

# Impact of Geospatial Reasoning Ability and Perceived Task-Technology Fit on Decision-Performance: The Moderating Role of Task Characteristics

*Research-in-Progress*

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## ABSTRACT

Consumer, business and governmental entities increasingly rely on spatial decision support systems (SDSS) for decision-making involving geospatial data. Understanding user- and task-characteristics that impact decision performance will allow developers of such systems to maximize geospatial decision-making performance. Furthermore, scholars will benefit from a more comprehensive understanding of what specific characteristics influence decision-making as such knowledge can guide future research in the decision sciences domain. This paper provides a synthesis of geospatial reasoning ability, task-complexity, geovisualization and decision-performance research. A two-factor experiment designed to measure the impact of geospatial reasoning ability on decision-performance is performed. Two treatments, problem-complexity and map-complexity, are investigated for their moderating role on decision-performance. A partial least squares analysis is performed to assess the experiment results. Cognitive Fit Theory is used as the theoretical framework of this study and is extended, along with research in decision-performance and geospatial reasoning ability.

## Keywords

Decision-performance, user characteristics, task characteristics, geospatial reasoning ability, perceived task technology fit, maps, spatial decision support system, cognitive fit theory.

## INTRODUCTION

Consumer, government and business decision-makers increasingly rely on spatial decision support systems (SDSS). For example, consumers often use web-based SDSS for a variety of decision-making tasks, including locating a nearby bank, selecting the best route to an airport or more complex tasks, such as selecting an ideal neighborhood for a new home. In addition, business decision-makers utilize such tools to assign sales territories, determine sites for outdoor advertising campaigns and to achieve supply-chain efficiencies. Government and community groups apply such tools to communicate complicated geospatial concepts, to determine areas that could be impacted by civic projects, and to spatially correlate the effects of phenomena with their possible causes. These examples are just a few of the many ways that entities use SDSS to support geospatial decision-making.

Decision-makers often have access to large quantities geospatial data, which is continuously collected using mobile devices and shared from a variety of sources. Furthermore, several free or low-cost tools allow organizations to easily develop SDSS tools and provide such tools to decision-makers. As most business decisions utilize geographic data, understanding how such decisions are made and how such decision-making can be improved provides an important benefit to organizations (Tonkin, 1994; Mennecke, 1997).

While prior research papers address aspects of decision-performance, user-characteristics and task-characteristics (e.g., Jarupathirun and Zahedi, 2007; Ozimec, Natter and Reutterer, 2010), none of these specifically measure geospatial reasoning, problem-complexity and visualization-complexity with decision-performance simultaneously. Understanding how user- and task-characteristics influence decision performance when solving geospatial problems provides an important extension to existing knowledge in this area. Furthermore, industry will benefit by learning how user- and task-characteristics can be augmented to enhance decision-performance.

Three primary research questions provide the motivation for this study: 1) Does geospatial reasoning ability impact geospatial decision-making performance? 2) Does the complexity of the visualization impact geospatial decision-making

performance? 3) Does the complexity of the problem impact geospatial decision-making performance? Each of these questions is addressed in this research project.

The following section presents a literature review and theoretical framework for this study. Subsequently, a comprehensive research model and accompanying research method are presented. These sections are followed by initial findings derived through an early partial least squares analysis. Finally, a discussion, limitations, suggestions for future research and a conclusion are presented.

## LITERATURE REVIEW

This research extends the Cognitive Fit Theory by exploring the effects of user- and task-characteristics on decision performance. Specifically, the impact of user-characteristics, consisting of geospatial cognitive ability and perceived task-technology fit, on decision performance is examined.

### Cognitive Fit Theory

Vessey's (1991) Cognitive Fit Theory (CFT) provides the theoretical framework for this study. CFT suggests that higher quality decisions are made when the information presentation matches the problem-solving task. The CFT has been highly cited within the information systems scholarship and has been extended into several decision-making studies involving geospatial data (e.g., Smelcer and Carmel, 1997; Swink and Speier, 1999; Speier and Morris, 2003; Mennecke, Crossland and Killingsworth, 2000).

