

Review

Business Decision-Making Using Geospatial Data: A Research Framework and Literature Review

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Abstract: Organizations that leverage their increasing volume of geospatial data have the potential to enhance their strategic and organizational decisions. However, literature describing the best techniques to make decisions using geospatial data and the best approaches to take advantage of geospatial data's unique visualization capabilities is limited. This paper reviews the use of geospatial visualization and its effects on decision performance, which is one of the many components of decision-making when using geospatial data. Additionally, this paper proposes a comprehensive model allowing researchers to better understand decision-making using geospatial data and provides a robust foundation for future research. Finally, this paper makes an argument for further research of information-presentation, task-characteristics, user-characteristics and their effects on decision-performance when utilizing geospatial data.

Keywords: spatial decision support systems; geospatial data; information presentation; decision-performance; task-characteristics; user-characteristics

1. Introduction

While geospatial data permeates business computing there is only a limited understanding of how geographic information is utilized to make strategic and organizational business decisions, as well as how to effectively visualize geographic data for such decision-making.

As it has been estimated that over 75 percent of all business data contains geographic information and 80 percent of all business decisions involve geographic data [1,2], the ability to interpret geographic data and make decisions based on geographic information is essential for business decision makers. Common examples of business decision-making using geospatial data include risk assessment for insurers, site selection for retailers and granular customer analysis for customer relationship management. While geospatial data can be presented utilizing traditional methods such as charts and tables, unique relationships contained within geospatial data are often only apparent through a geospatial visualization process, commonly referred to as geovisualization [3].

The utilization techniques and benefits of databases and spreadsheets have been taught in most business school curricula, so most business professionals with a formal education have had a clear understanding of such technologies. However, as geospatial data has become prevalent within information systems (IS), researchers and business professionals have tried to better understand all aspects of decision-making using geospatial data. One of these aspects is the ability to understand decision-making processes as they relate to the unique abilities of geovisualization, or the ability to represent, understand and utilize geospatial data in map-like projections for decision-making.

This paper provides an analysis of current research concerning business decision-making using geovisualization. Specifically, this paper responds to calls for deeper exploration of the utilization of geospatial data, through the theoretical lens of the Cognitive Fit Theory [4].

As organizations continuously collect vast amounts of geospatial or geo-referenced data, two technologies have been developed to interpret such data in support of decision-making. These systems are Spatial Decision Support Systems (SDSS) and Geographic Information Systems (GIS) [5].

While traditional Decision Support Systems (DSS) have been implemented successfully for production planning, forecasting, business process reengineering and virtual shopping [6], such systems poorly utilize geospatial data. Thus, SDSS that operate much like DSS, but are tailored to handle the unique complexities of geospatial data, were developed to aid decision-making when utilizing complex geospatial data. SDSS provide capabilities to input and output geospatial data, provide analytic capabilities unique to geospatial data, and allow complex geospatial representations to be presented [5]. More specifically, a capability of continuous iterative analysis is provided directly to the decision-maker allowing a problem to be further defined and numerous alternate solutions to be evaluated. Although IS researchers are familiar with DSS concepts, many IS researchers are not yet familiar with key SDSS concepts such as “georeferencing, geocoding and spatial analysis [7]”.

While SDSS provide methods for geospatial decision-making, GIS allow geospatial experts to analyze and report geographic data. GIS can be used to populate information to SDSS as well as to perform complex geospatial analyses. While there are numerous aspects of GIS relevant to IS researchers, this paper examines the decision-making aspects of GIS [8]. Such an understanding is critical for IS researchers because the global GIS adoption rates continue to increase and research has shown that a strong understanding of geospatial data can lead to enhanced decision-making [7].

