems that were encountered in the present study and the elimination of low spatial ability individuals due to inability to complete the cases, the Ex Post Facto analysis provided some support for spatial ability as a moderating factor on decision making performance. Given these results, future research should continue to concentrate on identifying which factors of spatial ability are related to decision making performance.

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Appendix

Table of Contents

Appendix A

The Moderately Complex Case with No Decision Model (King Case)

Kings corporation is considering expanding one of its divisions. You have been asked to determine how many additional shares of common stock can be sold, while maintaining a price/earnings ratio that does not fall below 22.

Kings has 5000 shares of common stock outstanding. The current stock price is $60. The following table shows the effect issuing additional shares will have on the stock market price of Kings' stock.

Additional Shares Issued	Estimated Market Price Per Share
500	$57
1500	$43
2500	$35

Price/earnings ratio is calculated as the market price per common share of stock divided by the earnings per share(EPS). EPS is calculated as net income divided by the number of common shares issued.

Develop a decision model called KING to determine the amount of additional common stock that can be issued given that the P/E ratio can not fall below 22. King's expected net income is in datafile KINGSINC.dat as NET INCOME. Call the decision model KING.

What is the additional amount of capital stock that can be issued ____________?

Appendix B

The Complex Case with no Model (Delta Case)

Soc. Sec. Number ______________ Group __________

Delta Corporation needs $40,000 of external financing in the upcoming year to upgrade equipment. Two alternatives are being considered to raise the funds: 1) issuing common stock or 2) selling bonds. Your job is to develop a decision model called DELTA.MOD to evaluate the two financing alternatives based on the following criteria:

1) the debt/equity ratio must remain below the industry average,

2) the price/earnings ratio must be maximized.

Delta has 19,000 of its shares outstanding. The current market price of Delta's stock is $12. An investment banking firm projects that a new issue of $40,000 worth of Delta's stock would sell for $11 per share. Given the current market conditions, the bonds have an effective interest rate of 13 percent. Delta's average tax rate is 40 percent.

The debt/equity ratios are calculated as long-term debt divided by total equity. Earnings per share is calculated as net income divided by the number of common shares issued. P/E ratio is calculated as the market price per common share of stock divided by earnings per share.

Three datafiles have been prepared on IFPS for you to access. DELTABS.DAT contains data projected on selected accounts in the balance sheet for 1990. The projected Income Statements and Statement of Retained Earnings for 1990 are in datafile DELTAINC.DAT. The financial impact of the additional capital on earnings and operating costs are incorporated in these figures. Debt/equity ratios (1990) on representative firms in the industry are in datafile DELTARAT.DAT. The names of the line items in each datafile are provided on the attached page.

Based on the results of your model, fill in the following blanks:

Debt/equity with bonds ____________

Debt/equity with common stock ____________

Market average debt/equity ____________

Price/earnings with bonds ____________

Price/earnings with common ____________

Line Items in the Datafiles for 1990

DELTARAT.DAT

interlake inc
nvf corp

DELTABS.DAT

long term debt
total equity

DELTAINC.DAT

sales
operating cost
operating income
interest income
interest exps
income tax
net income
eps
beg bal ret earn
cash divid
end bal ret earn

Appendix C

The Moderately Complex Case with a Decision Model (King Case)

Kings corporation is considering expanding one of its divisions. You have been asked to determine how many additional shares of common stock can be sold, while maintaining a price/earnings ratio that does not fall below 22.

Kings has 5000 shares of common stock outstanding. The current stock price is $60. The following table shows the effect issuing additional shares will have on the stock market price of Kings' stock.

Additional Shares Issued	Estimated Market Price Per Share
500	$57
1500	$43
2500	$35

Price/earnings ratio is calculated as the market price per common share of stock divided by the earnings per share(EPS). EPS is calculated as net income divided by the number of common shares issued.

A model has been developed to analyze this case. Using the Model KING, perform what_if analysis to determine the amount of additional common stock that can be issued given that the P/E ratio can not fall below 22. Kings' expected net income is in datafile KINGSINC.dat as NET INCOME.

What is the additional amount of capital stock that can be issued ___________?

Appendix D

The Decision Model for the Moderately Complex Case (King Case)

```
columns 1990

new eps = net income / (shares + new shares)

shares=5000

new shares= 0


price to earn = market price / new eps


market price = 60
```

Appendix E

The Complex Case with a Decision Model (Delta Case)

Delta Corporation needs $40,000 of external financing in the upcoming year to upgrade equipment. Two alternatives are being considered to raise the funds: 1) issuing common stock or 2) selling bonds. Your job is to evaluate the two financing alternatives based on the following criteria:

1) the debt/equity ratio must remain below the industry average,

2) the price/earnings ratio must be maximized.

A model has been developed to analyze this case. Use the decision model called DELTA.MOD, to perform what_if analysis to solve this case.

Delta has 19,000 of its shares outstanding. The current market price of Delta's stock is $12. An investment banking firm projects that a new issue of $40,000 worth of Delta's stock would sell for $11 per share. Given the current market conditions, the bonds have an effective interest rate of 13 percent. Delta's average tax rate is 40 percent.

The debt/equity ratios are calculated as long-term debt divided by total equity. Earnings per share is calculated as net income divided by the number of common shares issued. P/E ratio is calculated as the market price per common share of stock divided by earnings per share.

Three datafiles have been prepared on IFPS for you to access. DELTABS.DAT contains data projected on selected accounts in the balance sheet for 1990. The projected Income Statements and Statement of Retained Earnings for 1990 are in datafile DELTAINC.DAT. The financial impact of the additional capital on earnings and operating costs are incorporated in these figures. Debt/equity ratios (1990) on representative firms in the industry are in datafile DELTARAT.DAT. The names of the line items in each datafile are provided on the attached page.

Based on the results of your model, fill in the following blanks:

Debt/equity with bonds	____________
Debt/equity with common stock	____________
Market average debt/equity	____________
Price/earnings with bonds	____________
Price/earnings with common	____________

Line Items in the Datafiles for 1990

DELTARAT.DAT

interlake inc
nvf corp

DELTABS.DAT

long term debt
total equity

DELTAINC.DAT

sales
operating cost
operating income
interest income
interest exps
income tax
net income
eps
beg bal ret earn
cash divid
end bal ret earn

Appendix F

The Complex Case Decision Model (Delta Case)

```
columns 1990
new income = net income - bond interest
bond interest =(bond * bond rate) * (1 - tax rate)
bond = 0
bond rate = 0
tax rate = 0

add common stock = 0
share out = 19000 + add common stock
new common stock = add common stock * 11

eps = 0
new eps = new income /share out

debt to equity ratio = (long term debt + bond) / (total equity + new common st
debt to equity markt avg = (interlake inc + nvf corp) /2

market price = 0
price to earn = market price/new eps
```

Appendix G

An Example of a Log File

```
@XM1@X
@ES/MODEL
/GET
kings
/VIEW
Undefined variable: net income.
     1   Columns            6   Variables       0   Simultaneous groups
     1   Undefined variables
 Compilation found undefined variables.  Please define them by editing the
 model.
 Compiled model cannot be solved
/MODEL
/GET
kings
/USING
kingsinc
Compiling model KINGS.MOD.
Compiling datafile KINGSINC.DAT.
     1   Columns            6   Variables       0   Simultaneous groups
 Compilation successful.  Model may be solved.
/VIEW
 Valid solution
/WHAT_IF
/EDIT_CASE
new shares = 500
market price = 57
@F0/SOLVE
/EDIT_CASE
@UA@UA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA1500@DA@LA@LA43@F0/SOLVE
/EDIT_CASE
@UA@LA@LA@LA@LA2500@DA@LA@LA35
@F0/SOLVE
/EDIT_CASE
@UA@UA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA@RA1@DA@RA@RA@LA43@F0/SOLVE
@ES@ES@ES/LOG
/SAVE
```

Appendix H

Postcase Questionnaire

Social Security Number _____________ Case:

Circle the appropriate number. Do **NOT** leave any blank.