Several studies explore the impact of task complexity on decision-making performance particularly when examining a problem involving geospatial data (e.g., Smelcer and Carmel, 1997; Swink and Speier, 1999; Jarupathirun and Zahedi, 2007; Ozimec et al., 2010). For instance, Swink and Speier (1999) validate that decision-making performance, as measured by decision-quality and decision-time, is superior for less complex problems. Additionally, while Mennecke et al. (2000) confirm that as task-complexity increases, accuracy is lowered, only partial support for task efficiency being lowered was found. Speier's (2006) review of research examining cognitive fit, noted that seven of the eight papers examined provided full or partial support of the CFT.

### Decision Performance

Numerous studies have examined objective decision-performance, measured by decision-accuracy and decision-time, when making decisions using geographic information (e.g., Crossland, Wynne and Perkins, 1995; Smelcer and Carmel, 1997; Dennis and Carte, 1998; Swink and Speier, 1999; Ozimec et al., 2010). Other decision-performance indicators have included perceptions of the decision outcome or process, such as perceived decision-quality and perceived decision-confidence (Jarupathirun and Zahedi, 2007; Ozimec et al., 2010).

Objective measures of decision-making time and decision accuracy are the most commonly validated measures of decision-making performance. However, research also suggests incorporating the use of perceptions of the decision-making process and performance, particularly as user perceptions have been shown to be significant aspects of technology acceptance (e.g., Jarupathirun and Zahedi, 2007; Ozimec et al., 2010).

### User Characteristics

Several studies have investigated the individual abilities and their impact on successfully processing geographic information and making use of it in decision-making. User characteristics such as sex, age, culture, cognitive ability, mental workload, spatial visualization, spatial orientation, and general spatial ability have been examined (e.g., Albert and Golledge, 1999; Slocum, Blok, Jiang, Koussoulakou, Montello, Fuhrmann and Hedley, 2001; Zipf 2002; Speier and Morris, 2003; Jarupathirun and Zahedi, 2007). Numerous studies utilize spatial visualization ability as a measure of user characteristics (e.g., Smelcer and Carmel, 1997; Whitney, Batinov, Miller, Nusser and Ashenfelter, 2011). Other studies have included spatial orientation (Swink and Speier, 1999), self-efficacy (Jarupathirun et al., 2007) and concepts including visual memory and perspective taking (Whitney et al., 2011). Lee and Bednarz (2009) raise a concern that many cognitive evaluation tools that should evaluate geospatial reasoning are based on 'table-top' measurements and may not actually evaluate cognitive abilities in the geospatial context. This concern was addressed through the development of a multi-dimensional construct designed to measure geospatial reasoning ability (Erskine and Gregg, 2011). Understanding user-characteristics that impact individual decision-making performance is essential as such knowledge will allow researchers to develop tools and presentation techniques that improve performance for those with lower cognitive ability without impacting those with high cognitive ability (Smelcer and Carmel, 1997).

In addition to user-characteristics, task-characteristics are also explored in similar studies.

**Task Characteristics**

Numerous task characteristics have been evaluated in previous studies, including map types, map symbolization, (Ozimec et al., 2010) and information presentation (Dennis et al., 1998). However, one of the most common task-characteristic measures is that of task difficulty (e.g., Smelcer and Carmel, 1997; Jarupathirun and Zahedi, 2007; Ozimec et al., 2010). Task difficulty can be manipulated through the complexity of the relationships of the data analyzed (Smelcer and Carmel, 1997) as well as the number of possible solutions and functionality of tools provided (Jarupathirun and Zahedi, 2007).

Table 1 provides an overview of relevant decision-performance studies that utilize task characteristics, user characteristics, and decision-performance.

