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IS A MAP MORE THAN A PICTURE? THE ROLE OF SDSS TECHNOLOGY, SUBJECT CHARACTERISTICS, AND PROBLEM COMPLEXITY ON MAP READING AND PROBLEM SOLVING[1]

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Abstract

This research investigated how the use of a spatial decision support system (SDSS)—a type of geographic information system (GIS)—influenced the accuracy and efficiency of different types of problem solvers (i.e., professionals versus students) completing problems of varied complexity. This research—the first to simultaneously study these variables—examined subjects who completed a problem involving spatially-referenced information. The experiment was guided by a research model synthesized from various perspectives, including the theory of cognitive fit, prior research on map reading and interpretation, and research examining subject expertise and experience. The results are largely supportive of the research model and demonstrate that SDSS, an increasingly important class of management decision-making technology, increased the efficiency of users working on more complex problems. Professionals were found to be more accurate but less efficient than students; however, professionals who used the SDSS were no more accurate than professionals using paper maps. Need for cognition, a construct that focuses on an individual's willingness to engage in problem solving tasks, was found to be marginally related to accuracy. The implications of these findings for researchers and practitioners are presented and discussed.

Keywords: Cognitive fit theory, geographic information systems, map reading, problem solving, spatial decision support systems, subject characteristics, task complexity.

ISRL Categories: AC0301, AC0401, AC0501, AD03, AD0503, AD0508, AI0105, GB0405, GB0406, HA03, HD0101.01, HD0101.02

Introduction ▮▮▮▮▮▮▮▮▮▮

When Ives (1982) discussed the role of graphics in business information systems, one of the types of graphics that he included in his discussion was the map. In fact, he observed that "The map, perhaps more than any other chart form, gains the most from the availability of computer graphics" (p. 16). One of the most commonly used types of graphics tool for managing and analyzing maps is a geographic information system (GIS). A GIS is a computer-based information system that provides tools to manage, analyze, and display attribute and spatial data in an integrated environment. GIS are often customized to create spatial decision support systems (SDSS); that is, software that "are explicitly designed to provide the user with a decision making environment that enables the analysis of geographical information to be carried out in a flexible manner" (Densham 1991, p. 405). GIS and SDSS are, therefore, more than merely mapping tools; they are spatial information systems in which data is structured for data management, analysis, and decision-making.

Key to this "structuring" of data is the concept of layering. Layering an object (or group of objects) refers to the ability of a GIS to superimpose a number of images on one display. The ability of a GIS to layer spatial and attribute data distinguishes this technology from many other decision support systems. This distinction is important because the way in which spatial and attribute data are presented to decision makers can have a significant influence on effectiveness and on the efficiency of the decision-making process (Smelcer and Carmel 1997).

A question this raises is, "Why would the layering of data in a visual display influence performance?"

Smelcer and Carmel showed that map displays are preferable to tabular representations for solving some types of problems because maps keep the number of knowledge states that a user must consider smaller. Maps reduce the number of knowledge states by placing data (e.g., the number of employees working at a particular factory) within a spatial context (e.g., the factory's location) on one display. Bertin (1967, 1983) proposed a theory of image processing—image theory—that is useful for explaining why this improves efficiency. A basic premise of image theory is that representations such as maps enable the decision maker to visualize multiple pieces of information simultaneously. Therefore, as the decision maker *reads the map* from the display, he/she is better able to develop a Gestalt understanding of the relationship between the data.

This phrase, "reads the map," is an interesting use of words when considering how maps are visualized and processed. Although many people consider map representations to be quite distinct from semantic representations such as tables and sentences, one line of research in geography has highlighted the similarities between reading text and reading maps. Specifically, Head (1984) suggests that the cognitive process used in map reading is similar to the process used in reading text (also see Pinker 1981, 1990). One could conclude from this perspective that maps, like sentences and other semantic representations, contain propositions about reality that are open to interpretation and exploration by the reader.

This perspective of comparing a map representation to a language is important because it provides a useful starting point for considering how factors like technology, task structure, user characteristics, and similar variables affect a decision maker's ability to interpret the propositions presented in a map. For example, technologies like GIS that enable a user to efficiently combine multiple map images into one display make data analysis easier (Crossland et al. 1995). The ability of GIS to create one image that is a compilation from multiple maps is analogous to taking a sentence from one line and combining it with a sentence from a second line. The resulting compound sentence would likely be easier to read

and understand than the two separate sentences. But the ability of the reader to digest and interpret the information will be dependent on other factors as well. For example, the size, scope, and complexity of the proposition being presented will influence whether and how information can be combined in a sentence. Further, when reading a sentence, the reader interprets what is read based on his/her experiences, knowledge, and cognitive effort. These same factors that influence the reader's ability to interpret text will also play a part in map reading (Head 1984).

With this said, it is surprising that only a few empirical studies examining the role of GIS in decision making have been reported in the IS literature (Crossland et al. 1995; Dennis and Carte 1998; Smelcer and Carmel 1997; Swink and Speier 1999).[2] In general, although there is a common assumption that GIS improves decision making, very little has been done in controlled settings to provide empirical support for this supposition (Morrison 1994). Much can be learned about both map interpretation and broader issues in human-computer interactions by studying the role of GIS as a tool to support map reading and interpretation.

The purpose of this research is to improve our understanding of GIS and also identify how factors like subject and task characteristics affect decision maker performance. To do this, a research experiment was conducted that was designed to examine SDSS use by subjects with different levels of work experience. The performance of students and professionals who used either paper maps or an SDSS to complete a low, medium, or high complexity version of a spatial task were

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[2]Interestingly, although researchers from the field of geography have studied GIS and related spatial technologies for many years, geographers have completed surprisingly few studies examining the role of GIS in decision making. In fact, it is only recently that leaders in the field of geography have called for research on GIS, decision making, and cognition of the type presented in the current research. For example, the University Consortium of Geographic Information Science (UCGIS) recently called for research examining how geographic knowledge is acquired through different media and by users with different levels of experience and training (UCGIS 1996). This study is an important step toward answering this call for research examining these issues.

examined and compared. To provide the theoretical research context, the next section includes background information and the hypotheses summarizing expected outcomes. Next, the experimental methodology and procedures are discussed. The paper concludes with the results, a discussion of the findings, and the implications for researchers and users.
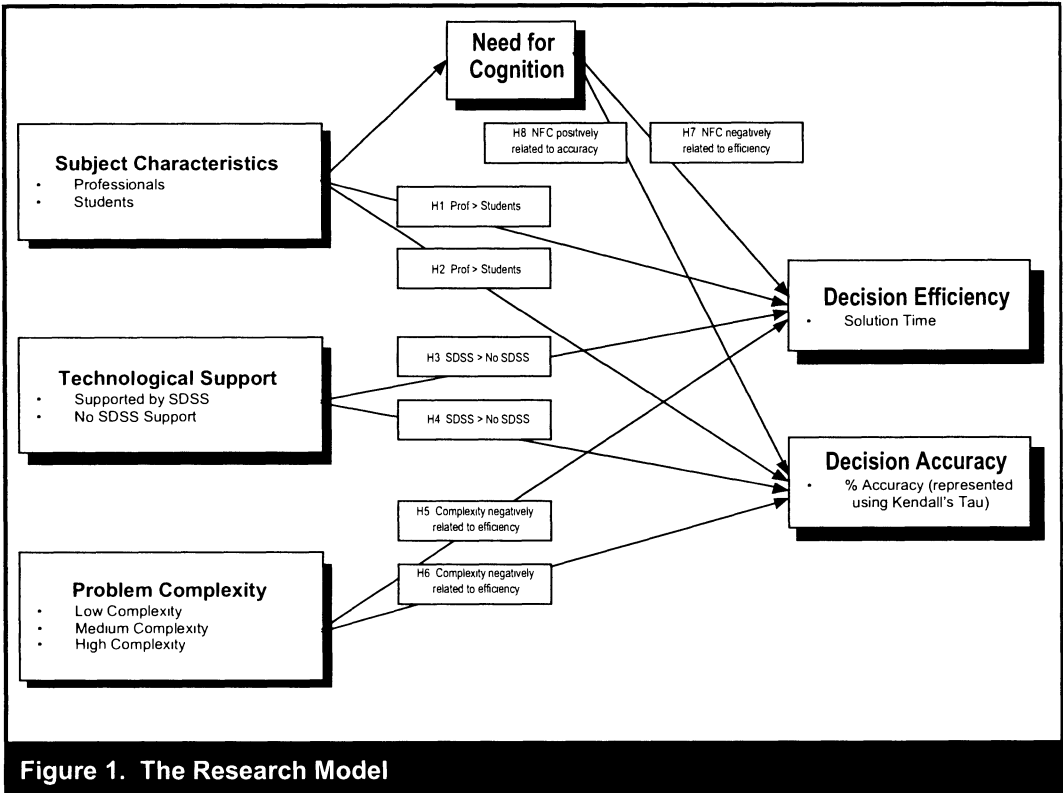
Background and Hypotheses ▬▬

This research is designed to examine the role of technology, subject characteristics, and task complexity on decision maker performance and perceptions (Figure 1). This section begins with a discussion of the role of subject characteristics. Next, research on SDSS technology is examined. The role of task complexity is then presented. Finally, the need for cognition (NFC) construct is discussed in the context of this research.