1. I am _____________ that my decision is correct.

1	2	3	4	5	6	7
extremely uncertain	very uncertain	somewhat uncertain	neither uncertain nor confident	somewhat confident	very confident	extremely confident

2. In arriving at a decision, I found the information in this case to be ______

1	2	3	4	5	6	7
extremely inadequate	very inadequate	somewhat inadequate	neither inadequate nor sufficient	somewhat sufficient	very sufficient	extremely sufficient

3. The presentation of the information in this case was ______to understand.

1	2	3	4	5	6	7
extremely difficult	very difficult	somewhat difficult	neither easy nor difficult	somewhat easy	very easy	extremely easy

4. I felt my decision effectiveness was _____________ when using the decision model provided for the case.

1	2	3	4	5	6	7
extremely hindered	hindered to a great extent	somewhat hindered	neither hindered nor enhanced	somewhat enhanced	enhanced to a great extent	extremely enhanced

5. The complexity level of this case was _____.

1	2	3	4	5	6	7
extremely straight forward	very straight forward	somewhat straight forward	neither straight forward nor complex	somewhat complex	very complex	extremely complex

Appendix I

Background Information

Social Security #: ____________________

1. Gender: Male _____ Female _____ Age: _____
2. Current Program of Study: _________ Undergraduate in accounting

   _________ Undergraduate in business

   _________ Master of Accountancy

   _________ Ph. D. in Accounting

3. Specialization in current Graduate Study: ____________________
4. Specialization in your Undergraduate Program: ____________________
5. Total work experience in accounting, finance or managerial position
   Years ____________ Months ____________
6. Please check which accounting and finance classes you have taken:
   Intermediate Accounting _____
   Cost Accounting _____
   Accounting Theory I _____
   Management Control _____
   Finance (undergraduate) _____
   Finance (graduate) _____
   Investments _____
   Marketing (undergraduate) _____
   Marketing (graduate) _____
7. The number of case studies you have completed in the past year _____
8. Please check which math or statistics courses you have had:
   1. Matrix Algebra _____
   2. Calculus _____
   3. Advanced Calculus _____
   4. Elementary Statistics (undergraduate) _____
   5. Advanced Statistics (graduate) _____
9. Based on the scale below, how familiar are you with the following terms?
   1. EXTREMELY UNFAMILIAR (I have never heard of this term.)
   2. RATHER UNFAMILIAR (I have heard of this terms before, but I have no idea what they mean.)
   3. SLIGHTLY FAMILIAR (I have heard this terms before, but I have only a slight idea what they mean.)
   4. SOMEWHAT FAMILIAR (I have heard of this term many times before and I have some understanding what it means.)
   5. EXTREMELY FAMILIAR (I have heard of this term many time before, and I have a very good understanding of what it means.)

   1. ROI (return on investment) _____
   2. Bond investments _____
   3. EPS (earnings per share) _____
   4. Cost of Goods Sold _____

10. Do you own a computer? Yes _____ No _____

11. How often do you use a computer? ________________________________

For question 12 and 13 use the following scale.

Proficiency Level:
1 = I can perform complex tasks without a manual.
2 = I can perform moderately complex computer tasks without a manual.
3 = I can perform simple tasks without a manual.
4 = I can not operate it without a manual.

12. List the software packages that you have used, the number of months spent using each package and your proficiency.

Software	Months Used	Prof. Level
____________	____________	________
____________	____________	________
____________	____________	________
____________	____________	________
____________	____________	________

13. Programming Experience

Programming Experience	Proficiency Level
1. Basic	____________
2. FORTRAN	____________
3. COBOL	____________
4. C	____________
5. ____________	____________
6. ____________	____________
7. ____________	____________

14. Have you ever used IFPS before? Yes _____ No _____

Appendix J

Consent Form

You are invited to participate in a study of managerial use of decision aids. We hope to learn about how people make business decisions when solving problems of differing complexity.

If you decide to participate in the study, you will be asked to complete a series of question, take a test on spatial ability and then read several business cases and make a business decisions for each case.

Any information obtained in connection with this study that can be identified with you will remain confident and will be disclosed only with your permission. In any written reports or publications, no one will be identified or identifiable and only aggregate data will be presented.

Your decision whether or not to participate will not affect your future relationship with the University of Virginia Tech in any way. If you decide to participate, you are free to discontinue participation at any time without affecting such relationships.

If you have any questions, please ask us. If you have additional questions later, Bernadette Ruf (951-5081) will be happy to answer them.

A copy of this form will be available to keep.

You are making a decision whether or not to participate. Your signature indicates that you have read the information provided above and have decided to participate. You may withdraw at any time without prejudice after signing this form should you choose to discontinue participation in this study.

______________________________ Signature

_______________ Date

I participated in your prior study.

Yes _____ No _____

Appendix K

Training Session Lecture Notes

The software I will be training you on is called IFPS. It is an interactive financial planning system. It is interactive in the sense that it works along with you as you solve a problem. Because I have access to only one software package, I have to load the system on each computer separately which takes several minutes. Therefore, it is imperative that you do not exit out of the system.

As I go thru the training session I will be following the handout that I have given you. Because of the limited time, it is extremely important that you follow along with me and do not get behind or ahead. If you get behind, just raise your hand or scream out.

Lets view the overall structure of IFPS: Turn to page 1 on your handout. IFPS is a hierarchical menu driven system. On the hand out you can see the commands at the top level. This level is referred to as the IFPS menu. At the next level of commands, I have selected submenues that we will be using. This page provides you with an over view in which you can refer back to for future use.

How does IFPS work? Models are used to represent a situation. Within the model data can be entered, relationships can be defined, and/or data can be retrieved. For example: We want to evaluate the gross margin of a company.

Net sales - COGS = gross margin

With IFPS we can enter the data into the model ourselves or use the data from a datafile. We will discuss exactly how we do this later. (Turn to page 2.)