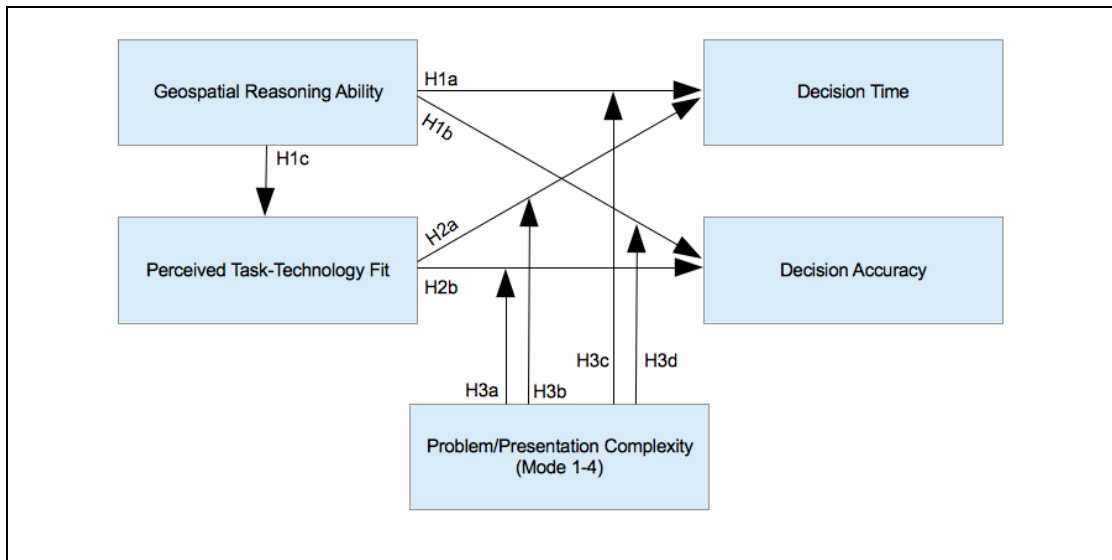
| <i>Study</i>             | <i>Task Characteristics</i>  | <i>User Characteristics</i>  | <i>Decision Performance</i>  |
|--------------------------|--|--|--|
| Crossland et al. 1995    | Visualization Tool   |  | Decision Time, Decision Accuracy   |
| Smelcer et al. 1997      | Task Difficulty, Geographic Relationships, Data Representations      | Spatial Visualization  | Decision Time, Decision Accuracy   |
| Dennis et al. 1998       | Information Presentation   |  | Decision Time, Decision Accuracy   |
| Swink et al. 1999        | Problem Size, Data Aggregation, Data Dispersion                      | Spatial Orientation  | Decision Quality, Decision Time  |
| Jarupathirun et al. 2007 | SDSS Functionality, Site Selection, Task Complexity, Goal Difficulty | Visualization, Spatial Orientation, Self Efficacy, Perceived Task Technology Fit | Perceived Decision Quality, Perceived Decision Efficiency, Decision Satisfaction, SDSS Technology Satisfaction |
| Ozimec et al. 2010       | Map Type, Map Symbolization, Task Complexity, Goal Difficulty        | Spatial Ability, Map Experience  | Decision Efficiency, Decision Accuracy, Decision Confidence, Perceived Ease of Task                            |
| Whitney et al. 2011      | Address Verification   | Spatial Visualization, Visual Memory, Perspective Taking                         | Field Travel Distance, Total Time, Number of Errors  |

**Table 1. Summary of Geospatial Decision-Making Performance Research**

**Note: Only measures directly relevant to this study are shown, see original works for further information.**

**RESEARCH MODEL**

This research project utilizes geospatial reasoning ability and perceived task-technology fit as user-characteristics, presentation complexity and problem complexity as task-characteristics, and decision-time and decision-accuracy as measures of decision-performance. See Figure 1 for a visual representation of the proposed research model. This research paper builds upon previous experiments, as shown in Table 1, by including the multi-dimensional measure of geospatial reasoning ability to measure spatial cognition within the context of a geographic scale. As the literature review demonstrated that objective measures of decision-making are widely used measures of decision-making performance, they are also used in this study.