Subject Characteristics

Prior research suggests that the experience a decision maker has with solving a particular type of problem can have important impacts on the processes they use and the outcomes they generate (Bereiter and Scardamalia 1993; Hughes and Gibson 1991; Larkin et al. 1980; Mayer 1997; Shanteau 1992; Simon, and Simon 1978; Sweller et al. 1983). For example, Shanteau suggests that four *themes,* which highlight differences in the characteristics of experts and novices, emerge from research in the cognitive sciences. First, expertise is domain specific; expertise diminishes when the decision maker moves outside of his or her area of expertise (see Anderson 1990). Second, expertise is acquired over time and the *expert* progresses through several stages of experiential development (see Fitts and Polson 1967). Third, experts use different, usually more efficient, thinking strategies (Mayer 1997). Fourth, experts use a more automated problem-solving process (see Shiffrin and Schneider 1977).

The strategy or process used by experts, in particular, has been shown to be an important factor affecting their success. For example, Mackay and Elam (1992) suggest that novices and experts differ along four dimensions related to

Figure 1. The Research Model

the problem solving process. First, experts define and conceptualize the problem in such a way that they are better able to identify the important features of the problem and the ways in which these features are related. Novices, on the other hand, tend to quickly move past problem definition and immediately focus on solving the problem (see Chi et al. 1981; Hardiman et al. 1989; Hayes and Simon 1976; Leinhardt 1983; Newell and Simon 1972; Simon and Simon 1978). Second, experts tend to categorize problems into groups or types using much deeper structures that are relevant to identifying a way to solve the problem (Chi et al. 1981; Schoenfeld and Herrmann 1982). Novices tend to categorize problems based on surface cues that do not necessarily help them to identify the most efficient way to solve the problem. Third, experts tend to be able to develop a better and deeper understanding of the problem because they have more knowledge about the subject. Novices often lack this deeper understanding and, therefore, are not able to develop a

detailed conceptualization of the problem and a procedure for achieving desired goals. Fourth, experts apply different strategies for solving problems than do novices. As noted by Shanteau (1992), experienced decision makers use forward-thinking strategies while novices use backwards-reasoning approaches.

Mayer offered a useful synthesis of these different perspectives by observing that knowledge about a task domain will fall into one or more of four categories of knowledge:

(1) Syntactic Knowledge: Knowledge about the task domain's language and the rules for combining language elements into meaningful conceptualizations.

(2) Semantic Knowledge: Knowledge that allows the problem solver to develop a mental model of the system and the relationships between important elements within the system.

(3) Schematic Knowledge: Knowledge about how elements within the problem can be combined into functional units and usable chunks that can more easily be conceptualized or acted on.

(4) Strategic Knowledge: Knowledge about how to develop and implement solution plans or actions directed toward task completion.

This taxonomy is useful because it encapsulates much of the prior research and because it highlights the importance of viewing expertise as a multidimensional construct. Furthermore, it is also consistent with prior research that has shown that the development of expertise in a particular domain is gradually acquired and that a continuum of expertise will exist between novices and experts (Chi et al. 1988; Mayer 1997; Zachary and Ryder 1997). This implies that experienced decision makers that are not familiar with a particular task or domain may still be able to outperform novice decision makers because the former will have greater knowledge about strategies for setting up, organizing, and analyzing the components of the problem (i.e., they have semantic and strategic knowledge).

The role of knowledge and expertise is important because of the nature of the research task and the subjects who participated in this research. The task is a spatial problem-solving activity (i.e., a multi-criteria site selection problem) designed in the context of economic and labor market analysis. Since the professional subjects are closer to being experts in this domain[3] and since they are also experienced in solving location-related problems,[4] they are expected to have a greater amount of syntactic, strategic, and, to some degree,

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[3]Individuals with an average of more than 12 years of experience in labor market information comprise the population of experts. Novice problem solvers were drawn from a population of undergraduates in MIS courses.

[4]The labor market professionals routinely work with problem solving activities that involve location. For example, factors such as unemployment, labor force, market and economic conditions, etc., are routinely part of tasks that they process. Each of these factors has a locational element that must be considered in most, if not all, analyses.

schematic knowledge than would students. On the other hand, because the task is about a fictional organization in an area of the country that would likely be unfamiliar to subjects, there would be little difference between professionals and students in the semantic knowledge they possess.

In summary, prior research suggests that expert decision makers should have greater knowledge about the terminology associated with the task, they will be able to build more effective mental models, they will be better able to chunk concepts into meaningful units, and they will be able to build and use more sophisticated problem solving strategies. As a result, professionals should be able to solve problems more efficiently and accurately than undergraduate students.

> H1: For the same task, professionals will solve the problem more efficiently than students.

> H2: For the same task, professionals will solve the problem more accurately than students.

SDSS and Computer Support

A number of IS researchers are beginning to place a greater emphasis on examining GIS, SDSS, and geographic problems. For example, Smelcer and Carmel (1997) examined the effectiveness of maps versus tables and found that maps are more efficient for a variety of levels of task complexity. They concluded that for certain problems maps reduce the number of knowledge states and thus reduce the complexity of the problem. Dennis and Carte (1998) extended research on cognitive fit theory (Vessey 1991a, 1994; Vessey and Galletta 1991) to geographic tasks. They found that a map presentation improved decision-making performance and efficiency for tasks involving adjacency relationships between geographic areas but a map diminished effectiveness when there were no geographic adjacency relationships. Swink and Speier (1999) examined the effects of data aggregation and dispersion on solving geographic problems. They found that performance was lower on larger sized problems, data dispersion and disaggregation influenced performance, and

a user's spatial orientation skills were related to outcomes. Finally, Crossland et al. (1995) examined the impact of using an SDSS on decision-making effectiveness and efficiency. In their study, students[5] processed a spatial decision making problem either with the aid of an SDSS and paper maps or with paper maps alone. They found that SDSS use improved performance for three levels of task complexity and that user characteristics were related to outcomes. They also found an interaction for solution time; while SDSS significantly improved efficiency for medium and high complexity tasks, it did not lead to significant time improvements for low complexity problems.

One of the benefits of GIS is that it enables users to do more than simply change the color, style, and form of displays. For example, Ives (1982) noted that the ability to electronically manipulate maps and data enables the user to process information and displays that would be impossible or impractical using manual approaches. In particular, one of the things that GIS enables the user to do is to easily layer maps on top of one another. This is significant because by layering maps, the user can bring individual layers together on one display. This should improve the likelihood that as the decision maker reads the map, he/she will develop a Gestalt perspective that will improve understanding and performance.

Head (1984) proposed a theoretical model for understanding how people read maps that is useful in this context. Head's model states that map reading is comparable to the reading of text and other semantic representations. Map reading is a complex process that requires the viewer to not only detect and initially recognize map components, but also to abstract and group individual map features into collections of related features and chunks. During this process, recognition occurs when information stored in long-term memory is compared with the features detected

from the map. This process of image recognition and integration occurs in short-term memory, thus the more complex the visual array or the more disjointed the visual components (e.g., when image components are located on separate pieces of paper), the greater will be the cognitive complexity involved in recognizing and interpreting the image.

Head's model, when considered in light of the brain's cognitive processes and limitations, helps us to understand how the complexity of a single map image affects interpretation and understanding. For example, as more features are added to the map, the process of grouping these elements into meaningful concepts and relationships becomes more difficult. This also provides a justification for developing measures of map reading efficiency and effectiveness. In particular, one of the seminal works on graphical constructions, image interpretation, and efficiency metrics is Bertin's *Semiology of Graphics* (1967, 1983). In this work, Bertin proposed *image theory*, which has as its primary thesis that some representations of data are more efficient. In this context, a representation is more efficient "If, in order to obtain a correct and complete answer to a given question, all other things being equal, one construction requires a shorter observation time than another construction" (1983, p. 139). To account for these differences in graphic constructions, Bertin proposed the concept of *images* and *figurations*. An *image* is a meaningful visual form perceptible in the minimum instant of vision. However, when graphical illustrations (i.e., graphical propositions) are not represented on one display, constructions called *figurations* that consist of multiple displays are needed to represent these illustrations. Because multiple displays must be processed to understand data represented in *figurations*, they are a less efficient representation of graphical concepts.