A model is a collection of statements that describe a certain situation. The statements take the form of a series of equations to represent variables and relationships between variables for a given time period. The model solution is in the form of a matrix consisting of rows and columns. The rows are user-defined variables and the columns are time periods. The first line of your model must state how many columns or time periods in the model. This may be done several ways:

```
Columns 1 thru 3
Columns 1..3
Columns 1985..1987
Columns 1985 thru 1987
```

The remaining lines in the model are referred to as variable definition statements. These statements define what each variable is equivalent to. This may be done several ways:

```
   labOr rate = 7500
Labor  rate = 7500, 7500, 7500
Labor  rate = rate * labor hours
labor rate = 0
```

```
* note that the letters in the words labor  do not have to be
  the same with respect to capitalization or spacing between the
  words.  A comma between the number indicates the next time
  period or column.
```

Turn on your screens and explain where they are and how you move around.

Creating a Model

1. From the IFPS menu, choose: EDIT. This can be done either by placing the cursor on Edit using the <spacebar> and pressing <enter>, or by typing the capitalized letter in the word Edit .

2. To enter file specification, type: MODEL MYMODEL or filename.extension

   * Note: 1)You must enter Edit from IFPS menu to create a new model and you must designate the file type.
3. To enter your model, select: Append . Append moves the cursor to the work space and creates a new line.

   Lets start with how we build a model. Say, you were a cost accountant and your supervisor asks you to evaluate the manufacturing cost of a particular toy. We know that we need labor hours, material and overhead costs. Enter the model:

```
Columns 1985 thru 1987
total cost = mat cost + labor cost + overhead
mat cost = mat unit cost * raw mat
mat unit cost=6.75
raw mat = 3000
labor cost = labor rate * labor hours
labor rate = 3.75, 4.10, 4.35
labor hours = 2000
overhead = 2000
```

4. Hit the function key <F10> to exit from the edit mode.
5. To save the model, select: SAVE
6. Press <esc> to return to the IFPS menu.

Activating an Existing Model

Before you can view or perform analysis on a model, the model must be activated. To activate an existing model from the IFPS menu, select: MODEL From the Model menu, choose: GET and enter: FILENAME

Viewing the model

To view a model that is already activated, in the model menu, select: VIEW. The model name should be at the bottom right handside of the screen if the model is activated. The model solution is in the upper window. The model statement appears in the lower window. The submenu View displays the commands valid in View mode. To move from window to window press the function key <F10>. To move around the window hit the arrow keys or page down key. (move around with arrow key) Before we exit back lets see how the format statement works. If you get all asterisks them you need to increase the columns. To exit back to the main menu enter <Esc>.

Editing a Model

Two ways to edit a model from the IFPS menu or when the model is already active then from the model menu.

1. To edit a model from the IFPS menu, select: GET

2. Enter file specification: MODEL FILENAME

3. To edit an already activated model, in the model menu enter: EDIT.

   Discuss the difference between append and visual!

4. To change the model in the edit mode, select: Visual. This places you in the upper window where you can begin editing by hitting the arrow key to the desired location.

   In our scenario we realize that we do not have the updated numbers so we decided we need to use a datafile that contains the up dated numbers. So, lets change overhead to

0. When a datafile is used with this model, the amount of overhead in the datafile will appear instead of zero. After your changes are complete enter the < F10 > key to exit.

5. To delete a line in the edit mode, select: DELETE and enter the first and last row number. Delete LABOR HOURS and RAW MAT

   In order to view this model a datafile needs to be used that has defined labor hours and raw mat.

6. To save your changes, select: SAVE

Viewing a Datafile

1. To view a datafile from the IFPS menu:
   Enter: DATAFILE
   Enter GET and type: var
   Enter: View

What If Analysis

1. From the IFPS menu, select: Model.
2. From the Model menu, select: GET and enter: MYMODEL
3. To select a database from the Model menu, choose: USING and enter: var,over
4. From the Model menu, select: VIEW
5. From the View menu, select: WHAT_IF. Now the screen is divided into three windows (solution, model and case).
6. To move to the solution window enter < F10 > and to move to the model window enter < F10 > again.
7. To move the cursor to case window, enter: EDIT_CASE. Then enter any line that you want to change. Lets say we want to consider the effect of the new labor raise on our total cost. Lets raise the pay to 4.75.
   labor rate = 4.75
   We can type it in or copy the line from the model window. First, type it in. Then move down overhead with < F6 > key.
8. From the What_if menu, select: SOLVE
9. To solve a case, enter: SAVE and enter laborcase1
10. To return to the base solution (original) enter: BASE. The case can be retrieved by entering GET and the case name.

```
Arithmetic Operations
            + addition
            - minus
            * multiple
            / division
```

```
Average cost= mean(total cost[1985],total cost[1987])
 or
Average cost= mean(total cost[1],total cost[3])
```

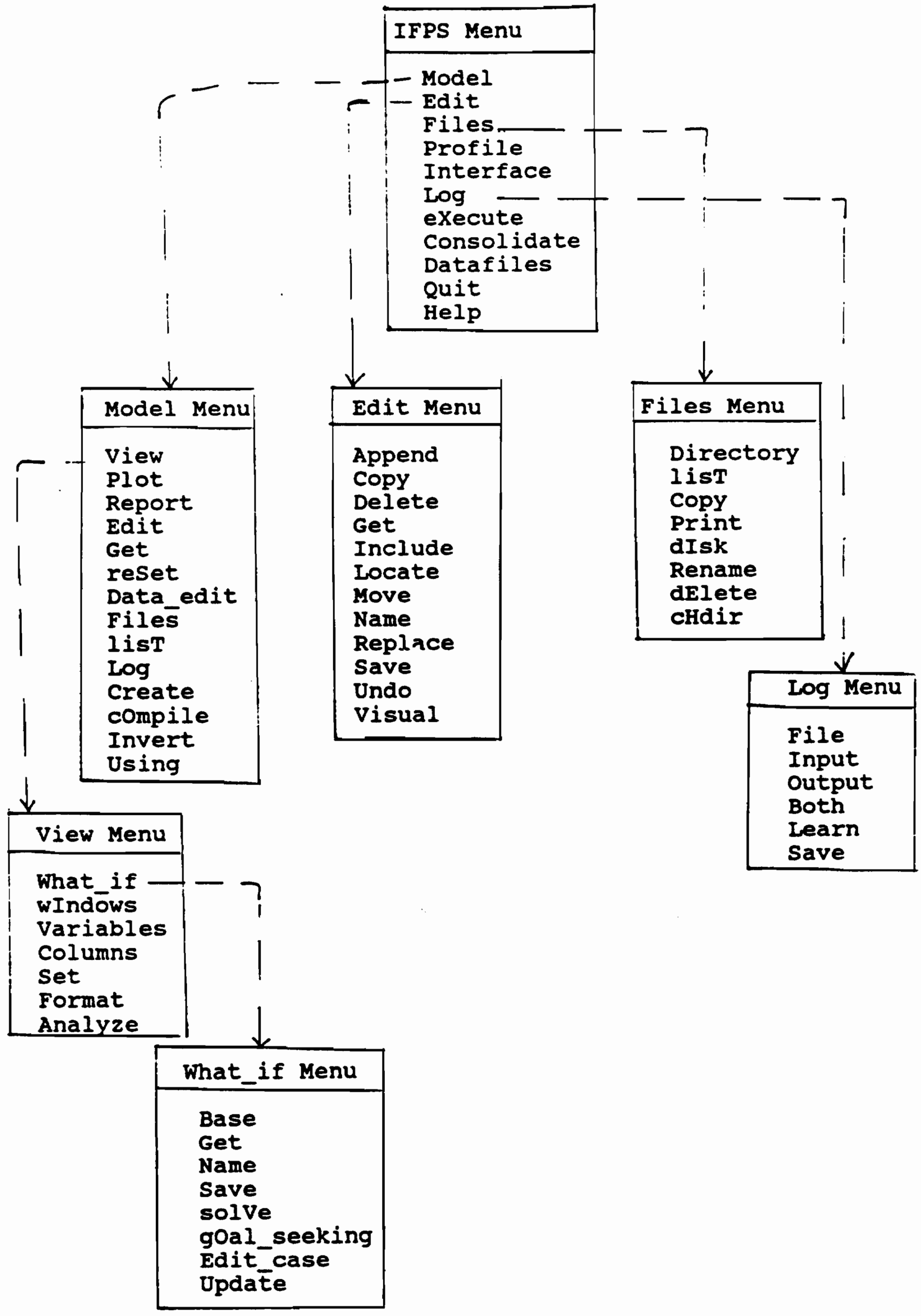
Review two common errors. Forgetting to put an extension on the end of a file and forgetting to put a column statement in the first line of the model.