**Figure 1. Proposed Research Model**

Prior research has shown conflicting results when measuring the effects of spatial ability on objective and subjective decision-making performance measures. For example, Albert et al. (1999) and Jarupathirun and Zahedi (2001) reported partial or no significant effect of spatial ability on their experiment outcomes. However, Smelcer and Carmel (1997), Swink and Speier (1999), Speier and Morris (2003), Lee and Bednarz (2009), Whitney et al. (2011) and Rusch et al. (2012) discovered a significant effect between spatial ability on the outcomes of their experiments. Many of these studies utilize measurement instruments that examine cognitive reasoning outside the geospatial context, measure only one or two dimensions of spatial reasoning and often require previous experience. However, the geospatial reasoning ability (GRA) scale examines such reasoning using three dimensions within the geospatial context and allows expert as well as non-expert responses (Erskine and Gregg, 2011). Furthermore, as decision-time and decision-accuracy have been commonly used as measurements of decision-performance, we suggest measuring the impact of GRA on these two measures. Based on these findings, we posit:

H<sub>1a</sub>: Higher geospatial reasoning ability (GRA) leads to lower decision time.

H<sub>1b</sub>: Higher geospatial reasoning ability (GRA) leads to increased decision accuracy.

H<sub>1c</sub>: Higher geospatial reasoning ability (GRA) leads to higher perceived task-technology fit (PTTF).

In addition to user characteristics, such as geospatial reasoning ability, task characteristics such as task complexity have been demonstrated to impact decision-making performance. Indeed, one of the most common measures of task characteristics is that of task difficulty (e.g., Smelcer and Carmel, 1997; Jarupathirun and Zahedi, 2007; Ozimec et al., 2010). Many of these studies cite Campbell's (1998) Complexity Theory, which indicates that as task complexity increases, the information presentation must be improved to counter the increased complexity. Finally, Jarvenpaa (1989) and Vessey (1991) found support between decision-making performance and task-technology fit. A perceived task-technology fit (PTTF) scale was used measure individual perceptions of SDSS performance using a seven-item scale with a statistically significantly impact (Jarupathirun and Zahedi, 2007). Furthermore, as decision-time and decision-accuracy have been commonly used as measurements of decision-performance, we also suggest measuring the impact of PTTF on these two measures. Based on these findings, we posit:

H<sub>2a</sub>: Higher perceived task-technology fit (PTTF) leads to lower decision time.

H<sub>2b</sub>: Higher perceived task-technology fit (PTTF) leads to increased decision accuracy.

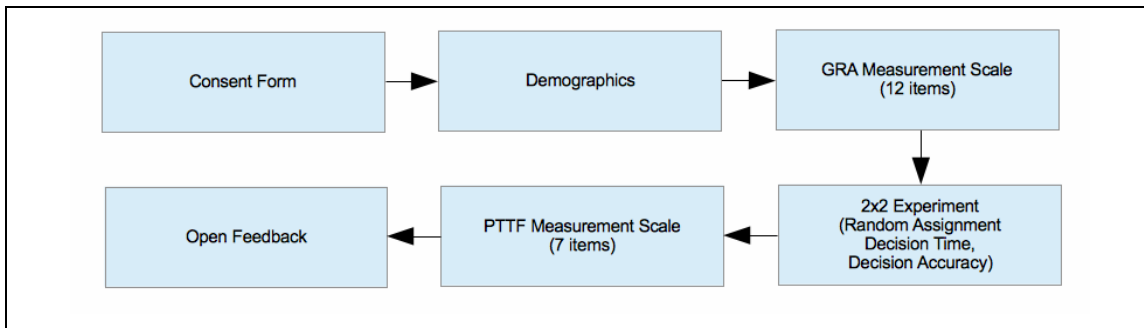
Finally, research has identified that increases in complexity leads to decreased decision-making performance (e.g., Smelcer and Carmel, 1997). Specifically, increases to the visualization complexity and task complexity have been shown to increase decision-making time. Smelcer and Carmel (1997) examined three levels of task-difficulty moderated by the number of sub-tasks each problem required. Their research revealed that task complexity impacted decision-making performance.

Furthermore, Jarupathirun and Zahedi (2007) tested two levels of goal difficulty of which one level asked participant to do their best and finish a single task, while the other level asked participants to complete three tasks. Based on these findings, we posit:

- H<sub>3a</sub>: Task complexity moderates the impact of perceived task-technology fit (PTTF) on decision accuracy.
- H<sub>3b</sub>: Task complexity moderates the impact of perceived task-technology fit (PTTF) on decision time.
- H<sub>3c</sub>: Task complexity moderates the impact of geospatial reasoning ability (GRA) on decision time.
- H<sub>3d</sub>: Task complexity moderates the impact of geospatial reasoning ability (GRA) on decision accuracy.