The theory of cognitive fit is a valuable framework for understanding why some graphical representations are more efficient than others. Vessey (1991; Vessey and Galletta 1991) suggests that a decision maker's task processing would be more efficient and effective not only when the task and technology fit, but also when the decision maker uses appropriate processes and thereby develops

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[5]A weakness of the Crossland et al. (1995) study is that it included a dual four-cell 2 x 2 factorial research design involving a mixed sample of undergraduate and graduate students. Graduate students were in one 2 x 2 cell for the medium and high complexity task, while undergraduates were in the second 2 x 2 cell for the low and medium complexity task.

appropriate mental representations of the problem. This happens when the technology used to address a problem presents to the decision maker a representation of the problem that is appropriate for the task. A match in the task and technology, therefore, enables a decision maker to use strategies and processes that facilitate the development of an accurate mental representation of the problem. This, in turn, facilitates successful problem solving. Thus, an *image* will create a display environment that is more likely to fit the cognitive requirements of the decision maker while he or she completes a spatial task.

When put into the context of image theory, one can see that the power of SDSS lies in its ability to automate the process of bringing individual *figurations* together into displays that more closely resemble *image* constructions. Since an Image contains an integrated view of the relevant data, this should create a decision-making environment that more consistently *fits* the cognitive requirements of the decision maker and thereby reduces cognitive load. For example, envision a situation where a decision maker needs to identify whether a pipeline is within a given distance of a manufacturing facility. In this scenario the objective is to view information about the location of the pipeline in combination with information about the location of the facility. If each layer were displayed on separate paper maps, this would be typical of a *figuration* and would require greater cognitive effort and consume more time. On the other hand, when an SDSS is used, the software can be used to integrate the separate views into one visual array that can be processed more effectively. In other words, the SDSS creates a visual array that is closer to that of an *image*; therefore, it should require less cognitive effort to process and allow decision makers to solve tasks more accurately and in less time.

> H3: For the same spatially oriented task, decision makers using the SDSS will solve the problem more efficiently than those using only paper maps.

> H4: For the same spatially oriented task, decision makers using the SDSS will solve the problem more accurately than those using only paper maps.

Task Complexity

A variable that has consistently been shown to be important in decision-making research is the research task (Hackman 1969; Mennecke and Wheeler 1993; Strauss 1999; Tuttle and Stocks 1997). Of particular relevance for this research is the number of features and layers in the task that need to be processed and integrated by the decision maker. One of the implications of the research by Bertin (1983), Head (1984), and others is that the greater the number of features and layers, the more difficult it will be for the decision maker to form an integrated view of the information presented in the visual array. As a result, task complexity should have a significant impact on decision maker performance (Crossland et al. 1995; Campbell 1988).

Prior research examining spatial tasks has used the definition of task complexity offered by Wood (Farmer and Hyatt 1994; Wood 1986). Wood defines the complexity construct using three dimensions: component complexity, coordinative complexity, and dynamic complexity. Component complexity "is a direct function of 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" (Wood 1986, p. 66). Coordinative complexity "refers to the nature of the relationships between task inputs and task products" (p. 68). As information cues, acts, products, and input sequences change, so too does task complexity. Dynamic complexity "is due to changes in the states of the world which have an effect on the relationships between task inputs and products" (p. 71). Thus, from Wood's viewpoint, task complexity can be thought of as a multi-dimensional construct.

This perspective is instructive when considering the task used in this research. The task is a site selection problem that requires that subjects rank order a list of facilities based on how well each site satisfies various spatial criteria. Each criterion is represented as a separate layer or map. In addition, each layer contains a number of features that must be considered in the process of solving

the problem. To operationalize a manipulation of task complexity, the number of features and the number of criteria were systematically varied. This resulted in significant variation in the first two dimensions of Wood's definition. For example, as more alternatives and criteria are added to the problem, more distinct acts and information cues must be processed and the task of coordinating these acts becomes more difficult. Prior research has shown that as task complexity increases, task difficulty increases and at the same time decision makers take more time and produce less accurate results (Campbell 1988; Crossland et al. 1995; Swink and Speier 1999).

> H5: Increasing task complexity will lower problem solving efficiency.

> H6: Increasing task complexity will lower problem solving accuracy.

Cognitive Characteristics: The Need for Cognition

One potentially important factor affecting a subject's performance on a problem-solving task is the amount of cognitive effort that the subject is willing to exert in working on the problem. For example, Crossland et al. found that a subject's need for cognition (NFC) (Cacioppo and Petty 1982) was related to efficiency. The NFC measures an individual's internal motivation to pursue and enjoy cognitive activities and tasks. Thus, it is likely that subjects who score high on the NFC instrument would be more likely to be engaged by a problem solving task such as that used in this research. If a subject is more engaged, this should generate higher interest in the task, which should lead to greater effort and higher performance (Davis et al. 1992; Deci 1975). In addition, subjects who are more engaged in the problem should also be expected to take more time solving the problem.

> H7: A subject's NFC score will be negatively related to problem solving efficiency.

> H8: A subject's NFC score will be positively related to problem solving accuracy.

Research Methodology ■■■■■

Independent Variables

The experiment was a mixed, three-factor design (Table 1). The three independent variables are subject characteristics (students versus professionals), SDSS support (SDSS versus no SDSS), and problem complexity (low, medium, and high). This results in a 12 cell, 2 x 2 x 3, factorial design. The unit of analysis is the individual decision maker.

Dependent Variables

Consistent with prior research examining GIS technology, time and accuracy[6] were examined as the dependent variables (Crossland et al. 1995; Dennis and Carte 1998; Smelcer and Carmel 1997; Swink and Speier 1999). The task was adapted from Crossland et al. and required that subjects rank order a series of sites based on the various spatial criteria. Each subject recorded solutions on a scoring sheet that was included with the task materials (Appendix A). Solution accuracy was determined by calculating Kendall's correlation coefficient (T), which is a measure of the agreement between the subject's ranking and the correct ranking (Siegel and Castellan 1988). To measure solution time subjects were asked to record the time that they began and finished completing the task. No artificial time constraints were imposed on subjects.

Covariates

Several covariates were examined in the research. Need for cognition (NFC) was examined

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[6]Other IS researchers such as Vessey (1991) have also called for the use of both accuracy and efficiency in the study of technological impacts on decision making.

Table 1. Independent Variables			
Independent Variable	**Factors**	**Description**	
Problem Complexity	3	Low Medium High	5 Alternatives, 3 criteria 10 Alternatives, 7 criteria 15 Alternatives, 10 criteria
SDSS Support	2	No SDSS Support SDSS Support	Paper Maps SDSS technology, Paper Maps
Subject Characteristics	2	Novice DM Experienced DM	Students, minimal work experience Professionals, significant work experience in employment security and labor market information

as a primary covariate to identify the relationship between this variable and performance. The NFC instrument is a shortened 18-item version of that proposed by Cacioppo and Petty (1982) (reliability α = 0.88). In addition to NFC, gender, each subject's interest in the task, and the subject's satisfaction with the solution were examined as possible covariates. Finally, data about subject skills with spreadsheets, databases, and other computer tools were collected and analyzed as a manipulation check.

Subjects

Student subjects were recruited from various sections of management information systems courses at East Carolina University. Student subjects received partial course credit for participation in the study. All student subjects were randomly assigned to one of the treatments.

The subjects classified as professionals were labor market professionals working for various state employment security offices in the United States. These subjects were drawn from a population of participants in several professional development training sessions that took place between 1996 and 1998. Training sessions

covered topics such as economics, labor markets, interpersonal communication, and information technology. The professionals were randomly assigned to a treatment condition within the constraints of scheduling and the availability of computers. Since participation in the research was voluntary, participants included in the research are those trainees who returned solution forms and questionnaires.