Appendix L

IFPS Training Session Handout

Page

Bold print indicates the selection from the menu.
Italic print represents what is typed in by hand.


IFPS Menu
Model
Edit
Files
Profile
Interface
Log
eXecute
Consolidate
Datafiles
Quit
Help
Model Menu
View
Plot
Report
Edit
Get
reSet
Data_edit
Files
lisT
Log
Create
cOmpile
Invert
Using
Edit Menu
Append
Copy
Delete
Get
Include
Locate
Move
Name
Replace
Save
Undo
Visual
Files Menu
Directory
lisT
Copy
Print
dIsk
Rename
dElete
cHdir
Log Menu
File
Input
Output
Both
Learn
Save
View Menu
What_if
wIndows
Variables
Columns
Set
Format
Analyze
What_if Menu
Base
Get
Name
Save
solVe
gOal_seeking
Edit_case
Update

Model Building

A model is a collection of statements that describe a certain situation. The statements take the form of a series of equations to represent variables and relationships between variables for a given time period. The model solution is in the form of a matrix consisting of rows and columns. The rows are user-defined variables and the columns are time periods.

The first line of your model defines how many columns or time periods in the model. This may be done several ways:

Columns 1..3
Columns 1 thru 3
Columns 1985..1987
Columns 1985 thru 1987

The remaining lines in the model are referred to as variable definition statements. These statements define what each variable is equivalent to. This may be done several ways:

LabOr rate = 7500
Labor rate = 7500,7500,7500
Labor rate = rate * labor hours
labor rate = 0

* note that the letters in the word "labor" do not have to be the same with respect to capitalization or spacing between the words. A comma between the number indicates the next time period or column.

Creating a Model

1. From the IFPS menu, choose: **Edit** This can be done either by placing the cursor on **Edit** using the <spacebar> and pressing <enter>, or by typing the capitalized letter in the word **Edit**.

2. To enter file specification, type: *Model filename* or type: *filename.mod.*

   * Note that you <u>must</u> enter **Edit** from the IFPS menu to create a new model and you <u>must</u> designate the file type.

3. To enter your model, select: **Append.** Append moves the cursor to the work space and creates a new line.

Case 1

Your supervisor asks you to evaluate the manufacturing costs for the years 1985 thru 1987. Develop a model to represent the total cost of producing this toy.

```
Columns 1985 thru 1987
Total cost = mat cost + labor cost + overhead
mat cost = mat unit cost * raw mat
mat unit cost = 6.75
raw mat = 3000
labor cost = labor rate * labor hours
labor rate = 3.75,4.10,4.35
labor hours = 2000
overhead = 2000
```

4. Hit the function key <F10> to exit from the edit mode.
5. To save the model, select: **Save**
6. Press <esc> to return to the IFPS menu.

Activating a Model

Before you can view or perform analysis on a model, the model must be activated. To activate an existing model from the IFPS menu, select: **Model**. From the Model menu, choose: **Get** and enter: *filename*.

Viewing the Model

1. To view a model that is already activated from the Model menu, select: **View**. The model name should be at the bottom right hand side of the screen if the model is activated.

The model solution is in the upper window. The model statement appears in the lower window. The submenu View displays the commands valid in the View mode.

To move from window to window press the function key <F10>. To move around the window hit the arrow keys or page down key.

To exit back to the main menu enter <Esc>.

Editing a Model

1. To edit a model from the Model menu, select: **Get** and Type: *filename*.

2. In the Model menu, enter **Edit**.

3. To change the model in the edit mode, select: **Visual**. This places you in the upper window where you can begin editing by hitting the arrow key to the desired location.

   Now change overhead to zero. When a datafile is used with this model, the amount of overhead in the datafile will appear instead of zero.

   After your changes are complete enter the <PF10> key to exit.

4. To delete a line in the edit mode, select: **Delete** and enter the first and last row number.

   Delete: *labor hours*
   raw mat

   In order to View this model a datafile must be used that has defined labor hours and raw mat.

5. To save your changes, select: **Save** <esc> to the IFPS menu.

Viewing a Datafile

1. To view a datafile from the IFPS menu:

Enter: **Datafile**
Enter: **Get** and type: *filename*
Enter: **View**

What If Analysis

1. From the IFPS menu, enter: **Model**
2. From the Model menu, choose: **Get** and enter: *filename*. The model is now activated.
3. To select a datafile from the Model menu choose: **Using** and enter: *over, var*
4. From the Model menu, select: **View**.
5. From the View menu, select: **What_if**. Now the screen is divided into three windows (solution, model and case).
6. To move to the solution window enter <F10> and to move to the model window enter <F10> again.
7. To move the cursor to the case window, enter: **Edit_case**. Then enter any line that you want to change.
8. To copy lines from the base model window to the case window, first move to the base model by entering <F10>, and then place the cursor over the line to be moved and enter <F6>.
9. To solve the case from the What_if menu, select: **solVe**
10. To save a case, enter: **Save** and the *casename*
11. To return to the base solution (original) enter: **Base**
12. To retrieved the old case enter: **Get** and type the *casename*.

Operator Arithmetic Operations

+ addition
- minus
* multiple
/ division

Average cost = mean(total cost [1985], total cost [1987])

or

Average cost = mean(total cost [1], total cost [3])

Appendix M

Practice Problems

Problem 1

Using Model KUNEY, perform what-if analysis to determine the minimum number of units Kuney company needs to sell without incurring a loss in any of the five years. Assume the number of units sold is the same for all five years.