**RESEARCH METHODOLOGY**

This research project will be evaluated using an experiment with a two-by-two treatment design. Specifically, subjects will be asked to perform a geospatial decision-making task where the problem-complexity and the visualization-complexity are manipulated. In addition to the experiment, participants will be asked to provide demographic information and complete a geospatial reasoning ability and perceived task-technology fit measurement scales. Figure 2 demonstrates the experiment workflow as perceived by the research subjects.



**Figure 2. Experiment Workflow**

First, the subject is presented with a consent form. Upon agreement, demographic information is collected, including age, gender, education and cultural background. Next, the subject is asked to complete the 12-item GRA measurement scale. Then the experiment is presented, which collects decision-time and decision-accuracy data. One of four experiment modes is randomly selected. These four experiment modes consist of low complexity and static visualization, high complexity and static visualization, low complexity and dynamic visualization, as well as, high complexity and dynamic visualization. See Table 2 (below) for a tabular comparison of the experiment modes. Finally, the 7-item PTTF measurement is presented and the data collection is completed.

| <i>Experiment Mode</i> | <i>Visualization Complexity</i> | <i>Task Complexity</i> |
|------------------------|---------------------------------|------------------------|
| Mode 1                 | Low/Easy                        | Low/Easy               |
| Mode 2                 | Low/Easy                        | High/Hard              |
| Mode 3                 | High/Hard                       | Low/Easy               |
| Mode 4                 | High/Hard                       | High/Hard              |

**Table 2. Experiment Modes**

**Experiment Design**

The experiment asks participants to evaluate a decision-making tool in a hypothetical scenario in which they must select the ideal apartment for a friend moving to another country. Detailed evaluation criteria, which include spatial and non-spatial criteria, are provided (e.g., cost and location preferences). The complexity of the decision criteria and the problem scale are manipulated to create realistic scenarios, yet still allow variations in the treatment. Figure 3 presents an overview of the apartment finder tool. Additionally, subjects were provided with an opportunity for open-feedback opportunity at the end of the experiment.