SDSS and GIS that leverage geovisualization are provided to professionals and consumers through a variety of sources. Prominent tools for the search of information using geovisualization include Google Maps and Bing Maps, which allow a user to visually locate geo-referenced information, such as addresses, businesses and even people [9,10]. Other domain-specific examples include the capability to determine wireless signal strength at street level, automated banking kiosk location information and interactive real estate search tools [11–13]. However, the use of geospatial data is not limited to only consumers and business organizations. Government agencies leverage geospatial data for decision-making when solving large societal problems. For instance, while governments have collected vast amounts of geospatial knowledge throughout history, the introduction of early computerized cartography in the 1950s [14] through today's contemporary geographic information systems has reduced redundant data collection and agencies are better able to retrieve, analyze and share geospatial data [15]. Examples of how federal, state and regional governments leverage such systems include analyses of natural resources, transportation and logistics, disaster response and property assessment. More recently, immense geospatial-specific infrastructure systems have been implemented, such as the National Spatial Data Infrastructure (NSDI) in the United States and the Infrastructure for Spatial Information in the European Community (INSPIRE) in the European Union [16,17]. Goals of such systems are to enable nearly every agency of a government to share large volumes of geographic data locally, nationally and globally [16]. Early demonstration projects of the NSDI included a geospatial crime tracking system for a metropolitan police department as well as a regional system to help communities perform effective master planning activities [18].

As mobile devices, such as smart phones and tablet computing, become increasingly networked and gain capabilities to detect their position, more and more collected data will consist of geographic or geo-referenced data. With this increase in the amount of geospatial data that is available to decision-makers, it is crucial that IS professionals and researchers expand their knowledge of geospatial systems and better understand their unique characteristics, benefits and potential drawbacks. For instance, the ability to aggregate and geo-reference consumer characteristics and behavior information has led to a strategic concept in social science and marketing research known as geodemographics [19–21]. Additionally, four research streams contributing to the effectiveness of geovisualization have been identified, including information representation, task difficulty, geographic relationship and cognitive skill [22]. This review will expand on these findings, attempt to clarify the unique aspects that geovisualization brings to business decision makers, and will suggest specific future research goals.

While many of the aforementioned consumer, business and governmental applications utilize geospatial data, computer scientists have addressed computationally intense problems through the use of spatial computing [23]. For instance, with the ever-increasing granularity (*i.e.*, number of sensors) and resolution (*i.e.*, detail of data) of collected data, increased efficiencies to process such large quantities of data are essential. While traditionally the physical location of computing resources has been abstracted by system architects, the field of spatial computing has demonstrated that computational efficiencies can be achieved by distributing computing resources methodologically [24].

This paper begins with a literature review emphasizing theoretical backgrounds of existing research, then analyzes existing research within key areas of decision-making utilizing geovisualization including task-characteristics (*i.e.*, task complexity, task type, collaboration requirements),

user-characteristics (*i.e.*, mental workload, goal setting, self-efficacy, spatial reasoning ability), as well as decision-making performance and presentation techniques. The goal of this review is to explore the most relevant research from the IS, decision sciences, geography and psychological realms in order to develop a comprehensive model toward forming a better understanding of decision-making using geospatial data. Limitations of the reviewed literature and future research suggestions are also discussed. Finally, a conclusion is presented.

2. Literature Review

Research reveals the importance of information-presentation, task-characteristics and user-characteristics on decision-performance. An emphasis is placed on exploring theories that have been suggested to explain these themes. Specifically, literature related to information visualization and its effects on decision-making often cites Cognitive Fit Theory, Complexity Theory, Task Fit Theory, Image Theory as well as research on task-technology fit, self-efficacy, motivation, goal-setting and spatial abilities (see Table 1). Of the four research streams Smelcer and Carmel [22] identified, each potentially relates to an existing theory, including Task Fit (relating to information representation and geographic relationship), Complexity Theory (relating to task difficulty), and Cognitive Fit Theory (relating to cognitive skill). This review expands on these findings.

Table 1. Common theories related to geospatial decision making.

Theory	Study
Cognitive Fit Theory	[4,22,25–28]
Complexity Theory	[22,29]
Task Fit/ Task-Technology Fit	[22,30]
Self-Efficacy	[30]
Motivation Theory	[30]
Goal-Setting Theory	[30]
Image Theory	[31]

The following sections explore reoccurring themes found in literature related to the visualization of geospatial data. These themes include information presentation, task characteristics, user characteristics and decision performance.