Research Task

Each subject solved a multi-criteria site selection task that asked subjects to assume the role of a labor market professional who is helping a company prioritize the locations of plants where a new technology would be implemented. Subjects were told that the company desired to replace equipment at some of its facilities with newer technologies. To solve the problem, subjects prioritized potential sites against criteria that defined the suitability of each site. All of the criteria included spatial components (e.g., "Is the site contained in an economic development area?") and dealt with factors such as population, location relative to high unemployment zones, and other spatially-referenced information (Appendix). The task was designed so that the criteria would
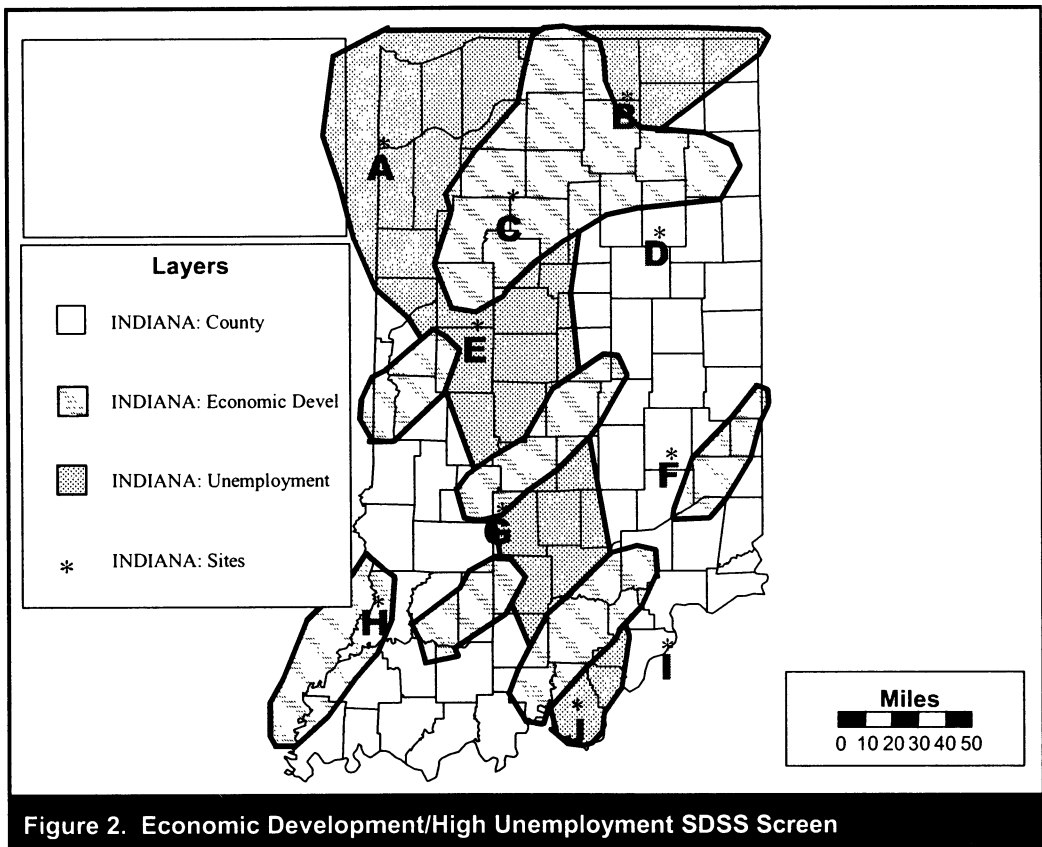
Figure 2. Economic Development/High Unemployment SDSS Screen

be similar to the type of information that many business people as well as most labor market professionals would work with in their jobs.

The priority ranking used a scoring rule that assigned points to sites based on whether or not each site met a particular criterion. Points for each site were recorded on a scoring sheet that contained a listing of all sites, information about the criteria, and spaces for the entry of points and ranks. Figure 2 shows one of the maps that could be generated by the subjects that completed the medium complexity problem using the SDSS. For this criterion, a site might receive a given number of points for being within two of the areas. Figures 3a through 3c show the paper maps used by subjects in the non-SDSS treatment to display the same information. The final evaluation and ranking required that subjects sum the points for

each site and compare and rank the sites based on point totals.

Experimental Procedure

A short introduction was given to all subjects to familiarize them with the methodology to be used, the organization of the printed materials, and the nature of the task. All subjects were given an introduction to GIS technology, including a conceptual overview detailing how GIS could be used to solve problems similar to the experimental task. Immediately before they started the task subjects using the SDSS were also given instructions on how to use the SDSS to display and manipulate the screens needed to solve the

Layers

☐   INDIANA: County

*   INDIANA: Sites

3a.   Map Showing Location of Sites

Layers

☐   INDIANA: County

▨   INDIANA: Economic Devel

3b.   Map Showing Economic Development Zones

Figure 3.   Examples of Maps Used by Subjects in the Non-SDSS Treatment

Layers

☐ INDIANA: County

▨ INDIANA: Unemployment

Miles
0 10 20 30 40 50

3c. Map Showing High Unemployment Area

Figure 3. Continued

task. All subjects were exposed to these intro-
ductory comments and, where appropriate, were
given software training. The only variation in
training related to the broader training session
presented to the labor market professionals. Prior
to the research session the professionals were
exposed to a longer presentation covering various
topics pertaining to information technology and
other components of the GIS software. These
other components related to GIS functionality that
was not needed to solve the problem. For
example, the SDSS used to solve the experi-
mental task required that a subject click the right
mouse button to bring up a dialogue box to select
the desired map(s). All subjects, regardless of
treatment, were given training on performing this
command. Although all subjects were also given
training on the characteristics of GIS technology
and its role in decision making, the training for
professionals also included training on the other
technical GIS features not directly related to the
experimental task.

When the task was delivered, subjects were told
that their objective was to find the best ranking as
efficiently as possible. The problem solving
process is modeled after the multi-criteria decision
making procedure offered by Jankowski (1995) for
use with spatial problems. Once the subjects
completed the entry of their rankings, they were
asked to record the time that they completed the
exercise and to answer several questions about
themselves and the problem solving process.
When they completed the questionnaires, sub-
jects were free to leave the room.

Experimental Setting

The GIS used for the study was Atlas GIS® from
ESRI. A workspace was stored on a floppy disk
that allowed subjects to load the task data in a
standardized way. Although subjects were pro-
vided with standard workspaces, individuals could,
if desired, change the views, content, or display

characteristics of the map features. In other words, the software was fully functional and was more than merely a set of static images.

Because the professionals participated in the experiment in association with a training program that was held in various locations in the United States, it was not possible to use the same facility for all sessions. Nevertheless, subjects participating in the experiment completed the task in settings that were similar. In all cases, the facilities were either training rooms or computer labs. In some instances, subjects completing the computer version of the task were in the same room with those who did not use a computer. In all cases, the same individual (the first author) provided GIS training, read experimental instructions, and supervised data collection.

Results ▰▰▰▰▰▰▰

A total of 240 subjects provided usable data for the study (45% female, 55% male). The average age of the participants is 28.6 years (SD = 10.9). The average age of student subjects is 21.7 years (SD = 3.9) while the average age of professionals is 39.4 years (SD = 9.7). The number of years of work experience reported by students was 4.6 years (SD = 4.7) while professionals reported an average of 11.7 years (SD = 8.9). An analysis was performed to identify whether there were any systematic differences between subjects in any of the treatments. Gender has been shown to have important impacts on outcomes (Gefen and Straub 1997); however, gender was found to have no significant correlation with the dependent variables. Therefore, this variable was not considered in subsequent analyses. Subjects were also asked about their experiences with using computers, spreadsheets, and databases. The results of this analysis show that, when compared to students, professionals reported a significantly higher level of experience using computers ($F(1,237) = 49.44$; p < 0.001) and using spreadsheets ($F(1,236) = 53.63$; p < 0.001) (Table 2). A correlation analysis shows that spreadsheet experience is significantly correlated with accuracy ($r = 0.148$; $p = 0.023$) while computer experience is not ($r = 0.095$; $p = 0.143$). However,

when spreadsheet experience was entered into an analysis of covariance (ANCOVA) model with the treatment variables, the covariate was non-significant ($F(1,236) = 0.696$; p = 0.405).

Subjects were also asked about perceptions related to the task, their solution, and other experimental conditions. The results show that professionals were more likely to report that the task was interesting ($F(1,237) = 6.9$; p = 0.009) and participants completing the low complexity version of the task found the task to be marginally less interesting than those completing the more complex versions of the task ($F(2,237) = 2.9$; p = 0.057). None of the other variables were found to be significantly different for any of the treatment conditions.

Analysis of the Dependent Variables

Kendall's correlation coefficient was used to evaluate solution accuracy across each manipulation. A Levine's test was performed to examine whether the error variances of the dependent variables were equal across all groups (Sokal and Rohlf 1969). The results were significant for both accuracy and efficiency; therefore, accuracy was transformed using a logarithmic transformation and efficiency using a square root transformation (Hair et al. 1995).

The primary focus of this study is to identify the relationships of the treatment variables to the dependent variables. Table 3 lists the descriptive statistics for the dependent variables and Table 4 summarizes the results of the hypothesis testing. A correlation was performed to examine the relationship between accuracy and time. The results show that these variables are significantly correlated ($r = 0.336$; $p < 0.001$); therefore, a multivariate analysis of covariance was examined. The multivariate and individual univariate models were significant; therefore separate univariate analyses were used to examine the dependent variables (Hair et al. 1995).