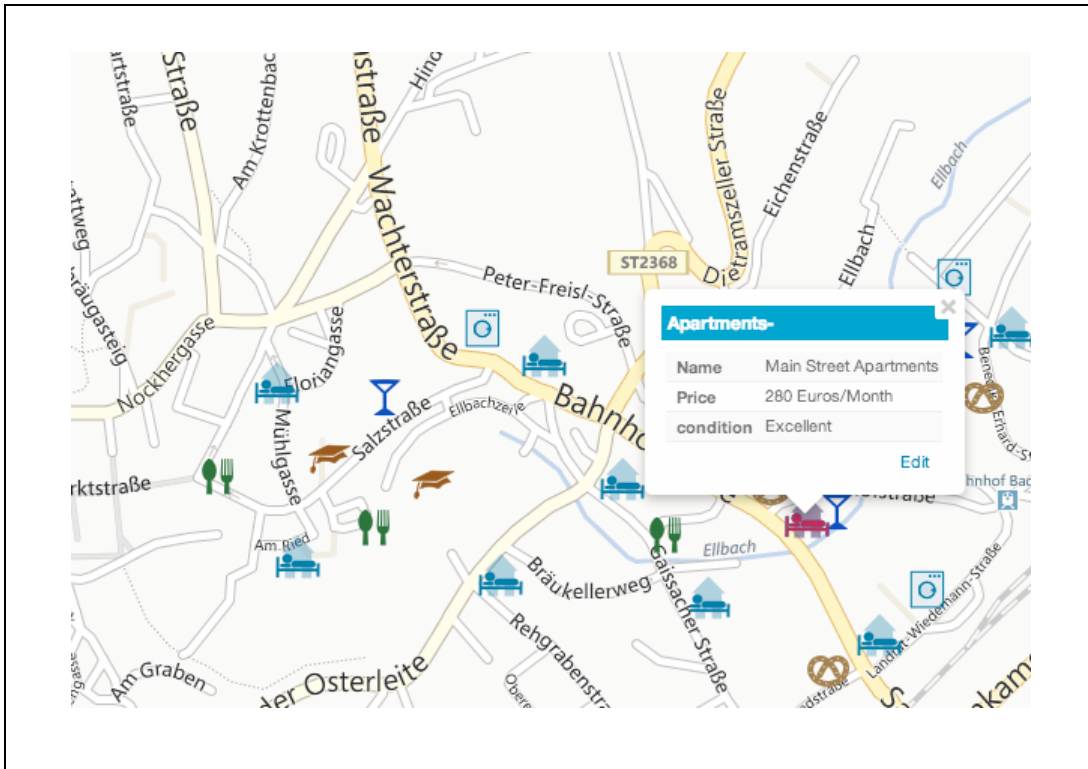


Figure 3. “Apartment Finder” Experiment Tool Developed using GISCloud and Bing Maps

**Subjects**

Responses from 200 subjects will be collected from January through May of 2013. Various methods will be employed to solicit subjects, including e-mails and social network participant recruitment. Participation in the study was voluntary and no rewards for participation were provided to the subjects.

**Geospatial Reasoning Ability Measurement Items**

To assess geospatial reasoning ability the twelve-item geospatial reasoning ability scale developed by Erskine and Gregg (2011, 2012) is utilized. This scale addresses three-dimensions of geospatial reasoning ability: 1) geospatial memorization and recall, 2) geospatial orientation and navigation and 3) geospatial geovisualization. These measurement items, as shown in Table 3, are presented prior to the experiment along with a 7-item Likert scale (Likert, 1932).

| Item ID | Item  |
|---------|---|
| GRA1    | I can usually remember a new route after I have traveled it only once.                            |
| GRA2    | I am good at giving driving directions from memory.   |
| GRA3    | After studying a map, I can often follow the route without needing to look back at the map.       |
| GRA4    | I am good at giving walking directions from memory.   |
| GRA5    | In most circumstances, I feel that I could quickly determine where I am based on my surroundings. |
| GRA6    | I have a great sense of direction.  |
| GRA7    | I feel that I can easily orientate myself in a new place.   |
| GRA8    | I rarely get lost.  |
| GRA9    | I can visualize geographic locations.   |
| GRA10   | I can visualize a place from information that is provided by a map without having been there.     |

|       |  |
|-------|--|
| GRA11 | I can visualize a place from a map.  |
| GRA12 | While reading written walking directions, I often form a mental image of the walk. |

**Table 3. Geospatial Reasoning Ability Measurement Items, Adapted from Erskine and Gregg (2011, 2012)**

**Perceived Task-Technology Fit Measurement Items**

In addition to geospatial reasoning ability, perceived task-technology fit is measured. To assess perceived task-technology fit, measurement items developed by Jarupathirun and Zahedi (2007) were adapted for this study. These items are presented to the research subjects upon completion of the decision-making experiment along with a 7-point Likert scale. Table 4 presents the seven-item perceived task-technology fit measurement scale used for this study.

| <i>Item ID</i> | <i>Item</i>   |
|----------------|---|
| PTTF1          | The functionalities of the [tool] were adequate for the task given.       |
| PTTF2          | The functionalities of the [tool] were appropriate for the task given.    |
| PTTF3          | The functionalities of the [tool] were useful for the task given.         |
| PTTF4          | The functionalities of the [tool] were compatible with the task given.    |
| PTTF5          | The functionalities of the [tool] were helpful in solving the task given. |
| PTTF6          | The functionalities of the [tool] were sufficient.                        |
| PTTF7          | The functionalities of the [tool] made the task easy.                     |

**Table 4. Perceived Task-Technology Fit Measurement Items, Adapted from Jarupathirun and Zahedi (2007)**

**ANALYSIS**

The results collected in the aforementioned experiment will be analyzed using partial least squares at the conclusion of the data collection phase.

**FINDINGS AND DISCUSSION**

As this is a research in progress, complete findings and hypotheses tests are not yet available and will be presented at the conclusion of the study. However, preliminary results for the initial subjects (n=53) who completed the study were analyzed.