2.1. Information Presentation

Numerous researchers have explored the importance of visual information presentation on decision performance (e.g., [4,22,25–28]). For example, in her work, Vessey [4] introduces the Cognitive Fit Theory, which examines two types of information presentation (tables and charts) as well as two types of problem-solving tasks (spatial and symbolic). Cognitive Fit Theory suggests that decision-performance, as measured through decision-time and decision-accuracy, is improved when the problem representation matches the problem-solving task. The objective measures of decision-time and decision-accuracy, as well as interpretation accuracy, are suggested as antecedents of performance; however, it is noted that confidence in the solution also could play a role [4]. Additionally, Vessey [4] mentions that while often-analyzed tasks from prior research utilized simple graphs and tables, actual

business problems are far more complex and not as well defined. Furthermore, prior research may have included, for example, numbers along with graphical representations actually presenting a mix of spatial and symbolic data.

Vessey's [4] Cognitive Fit Theory has been referenced as a theoretical background, extended into other domains and validated in numerous empirical studies (e.g., [22,26,28]). Speier [28] presented a review of eight empirical research papers that tested for cognitive fit and discovered that all but one paper either fully or partially supported the Cognitive Fit Theory.

Extensions of Cognitive Fit Theory include work performed by Dennis and Carte [26] who demonstrated that when map-based presentations are coupled with appropriate tasks, decision processes and decision performance are influenced. Additionally, Mennecke *et al.* [27] expand on the Cognitive Fit Theory by determining the effects of subject characteristics and problem complexity on decision efficiency and accuracy. Also, Cognitive Fit Theory has been extended from information presentation to query interface design in order to explain how one's ability to understand data visualizations will influence decision outcomes [25].

In addition to Cognitive Fit Theory, Task-Technology Fit has been utilized to demonstrate the importance of appropriate information presentation methods. For example, Ives [32] articulates the importance of visual information presentation and states that while researchers have responded to calls for additional research into data and information visualization techniques, there is still potential for additional research into geovisualization. Specifically, a more in-depth understanding of how multi-dimensional graphics could display complex information through simplified information or charts that overlay information, both of which are technologies inherent to even basic geovisualization systems, is suggested [32].

Densham [5] suggested that a SDSS must provide information in both graphical, or map space, and tabular formats, or objective space, while providing the capability to move between these representations or view these representations simultaneously to determine the most appropriate to facilitate problem solving. However, even with multiple display options, it is not yet understood if the decision-maker will know which of the output options provides the best visualization method for their particular decision-making process. To support a problem-solver who is unsure of how to select the most appropriate visualization method, several authors have suggested the inclusion of an expert system to provide guidance (e.g., [5,16]).

Additional studies exploring the visualization of geospatial data and information include Crossland *et al.* [31], Smelcer and Carmel [22], Speier and Morris [25] and Dennis and Carte [26]. Crossland *et al.* [31] performed a study in which some participants were provided with a paper map and tabular information, while others had access to a SDSS. They were able to confirm that the addition of a GIS-based SDSS contributed significantly toward decision-time and decision-accuracy, two measures of decision-making performance. Speier and Morris [25] tested the use of a text-based and graphical-based interface to determine the effects on decision-making. Smelcer and Carmel [22] tested whether spatial information is best represented through geovisualization and found that maps representing geographic relationships allowed for faster problem solving. The authors conclude that while low difficulty tasks can be solved quickly "regardless of representation", more difficult tasks "should be represented using maps to keep problem-solving times and errors from rising rapidly". Dennis and Carte [26] determined that geographically adjacent, spatial information was best presented using

geovisualization, while non-adjacent, symbolic information was best presented using tables. Furthermore, visualization research has attempted to identify how specific data types (nominal, ordinal, interval) are best represented using cartographic representations and interactivity [33–36].

Crossland *et al.* [31] extended Image Theory into the realm of decision-making by proposing that the efficiencies gained through the use of electronic maps, *versus* paper maps, would improve decision performance. Indeed, their study revealed that both decision-accuracy and decision-time improved with the use of electronic maps *versus* paper maps at two complexity levels.

Finally, some researchers suggest that reducing the amount of information presented to only include essential information could improve decision-making performance (e.g., [37,38]). For example, while early maps presented geospatial information with little precision, they were still able to convey sufficient and relevant information. The benefit of such simplified maps was demonstrated by Agrawala and Stolte [37], who collected feedback from over 2000 users of a technology that emulated hand-drawn driving directions, which often emphasize essential information while eliminating nonessential details. Additionally, Klippel *et al.* [38] suggests that modern cartographers can successfully develop schematic maps that are simplified, yet present “cognitively adequate representations of environmental knowledge”. Comprehensive, yet easy-to-read transit maps used in large metropolitan cities demonstrate a good example of the benefit of schematization. For example, the London Underground map designed in the early 1930s by Harry Beck has been used as an exemplar of successful schematization [39,40].