Problem 2

T.J. Corporation is deciding whether they should make or buy blades needed for lawn mowers they manufacture in house. To arrive at their decision, 1978-1987 data were collected on total direct materials costs and total direct labor costs. These costs are stored in datafile TJ as DIR MAT and DIR LAB. The volume of blades produced is in datafile TJPROD and referred to as VOL. Assume overhead will not change whether they make or buy the blades.

TJ could purchased blades for $60. During what year should T.J. have purchased the blades, rather then manufacture them? Develop a Model to arrive at a solution. Call the model PROBLEM2.mod.

Problem 3

Lampi Corporation maintains data on income statcment items in datafile LAMPI. Data is collected for 1985 thru 1989. Develop a model to calculate Lampi's net income and average net income amount. The average tax rate is 30 percent. Name the model PROBLEM3.mod. Line items in Lampi datafile are: NET SALES, COST OF SALES, SELLING EXPS and ADMIN EXPS.

Problem 4

Antique Furniture maintains data on the Lovebuck Division in the datafile called BUCK. Your job is to recommend whether the director of the Lovebuck Plant should receive a raise. To arrive at a decision you must assess two ratios: return on assets and profit margin on sales. Return on assets is calculated as net income divided by average total assets. Profit margin on sales is calculated as net income divided by net sales. BUCK datafile contains the following line items: TOTAL ASSETS, NET SALES, and NET INCOME. Develop a model called PROBLEM4.mod to support your decision.

Appendix N

Postexperiment Questionnaire

Social Security Number ____________

Circle the appropriate number. Do **NOT** leave any blanks.

1. In general, when using a computer I feel ________

1	2	3	4	5	6	7
extremely anxious	very anxious	somewhat anxious	neither anxious nor comfortable	somewhat comfortable	very comfortable	extremely comfortable

2. Using IFPS ________ my ability to solve the cases.

1	2	3	4	5	6	7
extremely hindered	hindered to a great extent	somewhat hindered	neither hindered nor enhanced	somewhat enhanced	enhanced to a great extent	extremely enhanced

3. In analyzing the cases, the training session was ________

1	2	3	4	5	6	7
extremely inadequate	very inadequate	somewhat inadequate	neither inadequate nor nor sufficient	somewhat sufficient	very sufficient	extremely sufficient

Appendix O

ANOVAs on Group Differences for Spatial Scores

Dependent Variable: Spatial Scanning

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	4	153.481	38.370	0.77	0.548
Error	51	2534.859	49.703		
Corrected total	55	2688.341			

Dependent Variable: Spatial Relations

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	4	328.690	82.172	1.21	0.317
Error	51	3460.841	67.859		
Corrected total	55	3789.531			

Dependent Variable: Field Independence

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	4	19.673	4.918	0.29	0.884
Error	50	853.587	17.071		
Corrected total	54	873.261			

Appendix P

Responses and Analysis of the Postexperiment Questionnaire

Q2. Using IFPS _____ my ability to solve the cases	Frequency	Percent
extremely hindered	1	2
hindered to a great extent	1	2
somewhat hindered	3	5.9
neither hindered nor enhanced	3	5.9
somewhat enhanced	20	39.2
enhanced to a great extent	22	43.1
extremely enhanced	1	2

Q3 In analyzing the cases, the training session was _____	Frequency	Percent
extremely inadequate	0	0
very inadequate	1	2
somewhat inadequate	1	2
neither inadequate nor sufficient	0	0
somewhat sufficient	18	35.3
very sufficient	26	51
extremely sufficient	5	9.8

	N	Mean	Std Dev.	Median
Q.2	51	5.15	1.13	5
Q.3	51	5.60	0.89	6

ANOVA - Group Differences

Dependent Variable: Question 2

Source	DF	Sum of Square	Mean Square	F Value	PR > F	R-Square
Model	7	9.945	1.420	1.11	0.371	.153
Error	43	54.800	1.274			
Corrected total	50	64.745				

Dependent Variable: Question 3

Source	DF	Sum of Square	Mean Square	F Value	PR > F	R-Square
Model	7	4.042	0.577	0.69	0.681	0.100
Error	43	36.114	0.839			
Corrected total	50	40.156				

Appendix Q

Postcase Questionnaire Responses - Model Formulation

	Moderately Complex Case		Complex Case	
Q2. In arriving at a decision, I found the information in this case to be	**Frequency**	**Percent**	**Frequency**	**Percent**
extremely inadequate	0	0	0	0
very inadequate	0	0	2	8.7
somewhat inadequate	1	3.4	3	13
neither inadequate nor sufficient	1	3.4	3	13
somewhat sufficient	4	13.8	10	43.5
very sufficient	17	58.6	5	21.7
extremely sufficient	6	20.7	0	0
Q3. The presentation of information in this case was _____ to understand	**Frequency**	**Percent**	**Frequency**	**Percent**
extremely difficult	0	0	0	0
very difficult	1	3.4	0	0
somewhat difficult	0	0	11	47.8
neither difficult nor easy	2	6.9	6	26.1
somewhat easy	9	31	4	17.4
very easy	12	41.4	2	8.7
extremely easy	5	17.2	0	0

Moderately Complex Case

Questions	N	Mean	Std Dev.	Median
Q.2	29	5.89	0.90	6
Q.3	29	5.58	1.08	6

Complex Case

Questions	N	Mean	Std Dev.	Median
Q.2	23	4.56	1.23	5
Q.3	23	3.86	1.01	4

Appendix R

Postcase Questionnaire Responses - Data Analysis

	Moderately Complex Case		Complex Case	
Q2. In arriving at a decision, I found the information in this case to be	**Frequency**	**Percent**	**Frequency**	**Percent**
extremely inadequate	0	0	2	6.9
very inadequate	0	0	2	6.9
somewhat inadequate	1	4.3	4	13.8
neither inadequate nor sufficient	0	0	0	0
somewhat sufficient	5	21.7	11	37.9
very sufficient	10	43.5	8	27.6
extremely sufficient	7	30.4	2	6.9
Q3. The presentation of information in this case was _____ to understand	**Frequency**	**Percent**	**Frequency**	**Percent**
extremely difficult	0	0	1	3.4
very difficult	0	0	2	6.9
somewhat difficult	2	8.7	9	31
neither difficult nor easy	1	4.3	4	13.8
somewhat easy	7	30.4	10	34.5
very easy	8	34.8	3	10.3
extremely easy	5	21.7	0	0
Q4. I felt my decision effectiveness was _____ when using the decision model provided for the case.	**Frequency**	**Percent**	**Frequency**	**Percent**
extremely hindered	0	0	0	0
hindered to a great extent	0	0	3	10.3
somewhat hindered	1	4.3	5	17.2
neither hindered nor enhanced	4	17.4	1	3.4
somewhat enhanced	3	13	11	37.9
enhanced to a great extent	10	43.5	6	20.7
enhanced extremely	5	21.7	3	10.3

Moderately Complex Case

	N	Mean	Std Dev.	Median
Q.2	23	5.95	0.97	6
Q.3	23	5.56	1.16	6
Q.4	23	5.60	1.15	6

Complex Case

	N	Mean	Std Dev.	Median
Q.2	29	4.65	1.67	5
Q.3	29	4.00	1.30	4
Q.4	29	4.72	1.50	5

Appendix S

T Test for Task Complexity

	N	Mean	Stand. Dev.	T statistic	Probability *
Model Formulation					
Moderately Complex	29	2.75	1.09	7.33	.001
Complex	23	4.82	.83		
Data Analysis					
Moderately Complex	23	2.08	.84	7.28	.001
Complex	29	4.27	1.33		

* The probability that t statistic will occur by chance.