Table 5 shows the results of the analysis of variance (ANOVA) for the transformed variable for efficiency and Figure 4a shows a graphical representation of the observed means for the non-
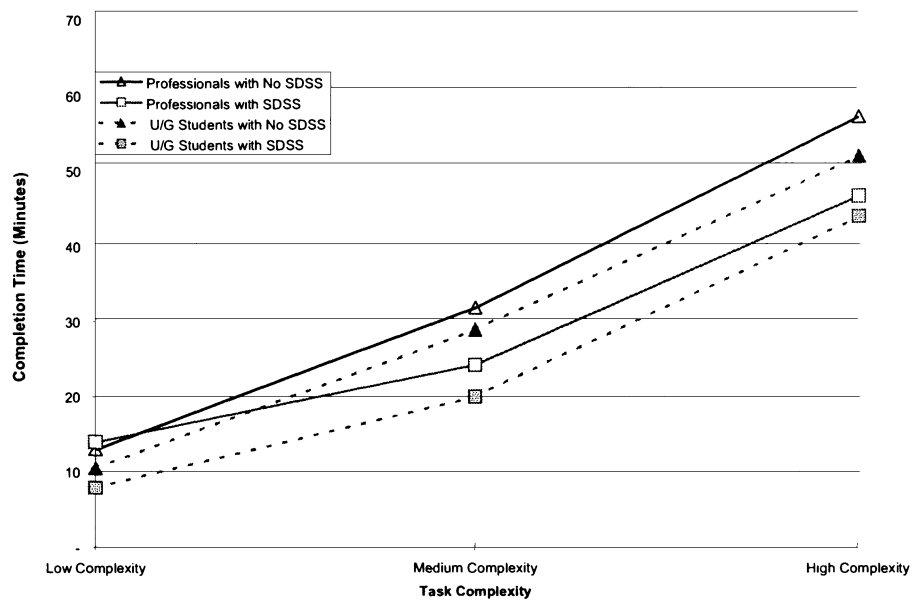
Table 2. Means and Standard Deviations for Perceptual Measures

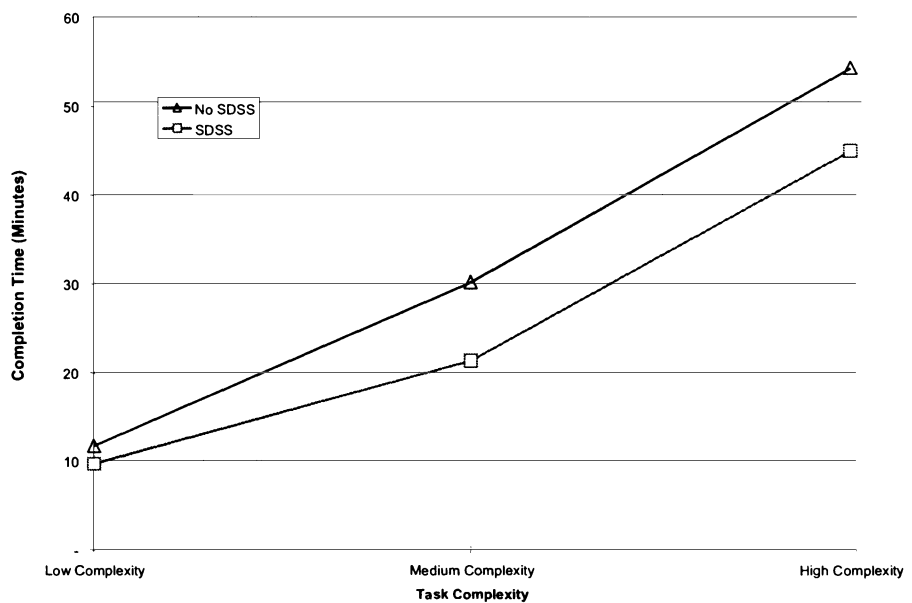|	Students						Professionals					
	Low Complexity		Medium Complexity		High Complexity		Low Complexity		Medium Complexity		High Complexity	
Measures	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS
Please rate yourself on your experience with computers (1 = expert, 5 = novice)												
Mean	2.65	2.71	2.87	2.52	2.45	2.68	2.15	2.17	2.29	1.79	2.00	1.86
Std. Dev.	0.75	0.81	0.69	0.69	0.51	0.65	0.65	0.39	0.69	0.43	0.52	0.36
n	20	28	23	29	22	22	22	12	17	14	16	14
Please rate yourself on your experience with spreadsheets (1 = expert, 5 = novice)												
Mean	3.53	3.25	3.43	3.03	3.27	3.23	2.50	2.42	2.35	2.50	2.63	2.36
Std. Dev.	0.70	0.89	0.66	0.91	0.63	0.87	0.76	0.90	1.11	0.85	0.89	0.93
n	19	28	23	29	22	22	20	12	17	14	16	14
Was the problem interesting?[a] (2 = strongly disagree; 12 = strongly agree)												
Mean	9.25	9.71	10.35	9.90	9.64	9.96	9.65	10.25	10.56	10.64	10.63	10.77
Std. Dev.	1.37	1.72	1.85	1.39	2.17	1.73	1.73	2.38	1.34	2.10	1.41	1.69
n	20	28	23	29	22	22	20	12	18	14	16	13
Need for cognition[b] (18 = Minimum NFC; 162 = Maximum NFC)												
Mean	102.15	107.21	109.35	106.41	103.91	103.43	118.70	128.50	112.39	125.50	129.88	125.86
Std. Dev.	16.48	19.90	17.65	20.03	16.45	18.90	16.77	19.90	18.75	17.86	13.09	15.86
n	20	28	23	29	22	23	20	12	18	14	17	15

[a]This scale was generated by combining two questions: "This was an interesting problem to work on" and "This problem was boring." The scale has a reliability of α = 0.68.

[b]This scale was generated by combining 18 questions from the Cacioppo and Petty (1982) questionnaire. The scale has a reliability of α = 0.88.

Table 3. Means and Standard Deviations for Dependent Measures

| | Students | | | | | | Professionals | | | | | |
| | Low Complexity | | Medium Complexity | | High Complexity | | Low Complexity | | Medium Complexity | | High Complexity | |
Measures	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS	No SDSS	SDSS
Solution Time (minutes)												
Mean	10.5	7.9	28.9	20.0	20.0	44.0	13.0	14.0	31.8	24.2	572	46.7
Std. Dev.	3.8	3.2	7.7	5.8	5.8	12.3	5.9	5.5	10.3	12.2	9.0	15.0
n	20	28	23	23	22	23	20	12	18	14	17	14
Solution Accuracy (Kendall's Correlation Coefficient [T]; a higher score implies greater accuracy)												
Mean	86.70	96.07	70.83	84.96	64.90	76.38	92.00	92.00	84.83	86.79	81.24	85.57
Std. Dev.	18.23	9.46	17.01	10.54	17.93	19.89	15.58	7.79	15.16	6.41	15.99	8.54
n	20	28	23	29	22	23	20	12	18	14	17	14

Table 4. Summary of Hypotheses Testing and Statistical Analysis

Solution Efficiency

Hypothesis	Result	Explanation	Statistic
H1 Professionals will be more efficient than students	Contradicted	Students more efficient	$F(1,240 = 13.34;$ $p < 0.001$
Interaction between SDSS and Complexity			$F(1,240) = 3.91;$ $p = 0.021$
H3 SDSS users will be more efficient than those using paper maps	Partially supported (interacts with complexity)	SDSS users are more efficient for medium and high complexity tasks	$F(1,240) =$ $28.01;$ $p < 0.001$
H5 Increase in task complexity will lower efficiency	Partially supported (interacts with SDSS)	No difference for SDSS use for low complexity task	$F(2,240) =$ $13.34;$ $p < 0.001$
H7 NFC negatively related to efficiency	Not supported		

Solution Accuracy

Hypothesis	Result	Explanation	Statistic
Interaction between SDSS and Subject Characteristics			$F(1,240) = 5.25;$ $p = 0.023$
H2 Professionals will be more accurate than students	Partially supported (interacts with SDSS)	Professionals are more accurate than students when using paper maps	$F(1,240) = 5.15;$ $p = 0.024$
H4 SDSS users will be more accurate than those using paper maps	Partially supported (interacts with subject type)	SDSS use leads to greater accuracy and increases only for student users	$F(1,240) =$ $14.30;$ $p < 0.001$
H6 Increase in task complexity will lower accuracy	Supported	Solution accuracy decreases as task complexity increases	$F(2,240) =$ $12.88;$ $p < 0.001$
H8 NFC positively related to accuracy	Marginally supported	NFC positively related to accuracy at marginal significance level	$F(1,240) = 3.71;$ $p = 0.055$

a. Solution Efficiency Observed Means by Treatment

b. Solution Efficiency Observed Means for SDSS and Complexity Interaction

Figure 4. Solution Efficiencies

Table 5. Results of ANOVA for Solution Efficiency[a]				
SOURCE	**df**	**MS**	**F**	**p***
Problem complexity	2	253.66	396.67	.000***
SDSS availability	1	17.91	28.01	.000***
Subject	1	8.53	13.34	.000***
Problem Complexity * SDSS Availability	2	2.50	3.91	.021**
Residual	228	0.64		
Total	240			
Model R Squared = .805 (Adjusted R Squared = .796)				

... significant at p<.01
..significant at p<.05

[a]The statistics reported for solution efficiency are based on a square root transformation of the raw data (Hair et al., 1995).