2.2. Task-Characteristics

In addition to information presentation, research has shown that the specific characteristics of the task being performed can play a vital role in decision-making performance. For example, Complexity Theory posits that as task complexity increases so does the need for information presentation to match problem-solving tasks. Complexity Theory demonstrates that key aspects of geovisualization, including data aggregation, data dispersion and task complexity, influence decision-making performance [29]. Additionally, Complexity Theory was validated by Smelcer and Carmel’s [22] research, which confirmed that increased task difficulty led to decreased decision-making performance. Moreover, Crossland and Wynne [41] discovered that decision-making performance decreased less significantly with the use of electronic maps, *versus* paper maps.

Jarupathirun and Zahedi [42] state that, based on research by Vessey [4], Payne [43], Campbell [44] and Zigurs and Buckland [45], tasks can be classified into simple and complex groups based on task characteristics. Example characteristics of complex tasks include multiple information attributes, multiple alternatives to be evaluated, multiple desired outcomes, solution scheme multiplicity, conflicting interdependence and uncertainty.

Several empirical studies have explored task complexity (e.g., [22,25,27,29,31]). Speier and Morris [25] discovered that decision-making performance increased when subjects utilized a visual query interface when working with complex decisions. Additionally, Swink and Speier [29] defined task characteristics to include the problem size, data aggregation and data dispersion. They discovered that decision performance, as measured by decision-quality and decision-time, were superior for smaller problems. In the context of data aggregation, there was no effect on decision-quality; however

there was a significant effect on decision-time indicating that more time was required for disaggregated problems. Additionally, it was found that decision-quality for problems with high data dispersion had a higher decision-quality, but there was no significant effect on decision-time. Smelcer and Carmel [22] confirmed that more difficult tasks increased decision-time. In their work, Mennecke *et al.* [27] discovered that as task complexity increases, accuracy is lowered, yet found only partial support for task efficiency being lowered. Research conducted on the effects of SDSS on decision-making performance also included measures of task-complexity [31]. It was discovered that the use of a SDSS *versus* data tables and paper maps significantly improved decision-making time, while there was no significant effect on decision-accuracy. The authors pointed out that there might have been too much similarity between the task complexity levels to ensure that decision accuracy would not be improved through the use of an SDSS. The authors also suggested that there might be levels of problem complexity that can only be solved through the use of an SDSS [31].

In their work, Albert and Golledge [46] developed three paper and pencil tests to assess task complexity across experience levels and gender. One of the findings was that subjects were better at performing map overlay tasks involving “or” (inclusive disjunction) and “xor” (exclusive disjunction) operators *versus* those utilizing “and” and “not” operators. The researchers also discovered that the boundary complexity of a visualized entity did not affect performance, as did the quantity of visualized entities.

Additional research suggests that the perception of complexity may be essential to better understand the effect of task-characteristics on decision-making performance. For example, Huang [47] performed an experiment of 10 popular Web-based shopping sites and determined that increased complexity decreased the desire to explore the site, but slightly increased the desire to purchase. Perhaps, when applied to SDSS decision-making, an increased complexity decreases the desire to explore additional solutions while encouraging a decision to be made quickly. This could explain some of the variances discovered in past research within the task-complexity and decision-making performance realm. Huang’s [47] research utilized the General Measure of Information Rate (GMIR) developed by Mehrabian and Russell [48] as a measure of the perceived complexity.

Speier [28] proposed a framework of complexity with four distinct levels, which are, in order of complexity: (a) trivial decision-making; (b) optimal decision-making; (c) satisficing decision-making; and (d) aided decision-making. Speier’s [28] empirical study furthered Cognitive Fit Theory by comparing the outcomes of spatial and symbolic information presentation with spatial and symbolic tasks on decision performance as measured by decision-quality and decision-accuracy while moderated by task-complexity. Findings were inconsistent with theory, as the decision time of symbolic tasks with low complexity, were found to be less when using spatial presentations. However, there are several extensions to the Cognitive Fit Theory demonstrating that tables and graphs are equally effective for tasks with a low complexity and that graphs can provide higher decision-performance at high complexity. Like Speier [28], Gill and Hicks [49] also suggested that there are multiple classes of complexity.