Appendix T

SAS Program Employed to Run Tests on the Hypotheses

```
//B808BMR  JOB 33429,SAS,TIME=3,REGION=2000K
/*PRIORITY STANDARD
/*JOBPARM LINES=5
//STEPA   EXEC SAS

DATA DISS1;
     INPUT GROUP $ 1-2 SOCSEC 3-8 SEX 9-10 AGE 11-13 CONC $ 14-15
     DM 16-19
     CE 20-23 PAP 24-27 MAP 28-32 MRT 33-37 HID 38-43 TYPE 44-45
     KANSR 46-47 KTIME 48-50 KDSS 51-53 KCONFID 54-55 DANSR 56-58
     DTIME 59-62 DDSS 63-65 DCONFID 66-67 GMAT;
LCOMP=LOG(CE);
LDEC=LOG(DM);
     CARDS;
PROC PRINT;

***********************************************************************
*                                                                     *
*   FIRST THE ANALYSIS OF KANSR AND DANSR FOR MODEL 1.                *
*                                                                     *
*        KANSR IS A 0,1 DEPENDENT VARIABLE ==>  LOGISTIC REGRESSION.  *
*                                                                     *
*        DANSR IS A CONTINUOUS DEPENDENT VARIABLE ==> OLS REGRESSION. *
*                                                                     *
**********************************************************************;

DATA DATASET2;
     SET DISS1;
     IF  TYPE = 1;

PROC LOGIST K=1;
     MODEL  KANSR    = LCOMP MRT HID  ;
     TITLE  'ANALYSIS OF KING WITH MODEL AND DELTA WITH NO MODEL';

PROC REG;
     MODEL  DANSR    = LCOMP MAP HID;

***********************************************************************
*                                                                     *
*   THEN THE ANALYSIS OF KANSR AND DANSR FOR MODEL 2.                 *
*                                                                     *
*        KANSR IS A 0,1  DEPENDENT VARIABLE ==>  LOGISTIC REGRESSION. *
*                                                                     *
*        DANSR IS A CONTINUOUS DEPENDENT VARIABLE ==> OLS REGRESSION. *
*                                                                     *
**********************************************************************;
```

```
DATA DATASET3;
     SET DISS1;
     IF  TYPE = 2;

PROC LOGIST K=1;
     MODEL  KANSR    = LCOMP MAP HID ;
     TITLE  'ANALYSIS OF KING NO MODEL AND DELTA WITH MODEL';
PROC REG;
     MODEL  DANSR    = LCOMP MRT HID;

************************************************************************
*                                                                      *
*   VARIABLE REASSIGNMENTS ARE MAKE SUCH THAT:                         *
*                                                                      *
*            MXXXXX = VARIABLE XXXXX FOR THE DATA CORRESPONDING TO     *
*                     AN ASSIGNED MODEL.                               *
*                                                                      *
*            NMXXXX = VARIABLE XXXXX FOR THE DATA CORRESPONDING TO     *
*                     NO MODEL.                                        *
*                                                                      *
***********************************************************************;
DATA DATASET4;
     SET DISS1;
     IF TYPE = 1 THEN DO;
                      MTIME    =  KTIME;
                      MCONFID  =  KCONFID;
                      MDSS     =  KDSS;
                      NMTIME   =  DTIME;
                      NMCONFID =  DCONFID;
                      NMDSS    =  DDSS;
                      END;

     IF TYPE = 2 THEN DO;
                      MTIME    =  DTIME;
                      MCONFID  =  DCONFID;
                      MDSS     =  DDSS;
                      NMTIME   =  KTIME;
                      NMCONFID =  KCONFID;
                      NMDSS    =  KDSS;
                      END;

     DROP KANSR DANSR;
     DROP KTIME KCONFID KDSS DTIME DCONFID DDSS;
```

```
**********************************************************************
*                                                                    *
*   ANALYSIS OF VARIABLES FOR MODEL DATA, SEPARATELY FOR EACH GROUP. *
*                                                                    *
**********************************************************************;

PROC SORT;
  BY TYPE;
PROC PRINT;
     VAR SOCSEC TYPE LCOMP MRT HID MTIME MCONFID MDSS;
     BY TYPE;
     TITLE 'ANALYSIS OF MODEL DATA, SEPARATELY FOR EACH GROUP';

PROC REG;
     MODEL  MTIME     = LCOMP MRT HID ;
     BY TYPE;

PROC REG;
     MODEL  MCONFID   = LCOMP MRT HID ;
     BY TYPE;

PROC REG;
     MODEL  MDSS      = LCOMP MRT HID ;
     BY TYPE;

*************************************************************************
*                                                                       *
*   ANALYSIS OF VARIABLES FOR NO MODEL DATA, SEPARATELY FOR EACH GROUP. *
*                                                                       *
*************************************************************************;

PROC PRINT;
     VAR SOCSEC TYPE MAP HID NMTIME NMCONFID NMDSS;
     BY TYPE;
     TITLE 'ANALYSIS OF NO MODEL DATA, SEPARATELY FOR EACH GROUP';

PROC REG;
     MODEL  NMTIME    = LCOMP MAP HID  ;
     BY TYPE;

PROC REG;
     MODEL  NMCONFID  = LCOMP MAP HID  ;
     BY TYPE;

PROC REG;
     MODEL  NMDSS     = LCOMP MAP HID  ;
     BY TYPE;
```

```
*************************************************************************
*                                                                       *
*   ANALYSIS OF INTERACTION EFFECTS FOR MODEL DATA                      *
*                                                                       *
************************************************************************;

PROC GLM;
     CLASS TYPE;
     MODEL  MTIME    = TYPE MRT HID TYPE*MRT   / SOLUTION;

PROC GLM;
     CLASS TYPE;
     MODEL  MCONFID  = TYPE MRT HID TYPE*MRT   / SOLUTION;

PROC GLM;
     CLASS TYPE;
     MODEL  MDSS     = TYPE MRT HID TYPE*MRT   / SOLUTION;

*************************************************************************
*                                                                       *
*   ANALYSIS OF INTERACTION EFFECTS FOR NO-MODEL DATA                   *
*                                                                       *
************************************************************************;

PROC GLM;
     CLASS TYPE;
     MODEL  NMTIME   = TYPE MAP HID TYPE*MAP   / SOLUTION;

PROC GLM;
     CLASS TYPE;
     MODEL NMCONFID = TYPE MAP HID TYPE*MAP   / SOLUTION;

PROC GLM;
     CLASS TYPE;
     MODEL  NMDSS    = TYPE MAP HID TYPE*MAP   / SOLUTION;
```

Appendix U

Multicollinearity Diagnostic

Experimental settings in which the independent variables cannot be controlled or manipulated have the potential problem of multicollinearity. Multicollinearity occurs when two or more independent variables are changing at a similar rate with respect to the dependent variables. As a result of highly correlated independent variables, the estimated coefficient terms are instable and the mean square error terms are inflated. To test for this in the data, collinearity diagnostics were run using the COLLIN option in SAS which was proposed by Belshley, Kuh, and Welsch (1980). The COLLIN option produces condition indices for each variable in the regression model which are the square root of the ratio of the largest eigenvalue to each individual eigenvalue. When the condition index is high, about 1000, a regressor is highly correlated with another regressor in the model [Meyers, 1988]. A regression model was run with the COLLIN option on all dependent variables for the model formulation and data analysis stages. No collinearity problems were detected (see the Table below). Note: because the COLLIN option is testing the collinearity among the independent variables, it does not matter which dependent variable, time, DSS feature, or, confidence is used.