transformed data in each treatment. The results for efficiency indicate that there is a significant interaction between task complexity and SDSS use ($F(2,240) = 3.81$; $p = 0.021$) (Figure 4b). When an interaction exists, an interpretation of the interaction should be made first followed by an examination of the main effects (Hair et al. 1995). The trend of the means shows that SDSS use resulted in superior efficiency only for the medium and high complexity problems. For the low complexity problem, no significant difference exists between solution times across the SDSS manipulation. Thus, hypotheses H3 and H5 are partially supported.
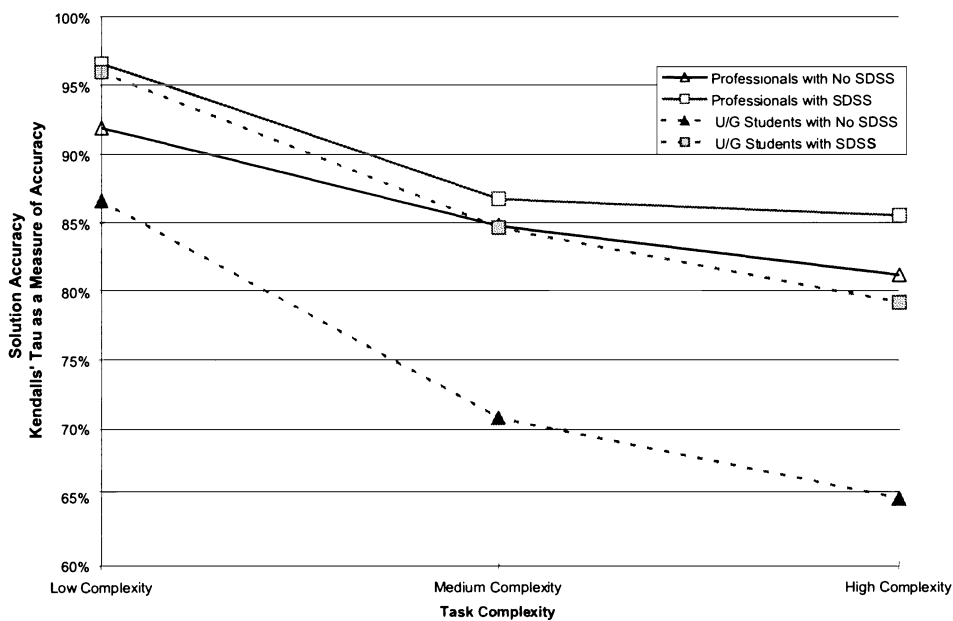
The results also show that there were significant main effects of time for subject characteristics ($F(1,240)=13.34$; $p<0.001$). However, because the trend of the means for efficiency are opposite to the predicted direction (i.e., professionals took more time to complete the task), Hypothesis H1 is not supported and is contradicted. One potential explanation for this finding pertains to a subject's interest in the task.[7] A post hoc correlation

analysis examining the relationship between interest and efficiency shows that the amount of interest that a subject had in the task is positively related to the amount of time they spent working on the task ($r = 0.177$; $p = 0.007$) (see Csikszentmihalyi 1975).[8]
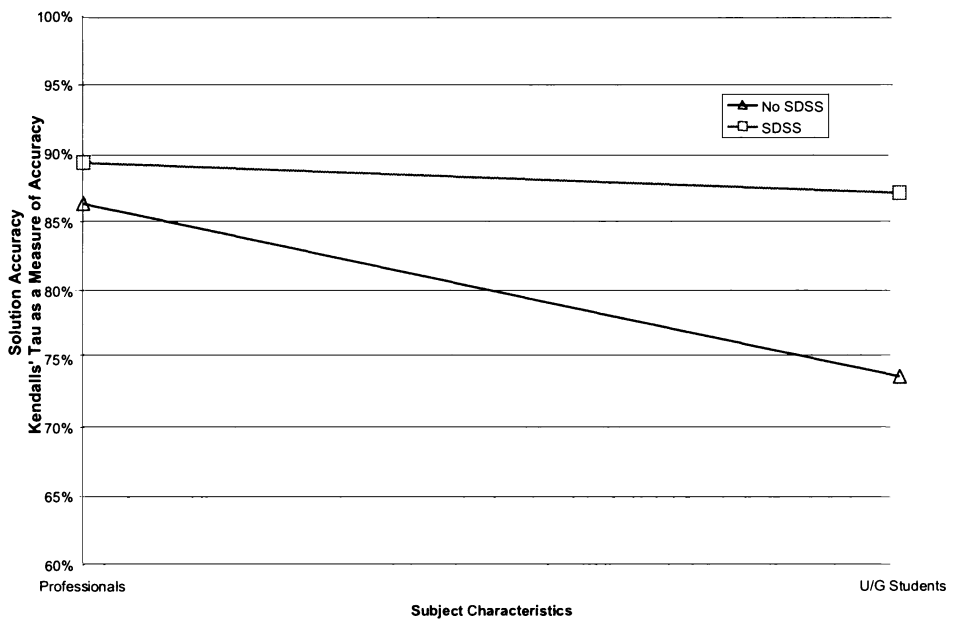
Table 6 shows the results of the ANCOVA for the transformed variable representing solution accuracy and Figure 5a shows a graphical representation of the observed means for the non-transformed data. The results show that, in addition to the significant main effects for subject characteristics and SDSS, there is also a significant interaction between these variables ($F(1,240) = 5.25$; $p = 0.023$). An examination of the trend of the means shows that the performance difference between professionals and students is greater when the problem was solved without the SDSS and that professionals using the SDSS did not significantly outperform professionals using paper maps (Figure 5b). To examine whether the lower levels of interest reported by students might account for their inferior accuracy relative to professionals, a post hoc correlation analysis examining the relationship between task interest and solution accuracy was performed. Results indicate that there was no significant direct correlation

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[7]Another explanation for this finding is that professionals took more time because they are more accustomed to precisely and accurately recording and completing work-related activities. In most professional jobs, employees quickly learn that errors can seriously harm a career (i.e., mistakes have consequences). Thus, the professionals who engaged in solving this research task may have processed it more fastidiously because such behavior would be part of their regular work routine.

[8]It should also be noted that although the student's interest in the task was lower than professionals, it was still relatively high (M = 9.81 out of 12 for students; M = 10.38 out of 12 for professionals).

a. Solution Accuracy Observed Means by Treatment

b. Solution Accuracy Observed Means for SDSS and Subject Interaction

Figure 5. Solution Accuracies

Table 6. Results of ANCOVA for Solution Accuracy[a]

SOURCE	df	MS	F	p.
Problem complexity	2	0.74	12.88	.000***
SDSS availability	1	0.82	14.30	.000***
Subject	1	0.30	5.15	.024**
Subject * SDSS availability	1	0.30	5.25	.023**
NFC	1	0.21	3.71	.055*
Residual	227	0.06		
Total	240			
Model R Squared = .248 (Adjusted R Squared = .213)				

...significant at p < .01
..significant at p < .05
.significant at p < .10

[a]The statistics reported for solution accuracy are based on a logarithmic transformation of the raw data (Hair et al. 1995).

between these variables (r = 0.046; p = 0.48). The results, therefore, offer partial support for hypotheses H2 and H4. Significant main effects of solution accuracy were observed for task complexity ($F(2,240)$ = 12.88; $p < 0.001$); as complexity increased accuracy decreased. Thus, hypothesis H6 is supported.

The results for NFC show that professionals have a significantly greater NFC compared to students ($F(1,240)$ = 56.65; $p < 0.001$) (Table 2). In addition, NFC was also found to be significantly correlated with solution accuracy (r = .174; p = .007). Because of these findings, NFC was examined in combination with accuracy (Table 6) and found to be a marginally significant covariate ($F(1,240)$ = 3.71; $p = 0.055$). An examination of the correlation between these variables indicates that as NFC increases, solution quality also increases. Thus, hypothesis H7 is rejected and H8 is marginally supported.

Discussion ▰▰▰▰▰

This research was designed to examine how SDSS, subject characteristics, and problem complexity affect the performance of subjects solving a problem involving spatially-referenced informa-

tion. As such, it is the first to systematically and simultaneously examine these variables in a controlled research setting. The findings are partially supportive of the research model and hypotheses and significantly advance our understanding of both the usefulness of SDSS technology and the relative influence of the other research variables. This study will, therefore, be useful for informing both the research and practitioner communities about the merits of GIS technology, the role of users and user characteristics, and the nature of research tasks.

Implications Associated with User and Subject Characteristics

Prior experimental research examining SDSS and GIS in a decision support context has exclusively used students as subjects (Crossland et al. 1995; Dennis and Carte 1998; Swink and Speier 1999). This research has generally found that SDSS improves user performance or extends the capabilities of the user to analyze certain types of data or to make decisions. The current research significantly extends this research stream by examining the impact of SDSS use by professionals who have significant work and decision-making experience.

The observed interaction for accuracy between SDSS use and subject characteristics has important implications for understanding the role of SDSS in enhancing the capabilities of different types of decision makers. An important finding associated with this is that when professionals complete the problem the SDSS does **not** appear to significantly improve their accuracy beyond that of professionals using paper maps (Figure 5b). This is somewhat surprising and unique given that prior research has shown that SDSS and similar technologies improve accuracy for a variety of users (e.g., Crossland et al. 1995).