While the initial results cannot yet be evaluated for statistical significance due to the small sample size, differences in decision accuracy and average decision time are noticeable, as shown in Table 5. These initial findings suggest that the four treatments adequately manipulate decision-performance.

| <i>Experiment Mode</i> | <i>Decision Accuracy</i> | <i>Average Decision Time</i> |
|------------------------|--------------------------|------------------------------|
| Mode 1 (n=15)          | 80%                      | 2.97 minutes                 |
| Mode 2 (n=13)          | 31%                      | 3.46 minutes                 |
| Mode 3 (n=9)           | 56%                      | 4.72 minutes                 |
| Mode 4 (n=16)          | 56%                      | 4.54 minutes                 |

**Table 5. Pilot Experiment Results**

Additionally, the Cronbach’s alphas for the GRA and PTTF measurement scales are at 0.9568 and 0.9597, respectively, indicating excellent construct reliability (Cronbach, 1951; Gliem and Gliem, 2003). An early partial least squares analysis has shown that GRA has a significant positive effect on PTTF with an average variance extracted (AVE) of 0.7714, a t-statistic of 2.760 and an R-square impact of 0.133. These AVE and t-statistic values exceed the recommended thresholds of .5 (Fornell and Larcker, 1989) and 1.96 (Gefen and Straub, 2005). Once sufficient data is collected additional statistical significance may present itself between the other hypothesized relationships and allow for a full analysis to be completed.

Feedback collected through the open-ended feedback opportunity included various comments regarding the overall experiment, perceived value of the tool, challenges encountered while performing the experiment, as well as perceived usability of the tool. These responses, with included mixed opinions, continue to demonstrate that there are varying

perceptions of SDSS. This study may help identify the underlying causes of such opinions and particularly if the user-characteristic of geospatial reasoning ability or the task-characteristics of presentation-complexity or problem-complexity impact such perceptions.

### Implications

Upon completion of this study, we feel that scholarly researchers can benefit from it for three key reasons. First, the decision sciences research area benefits from the additional perspectives of decision-performance using SDSS. Second, no prior research utilizing both visualization complexity and problem complexity as measures of task-complexity were found, thus a research gap is addressed. Third, the GRA measurement scale is further empirically validated, making it a viable alternative to spatial tests while providing a multi-dimensional measure of spatial cognitive ability. These benefits could provide tremendous benefits to future decision-performance research in the context of SDSS. Furthermore, such knowledge will allow information systems researchers to develop tools and techniques that improve decision-performance of individuals with low geospatial reasoning ability while not impacting those who already possess strong geospatial reasoning skills.

Industry can greatly benefit from this study as it highlights the importance of considering geospatial reasoning ability when developing and designing SDSS tools. Such knowledge could allow managers to allocate individuals with high geospatial reasoning ability to tasks involving problem-solving using SDSS. Furthermore, a more comprehensive understanding of the benefits and potential drawbacks of task complexity (moderated through visualization and problem complexity, herein) can guide systems designers and developers to help select the most appropriate visualization method for visualizing complex geospatial relationships.

### Limitations

This study is currently a research-in-progress. Until a sufficient data set is collected the results provide limited insight. Additionally, while this study provides an initial assessment of the impact of geospatial reasoning ability on decision-making performance, future studies will need to be conducted to better understand geospatial reasoning ability, geospatial decision-making and their interaction. Additionally, subjects included in this study were primarily students at an American research institution, so specific cultural and regional aspects of decision-making may not have been captured. Furthermore, while geospatial reasoning ability plays a role in the decision-making process, there are numerous other factors that may influence the process, which have not been addressed.

### CONCLUSION

Consumer, business and governmental entities increasingly rely on spatial decision support systems (SDSS) for decision-making involving geospatial data. Understanding user- and task-characteristics that impact decision performance will allow developers of such systems to maximize decision-making performance. While there have been several studies which explored the impact of task characteristics and user characteristics on decision performance, there have been inconsistent results. This study explores the potential reasons for these inconsistencies and provides a comprehensive design to eliminate such problems in future research. A two-factor experiment design was implemented to determine the moderating role of problem-complexity and presentation-complexity on decision-performance. As this is a research-in-progress results of the experiment are not yet available. When concluded, we hope that this research will provide an in-depth understanding of how geospatial reasoning ability impacts decision-making performance.

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