Model Formulation		
Independent Variables	**Condition Index**	**Variance Inflation Factor**
Complexity	1	12.05
Computer Experience	1	1.11
Spatial Scanning	1	2.18
Field Independence	4	1.09
Scanning * Complexity	49	13.29
Data Analysis		
Independent Variables	**Condition Index**	**Variance Inflation Factor**
Complexity	1	5.47
Computer Experience	1	1.03
Spatial Relations	1	2.54
Field Independence	4	1.13
Relations * Complexity	25	6.40

Appendix V

Analysis with Age and Decision Making Experience in the Model

Model Formulation

Dependent Variable: Time

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	209.843	41.968	1.350	0.2844
Error	20	621.694	31.084		
Corrected total	25	831.538		**R-Square**	0.2524

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	26.617	7.568	3.517	.0022
Computer Experience	1	-2.777	1.112	-2.497	.0214
Age	1	-0.101	0.219	-0.462	.6490
Decision Experience	1	0.079	0.680	0.117	.9083
Spatial Scanning	1	0.112	0.179	0.628	.5369
Field Independence	1	-0.105	0.294	-0.359	.7231

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	1676.269	335.253	1.308	0.3242
Error	12	3076.674	256.397		
Corrected total	17	4752.944		**R-Square**	0.3527

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	108.912	42.837	2.542	.0258
Computer Experience	1	-4.868	4.426	-1.100	.2930
Age	1	-1.163	1.549	-0.751	.4671
Decision Experience	1	-2.458	3.372	-0.729	.4800
Spatial Scanning	1	-0.364	0.667	-0.545	.5955
Field Independence	1	-0.133	1.051	-0.127	.9010

Dependent Variable: DSS Features

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	413.874	82.774	0.401	0.8423
Error	20	4128.471	206.423		
Corrected total	25	4542.346		**R-Square**	0.0911

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	37.321	19.503	1.914	.0701
Computer Experience	1	-2.651	2.866	-0.925	.3660
Age	1	0.012	0.565	0.21	.9831
Decision Experience	1	-1.261	1.753	-.720	.4801
Spatial Scanning	1	0.036	0.461	0.080	.9370
Field Independence	1	-0.199	0.757	-0.263	.7949

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	478.109	95.621	0.083	0.9936
Error	12	13811.501	1150.958		
Corrected total	17	14289.611		**R-Square**	0.0335

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	24.210	90.761	0.267	.7942
Computer Experience	1	2.960	9.379	0.316	.7577
Age	1	0.755	3.283	0.230	.8220
Decision Experience	1	-3.050	7.145	-.427	.6770
Spatial Scanning	1	0.032	1.415	0.023	.9821
Field Independence	1	0.621	2.227	0.279	.7851

Dependent Variable: Confidence

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	9.037	1.807	0.426	0.8251
Error	20	84.847	4.242		
Corrected total	25	93.884		**R-Square**	0.0963

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	4.655	2.795	1.665	.1115
Computer Experience	1	-0.192	0.410	-0.469	.6443
Age	1	-0.022	0.081	-0.274	.7866
Decision Experience	1	0.140	0.251	0.561	.5812
Spatial Scanning	1	0.083	0.066	1.267	.2196
Field Independence	1	-0.044	0.108	-0.410	.6862

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	5.746	1.149	0.421	0.8254
Error	12	32.753	2.729		
Corrected total	17	38.500		**R-Square**	0.1493

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	8.349	4.419	1.889	.0833
Computer Experience	1	-0.568	0.456	-1.245	.2368
Age	1	-0.165	0.159	-1.038	.3199
Decision Experience	1	0.332	0.347	0.956	.3581
Spatial Scanning	1	0.059	0.068	0.860	.4066
Field Independence	1	-0.035	0.180	-0.323	.7522

Model Formulation

Dependent Variable: Decision Accuracy

Moderately Complex Case

	DF	Chi-Square	Probability
Model	5	1.92	.6952

Variable	Beta	Std Error	Chi-Square	Probability
Intercept	4.817	3.010	1.89	.1540
Computer Experience	-0.768	0.654	1.45	.3230
Age	-0.165	0.159	-1.038	.3199
Decision Experience	0.332	0.347	0.956	.3581
Spatial Scanning	-0.018	0.132	0.04	.8070
Field Independence	0.026	0.293	0.06	.7560

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	16.324	5.672	1.548	0.3095
Error	12	75.763	5.008		
Corrected total	17	92.087		R-Square	0.1908

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	2.756	1.781	1.875	.2524
Computer Experience	1	0.228	0.567	0.989	.4544
Age	1	-0.022	0.081	-.274	.7866
Decision Experience	1	0.140	0.251	0.561	.5812
Spatial Scanning	1	0.091	0.062	0.139	.2995
Field Independence	1	0.017	0.213	1.931	.3263

Dependent Variable: Time

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	7	12359.765	1765.680	13.96	0.0001
Error	36	4554.120	126.503		
Corrected total	43	16913.886		**R-Square**	0.7307

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	308.04	2.44	.1274
Age	1	32.82	0.26	.6136
Decision Experience	1	190.50	1.51	.2277
Complexity	1	1293.25	10.22	.0029
Spatial Scanning	1	31.67	0.25	.6198
Field Independence	1	81.86	0.65	.4264
Spatial Scanning * Complexity	1	75.90	0.60	.4436

Dependent Variable: DSS Features

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	7	9408.528	1344.075	2.65	0.0258
Error	36	18279.199	507.755		
Corrected total	43	27687.727		**R-Square**	0.3398

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	27.576	0.05	.8170
Age	1	0.319	0.00	.9801
Decision Experience	1	224.918	0.44	.5099
Complexity	1	251.300	0.49	.4863
Spatial Scanning	1	90.595	0.18	.6752
Field Independence	1	5.271	0.01	.9194
Spatial Scanning * Complexity	1	80.851	0.16	.6922

Dependent Variable: Confidence

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	7	36.591	5.227	1.57	0.1770
Error	36	120.135	3.337		
Corrected total	43	156.727		**R-Square**	0.2334