Does this mean that SDSS is of little or no value for professionals who need to solve spatial problems? The answer to this question can probably best be addressed by considering two issues. First, the SDSS clearly lead to efficiency improvements for all users when they completed more difficult problems. So, although professionals using the SDSS were no more accurate than their counterparts who used paper maps, they were significantly more efficient. The second part to the answer can be found by considering the fact that the SDSS appears to have an equalizing effect on users. By collapsing multiple map displays into one screen display that is more like an *image*, the SDSS facilitates the development of a Gestalt understanding of the relationships in the problem. Through this process the SDSS significantly improves performance for students or, in other words, less experienced decision makers (e.g., students' accuracy when using the SDSS was close to and sometimes exceeded the performance of professionals using paper maps). This capability, in effect, helps to compensate for the students' lower levels of knowledge about the task, their lack of experience with problem solving, and their lower NFC. If, as these findings indicate, GIS can be used to improve the performance of users who have lower levels of knowledge and problem-solving skills, this suggests that SDSS and, by extension, GIS will prove to be helpful for a variety of users and decision makers. For example, new or lower-level employees, users of an organization's spatially-enabled website, consultants, and others who may lack various dimensions of knowledge about a problem will likely benefit significantly from the use of SDSS because it will help them compensate for their lower knowledge levels. Since

system developers, consultants, and venders would likely view the professionals studied in this research as comparable to users of their products and services, these findings should have important and widely generalizable implications for SDSS and GIS implementation and integration as well as product training and marketing.

In addition, these findings suggest that the study has important implications for the validity of research that involves student subjects. The results indicate that students can provide useful information about the relative impacts on performance. For example, although the accuracy of the students' solutions was generally inferior to that of the professionals, the relative pattern of students' performance was generally consistent with that of professionals (Table 3; Figures 4 and 5). Thus, when the focus is on making within-group comparisons, the findings suggest that students are a suitable population to use when studying decision-making, GIS, and other related decision support technologies. However, these findings indicate that students are not always valid surrogates for professionals when one wishes to generalize in an absolute sense. Specifically, the interaction between subject characteristics and SDSS availability implies that when researchers seek to compare students and professionals who are using technology, the differences between the performance of these groups is much less than would be the case without technology. Thus, when the focus of research is on making between-group comparisons (e.g., comparing students using technology to professionals without technology), great care must be taken in interpreting results. This is consistent with the recommendation offered by Hughes and Gibson (1991) in their examination of students and managers, "The suitability of students as surrogates in the decision process depends on case-specific circumstances" (p. 163).

Implications for Research on GIS and SDSS

These findings also improve our understanding of the relationship between task, the use of SDSS technology, and the characteristics of research subjects and users. The theory of cognitive fit has

been shown to be a useful perspective from which to understand when and where technology will be useful in supporting decision makers in other contexts (Vessey 1991; Vessey and Galletta 1991). In the original formulation of the theory, Vessey and Galletta suggested that three variables would influence the mental representation that the decision maker develops: (1) the problem representation, (2) the problem-solving task, and (3) the decision maker's problem solving skills. In the current research, similar variables were examined. For example, we can equate the cognitive fit variable "problem representation" with the SDSS manipulation since the SDSS, or lack thereof, created for each user a specific representation of the problem's components. Similarly, the cognitive fit variable "problem-solving task" was manipulated in this research vis-à-vis the complexity manipulation. But, what about the third variable in the cognitive fit model, problem solving skills? In this case the specific skill of the subject was not manipulated per se; rather, the experience, maturity, and cognitive characteristics of the decision makers were considered. However, since subject characteristics were found to influence performance, it is reasonable to expect that this was the result of differences in the ways that professionals and students form their mental representations of the problem. Therefore, subject characteristics represent an additional useful dimension to the domain of variables represented by "problem solving skills" that were identified in cognitive fit theory.

In this context, it is clear that the results of this research are compatible with cognitive fit theory. In fact, the insertion of these variables represents a useful starting point for considering the cognitive fit theory in light of the cumulative research completed on GIS and SDSS to date. Factors such as whether maps or tables are used (Smelcer and Carmel 1997), the nature of the data associations in the task (Dennis and Carte 1998), the complexity of the task (Crossland et al. 1995; Smelcer and Carmel 1997; the current research), the availability of SDSS, the characteristics of the subjects, and several other variables all appear to have an important impact on the mental representation that the decision maker develops as he or she works on tasks pertaining to maps and spatial data. This suggests that it is worthwhile to

apply cognitive fit theory to spatial tasks and expand and elaborate on the factors that appear to be important in influencing a user's formation of a mental representation. Toward this end, the model presented in Figure 6 is offered as a framework for examining cognitive fit in the context of geographic tasks and problems.[9] An important contribution of this framework is the recognition and inclusion in the cognitive fit model of numerous variables, including those examined in this study, that have been shown to be important for map reading and interpretation. Since the list of relevant variables is no doubt incomplete, future research examining other variables in combination with these would be useful to expand our understanding of these relationships.

An example from this study of the impact of these variables on the mental representation of the decision maker is illustrated by the interaction of task complexity with SDSS availability that was observed in this research. It appears that for the low complexity version of the problem, the benefits offered by the SDSS in lowering cognitive complexity did not outweigh the added costs of manipulating the software. This is likely due to the fact that the visual array presented to an SDSS user contains more elements than that presented to the problem solver examining paper maps. The SDSS visual array includes the maps plus the software's interface, hardware, and other support elements. At lower levels of task complexity, the added complexity of the visual array neutralized the benefits offered by the SDSS. At higher levels of complexity, however, the benefits provided by the SDSS outweighed the costs of its use, thus performance was improved.

When applied to spatial tasks, the cognitive fit model is useful as a starting point for framing our understanding about the variables that influence how the decision maker develops his or her mental representation of spatial (and non-spatial)

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[9]This model is expected to have application to the study of other related DSS, to the study of various types of subjects who possess a variety of skills and cultural histories, and to the study of other types of tasks. A detailed discussion of these issues is beyond the scope of this paper.
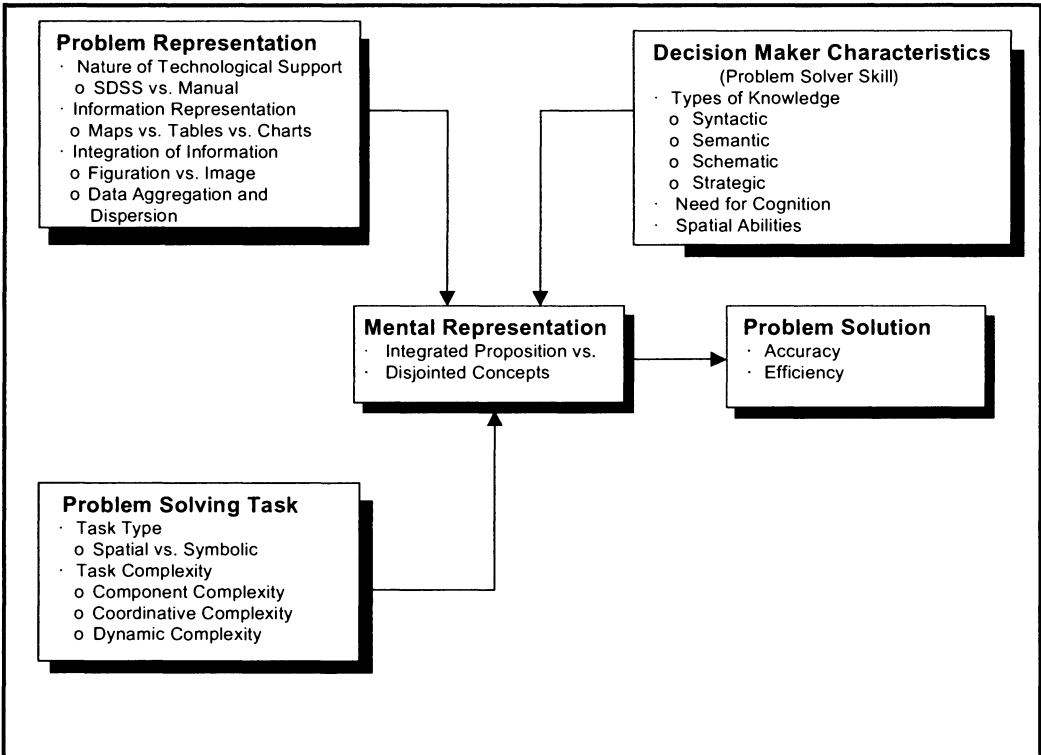
Problem Representation
· Nature of Technological Support
   o SDSS vs. Manual
· Information Representation
   o Maps vs. Tables vs. Charts
· Integration of Information
   o Figuration vs. Image
   o Data Aggregation and
      Dispersion

Decision Maker Characteristics
(Problem Solver Skill)
· Types of Knowledge
   o Syntactic
   o Semantic
   o Schematic
   o Strategic
· Need for Cognition
· Spatial Abilities

Mental Representation
· Integrated Proposition vs.
· Disjointed Concepts

Problem Solution
· Accuracy
· Efficiency

Problem Solving Task
· Task Type
   o Spatial vs. Symbolic
· Task Complexity
   o Component Complexity
   o Coordinative Complexity
   o Dynamic Complexity

Figure 6. A Model of Cognitive Fit for Geographic Problems and Tasks

problems and, more directly, how these variables influence problem outcomes. What is lacking is a useful and detailed framework for describing how the mental representation of spatial problems is formed, the strength of the relationship between the variables that influence the formation of this representation, and how the mental representation, once formed, is tied to outcome variables (UCGIS 1996). Therefore, it would be useful to develop an integrative model examining the processes involved in forming a mental representation of maps as well as figures and images. The perspective offered by several of the authors cited in the introduction to this paper, when considered together, would likely be useful to accomplish this goal (Bertin 1983; Head 1984; Mayer 1997; Vessey and Galletta 1991). For example, Head (1984) suggests that map reading involves processes similar to those involved in reading symbolic languages and that the outcome of the map reading process results in the development of

something akin to a proposition in the map reader's mind. This proposition is, of course, the mental representation discussed by Vessey and Galletta. Thus, a framework based on a linguistic paradigm might prove useful for delving deeper into the processes of map reading and interpretation that are implied by cognitive fit theory.