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	3.139	0.94	.3386
Age	1	1.251	0.38	.5441
Decision Experience	1	2.504	0.75	.3921
Complexity	1	0.262	0.08	.7805
Spatial Scanning	1	0.011	0.00	.9526
Field Independence	1	0.941	0.28	.5986
Spatial Scanning * Complexity	1	0.681	0.21	.6540

Dependent Variable: Time

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	515.170	103.034	3.290	0.0422
Error	12	375.774	31.314		
Corrected total	17	890.944		**R-Square**	0.5782

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	36.111	14.968	2.412	.0328
Computer Experience	1	-5.108	1.511	-3.379	.0055
Age	1	-0.094	0.536	-0.177	.8627
Decision Experience	1	-1.200	1.145	-1.049	.3150
Spatial Relations	1	0.041	0.191	0.215	.8336
Field Independence	1	-0.241	0.347	-0.696	.4997

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	400.541	80.108	0.598	0.7020
Error	20	2679.612	133.980		
Corrected total	25	3080.153		**R-Square**	0.1300

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	30.034	14.212	2.113	.0473
Computer Experience	1	-1.358	2.170	-0.626	.5384
Age	1	0.571	0.450	1.271	.2184
Decision Experience	1	-0.995	1.434	-0.694	.4954
Spatial Relations	1	-0.237	0.288	-0.825	.4189
Field Independence	1	0.017	0.604	0.029	.9774

Dependent Variable: DSS Features

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	789.254	157.850	1.456	0.2742
Error	12	1300.745	108.395		
Corrected total	17	2090.000		R-Square	0.3776

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	42.983	27.848	1.543	.1487
Computer Experience	1	-5.408	2.812	-1.923	.0785
Age	1	0.319	0.998	0.320	.7545
Decision Experience	1	-1.851	2.130	-0.869	.4020
Spatial Relations	1	0.289	0.355	0.814	.4312
Field Independence	1	-0.998	0.646	-1.544	.1485

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	719.181	143.836	0.452	0.8068
Error	20	6363.472	318.174		
Corrected total	25	7082.653		R-Square	0.1015

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	37.464	21.902	1.711	.1026
Computer Experience	1	-0.879	3.344	-0.263	.7952
Age	1	-0.241	0.693	-0.348	.7317
Decision Experience	1	-0.180	2.210	-0.082	.9358
Spatial Relations	1	0.039	0.444	0.088	.9308
Field Independence	1	1.224	0.931	1.314	.2036

Dependent Variable: Confidence

Moderately Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	3.801	0.760	1.049	0.4339
Error	12	8.698	0.724		
Corrected total	17	12.500		**R-Square**	0.3041

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	7.028	2.277	3.086	.0094
Computer Experience	1	0.094	0.229	0.041	.9680
Age	1	-0.050	0.081	-0.624	.5442
Decision Experience	1	0.048	0.174	0.281	.7835
Spatial Relations	1	-0.032	0.029	-1.103	.2918
Field Independence	1	0.112	0.052	2.130	.0545

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	22.871	4.574	2.300	0.0835
Error	20	39.782	1.989		
Corrected total	25	62.653		**R-Square**	0.3650

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	2.912	1.731	1.682	.1082
Computer Experience	1	0.097	0.264	0.370	.7151
Age	1	-0.050	0.054	-0.926	.3656
Decision Experience	1	0.274	0.174	1.573	.1315
Spatial Relations	1	0.085	0.035	2.447	.0237
Field Independence	1	0.049	0.073	0.678	.5053

Dependent Variable: Decision Accuracy

Moderately Complex Case

	DF	Chi-Square	Probability
Model	5	3.25	.3118

Variable	Beta	Std Error	Chi-Square	Probability
Intercept	1.452	4.248	0.18	0.7218
Computer experience	-0.887	0.450	0.56	0.4266
Spatial Relations	1.459	0.278	0.51	0.4042
Field Independence	2.010	0.457	0.42	0.4790

Complex Case

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	5	10.116	3.372	0.740	0.5384
Error	18	109.312	4.554		
Corrected total	21	119.428		R-Square	0.0847

Variable	DF	Parameter Estimate	Standard Error	T Statistic	Probability
Intercept	1	8.921	1.658	5.378	.0001
Computer Experience	1	-0.140	0.377	-0.373	.7124
Age	1	0.233	0.452	0.546	.3440
Decsion Experience	1	0.350	0.114	0.870	.4550
Spatial Relations	1	0.040	0.050	0.803	.4300
Field Independence	1	0.941	0.450	0.285	.5986

Dependent Variable: Time

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	7	6167.664	88130945	9.70	0.0001
Error	36	3270.221	90.839		
Corrected total	43	9437.886		R-Square	0.6535

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	239.029	2.63	0.1135
Age	1	210.123	2.31	0.1370
Decision Experience	1	190.059	2.09	.1567
Complexity	1	1041.497	11.47	.0017
Spatial Relation	1	1.297	0.01	0.9055
Field Independence	1	9.255	0.10	0.7514
Spatial Relation * Complexity	1	11.383	0.13	0.7254

Dependent Variable: DSS Features

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	7	1526.006	218.000	0.91	0.5077
Error	36	8596.243	238.784		
Corrected total	43	10122.250		R-Square	0.1507

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	252.925	1.06	.3103
Age	1	0.127	0.00	.9817
Decision Experience	1	97.462	0.41	.5269
Complexity	1	145.364	0.61	.4404
Spatial Relation	1	0.253	0.00	.9742
Field Independence	1	54.318	0.23	.6263
Spatial Relation * Complexity	1	4.157	0.02	.8958

Dependent Variable: Confidence

Source	DF	Sum of Square	Mean Square	F Statistic	Probability
Model	7	68.714	9.816	6.90	0.0001
Error	36	51.194	1.422		
Corrected total	43	119.909		R-Square	0.5730

Source	DF	Sum of Square*	F Statistic	Probability
Computer Experience	1	0.343	0.24	.6259
Age	1	2.01	1.55	.2214
Decision Experience	1	4.026	2.83	.1011
Complexity	1	27.433	19.29	.0001
Spatial Relation	1	4.642	3.26	.0791
Field Independence	1	3.067	2.16	.1506
Spatial Relation * Complexity	1	8.657	6.09	.0185

Vita

EDUCATION

Masters of Science in Accounting, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, Winter 1987.

Bachelor of Arts degree, State University of New York at Plattsburgh, New York, 1981. Psychology(major) and Math(minor).

PROFESSIONAL EXPERIENCE

System Analyst, Controllers Office, Virginia Polytechnic Institution and and State University, June 1987 to November 1987.

Customer Service-- Coastline Commodities, White Plains, N.Y. 1982 to 1984.

PROFESSIONAL MEMBERSHIPS

National Accounting Association
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TEACHING EXPERIENCE

Instructor, 1986 AICPA National Personal Computer Training Program, Virginia Polytechnic and State University, September 1986.

Graduate Teaching Assistantship, Virginia Polytechnic Institute and State University, 1986 to 1989.