Several additional research studies derived from this perspective are possible. For example, the level or type of task knowledge (i.e., syntactic, semantic, schematic, strategic) that a subject had when they completed the task was not systematically varied in this research. It would be useful to examine how each of these types of knowledge uniquely affects performance. Similarly, since maps do not always use the same symbology or naming conventions, what impact would variations in the nature of the map schema in the task have on outcomes when subjects have significant syntactic and semantic knowledge (e.g., when

they approach the task with well defined schemas for map reading)? In addition, it would be useful to examine the limits of SDSS in collapsing *figurations* into *images*. In this case, no more than four separate layers of information were combined. At what point does it become effectively impossible to combine displays? It might also be useful to examine to what degree computing technology is needed to create images from figurations. Cartographers have for years examined maps using light tables, transparencies, and similar tools to overlay one map upon another. A question that this raises is how much does the SDSS add in image formation relative to these less sophisticated approaches? Finally, each of these questions as well as many others can be applied to examining spatial technologies such as GIS not only in relation to stand-alone applications but also in the context of applications delivered via the Internet. Since maps and spatial data are becoming an integral part of many e-commerce applications (Francica 2000; Weber 2000), future research should examine how these and other variables affect the use of spatial data and applications that are delivered via the Internet.

Implications for Practice

Although this research has focused significant attention on theoretical issues, the findings do have important practical implications for developers and users of spatial technologies. This research is unique because it involves participants who are professionals with significant work experiences; thus, the results should be generalizable to many organizational settings. An important implication of the research is that the findings highlight the value of investing in SDSS, GIS, and similar technologies for certain types of users. In particular, it appears that GIS can be used to extend the range of problems that can be solved using technology by allowing users to more efficiently complete problems that are more complex. Often GIS implementations can be quite expensive when hardware, software, training, and the acquisition of data are considered. In fact, an important impediment to GIS implementation efforts has been the high cost associated with its deployment (Mennecke and West 1998; forthcoming; Onsrud and Pinto 1991; Smith and

Tomlinson 1992). The finding demonstrating the GIS' superiority offers evidence that helps to justify these investments. Of course, it must be acknowledged that since SDSS use did not bring significant accuracy improvements to professionals who used the technology, there may be circumstances where minimal benefits would be realized from making such investments.

This research also suggests opportunities for improving user training and intelligent decision aids. For example, as we develop a better understanding of how the various forms of user knowledge impact performance, it should be possible to more precisely target training and assistance to users who may lack knowledge about various components of the GIS display environment or about the problem domain. In addition, this line of research should be useful in the development of intelligent support systems (e.g., wizards and agents) that could assist less knowledgeable users with both building appropriate map displays and interpreting the components present on the map. This would be particularly valuable for improving the delivery and display of spatial data in situations where users have little or no knowledge about how to use or interpret these data. For example, with the debut of desktop GIS such as Microsoft's MapPoint and the widespread deployment of maps on web sites, a large number of users who do not have sophisticated knowledge about interpreting maps have begun to use GIS technology. These users will often need intelligent support to use these maps effectively. In many ways, this situation is similar to what occurred in the 1980s when spreadsheet-charting capabilities proliferated. Much of the basic research on color, chart types, and similar variables was useful to both designers and users of these technologies. Research on GIS such as that reported here should provide similar practical benefits to developers and users.

Limitations

It should be remembered that an interpretation of these findings must be qualified by the nature of the experimental setting, the subject population, the SDSS, and the task type. Further, because some of the data were collected in a field setting,

some variables were not controlled as well as would be the case in the laboratory. For example, data for professionals were collected in different training sessions held in different cities; thus the settings for these sessions were similar but not identical. Likewise, although subjects received the same instructions on how to use the SDSS to complete the task, professionals were provided with a more thorough introduction to broader issues related to GIS. Additionally, the same person—the first author—read instructions, provided training, and supervised all data collection. Although an attempt was made to follow the scripted instructions consistently, the fact that the experimental administrator was not blind to the purpose of the study should be considered in interpreting the results. Finally, the SDSS used in this research was designed to assist with a specific problem scenario. GIS and SDSS potentially offer many benefits that were not considered in this study. For example, GIS facilitate the collection, management, manipulation, and distribution of spatial data, which offers significant advantages relative to a manual approach. Therefore, the findings from this research need to be considered in light of the broader issues associated with selecting and implementing GIS in an organizational setting. For this reason as well as those cited above, the results and implications of this study must be qualified by and considered in light of the methods used.

Conclusions

The study of how users interpret imagery has been of interest to IS researchers and practitioners for quite some time. This paper adds to this research stream by building on prior SDSS and GIS research and by integrating the work of Bertin (1983), Head (1984), Vessey and Galletta (1991), and others. To examine these issues, a research experiment was conducted that focused on studying the role of SDSS, subject characteristics, and task. This research generated a number of findings and conclusions that will be useful for improving our understanding of the impact of SDSS technology and task on problem solving. Further, the results also offer valuable insights into how subject characteristics such as experience and cognitive effort affect outcomes.

As such, the findings from this study represent a valuable contribution to the ongoing research on decision making and spatial decision support technologies.

Acknowledgments

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Appendix

Scoring Sheet for Medium Complexity Problem[10] ■■■■■■■■■

Scoring of Sites
Enter the point score for each site

	A	B	C	D	E	F	G	H	I	J
Population										

Guidelines   No points if in a county with *more* than 50,000 population
    5 points if in a county with *less* than 50,000 population
    8 points if in a county with *less* than 50,000 population *and* all adjoining counties also *less* than 50,000 population

	A	B	C	D	E	F	G	H	I	J
Natural Gas Pipeline										

Guidelines   No points if *more* than 10 miles from *any* pipeline
    4 points if *less* than 10 miles from a Texas Extern pipeline
    7 points if *less* than 10 miles from an ANR pipeline
    11 points if *less* than 10 miles from an ANR pipeline *and also less* than 10 miles from a Texas Eastern pipeline

	A	B	C	D	E	F	G	H	I	J
Parks/Recreation Areas										

Guidelines   No points if *more* than 10 miles from *any* recreation area/park/forest
    3 points if *less* than 10 miles from *any* recreation area/park/forest

	A	B	C	D	E	F	G	H	I	J
Economic Development Zone										

Guidelines   No points if *outside* an economic development zone
    3 points if *inside* an economic development zone

	A	B	C	D	E	F	G	H	I	J
Population/Major Market										

Guidelines   No points if *outside* a major market area
    2 points if *less* than 50,000 population and *inside* a major market area
    4 points if *more* than 50,000 population and *inside* a major market area

	A	B	C	D	E	F	G	H	I	J
Environmental Sensitivity										

Guidelines   No points if *outside* a high environmental sensitivity area
    2 points if *more* than 10 miles from recreation area/park/forest *and inside* environmental sensitivity area
    4 points if *less* than 10 miles from recreation area/park/forest *and inside* environmental sensitivity area

	A	B	C	D	E	F	G	H	I	J
Labor Economic Data										

Guidelines   Include economic development zones, skilled workers, and high unemployment
    No points if *not inside at least two* labor or economic criteria
    2 points if *inside any two* types of labor or economic areas
    6 points if *inside all three* types of labor or economic areas

	A	B	C	D	E	F	G	H	I	J
GRAND TOTAL POINTS										

Guidelines   ENTER THE TOTAL POINTS FOR EACH SITE

	A	B	C	D	E	F	G	H	I	J
RANK FOR EACH SITE										

Guidelines   ENTER THE PRIORITY RANK NUMBER (1 – 10) FOR EACH SITE

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[10]Solution sheets for low and high complexity versions of the task are available from the first author upon request.