While Complexity Theory focuses on the relationship between the complexity of the task and the information presentation, Task-Technology Fit Theory posits that a technology will improve task performance if the capability of the technology matches the task to be performed [50,51]. Additionally,

Jarupathirun and Zahedi [30] synthesized research on task-technology fit with the psychology-based constructs of goal-setting and self-efficacy to further explain and determine success factors of SDSS usage.

Another measure of task complexity may lie within the represented geographic relationships required by the task. For example, in both tables and maps, geographic relationships common to business decision-making are utilized. These geographic relationships include proximity, adjacency and containment. Examples of proximity in the context of geographic relationships include route optimization, examples of adjacency include territory assignment, and examples of containment include site selection [22]. In their study of geographic containment and adjacency tasks, Dennis and Carte [26] discovered that when users are presented with geographic data that represents geographic containments, tabular data presentations might lead to better decision making, while adjacency tasks benefit from map-based visualization.

While most research into Complexity Theory (as pertaining to decision-making) and Task-Technology Fit Theory has focused on decision performance of individuals, recent technological innovations have led to collaborative uses of geospatial data and information that may require these theories to be revisited through a collaborative perspective. Geospatial data and information can lead to collaborative decision-making through two distinct ways. First, decision-making tools utilizing geospatial information can be used for collaborative decision making with geographically and temporally distributed participants. These tools are often referred to as participatory geographic information systems (PGIS). Second, through the recent phenomenon of online social networks, geospatial information can be shared and utilized through social networks. Each of these problem-solving methods is discussed next.

Several researchers have explored the area of collaborative decision-making utilizing geographic data. In their framework development research, Mennecke and Crossland [8] call for additional exploration in the areas of GIS and its capabilities in collaborative decision-making. PGIS provides the capability for decision-making utilizing geospatial information collaboratively with geographically and temporally distributed participants. Through the ubiquity provided by networked computing and recent technologies, it may be possible for groups of organizations to collaborate and form virtual organizations [52]. In addition to PGIS, grassroots groups and community organizations have adopted public-participatory geographic information systems (PPGIS) to address the need for public decision-making utilizing complex geospatial data [53]. In their work, Conroy and Gordon [54] empirically analyzed a software application to increase citizen involvement in complex policy discussions and proposed that geovisualization can offer citizen participants opportunities to better envision scenarios and can provide additional communication channels to decision makers. Jankowski and Nyerges [55] studied the use of GIS in a collaborative decision-making environment and discovered that decision outcomes such as participant agreements and shared understanding could be more effectively reached through the use of PPGIS. While there are numerous potential benefits to implementing PPGIS, there are also challenges, including diminished participation and limited evaluations of real-life PPGIS implementations [56]. However, while evaluations of decision-quality are difficult to measure when using a PPGIS, as such evaluations are generally based on future complaints if at all evaluated, research has shown that participants in public-participatory decision-making have shown a significant amount of satisfaction in the decision process [57]. Furthermore, there have been varied opinions and examples regarding the benefits of public-participatory

planning, or visioning [58], which emphasize that future research will be needed to better understand the benefits of PPGIS.

While this paper primarily addresses geospatial decision making in the context of individual decision-makers, group decision-making must be further explored, as there are significant differences. For instance, prior experience, education, language and cultural differences could present themselves as barriers to effective decision-making. Finally, unlike individual decision-making, behavioral phenomena found in groups, such as the concept of “group think”, may present themselves [59,60].

In addition to collaborative decision-making, another area of research in the usage of geospatial data involves how such data is utilized within online social networks. This is especially important with the increasing use of online social networks, where large quantities of geospatially-referenced data are shared quickly and easily. Goodchild [61] labels the geographic data that is commonly shared through online social networks as Volunteered Geographic Information (VGI). Some online social networks have included geographic information as a core component in their implementations. The availability of geographic information within online social networks has even allowed researchers to map online social networks in relation to the physical world [62]. Thus, a geographic visualization of online social networks can provide researchers with a geospatial representation of a virtual phenomenon. From a business perspective, a geospatial understanding of social networks can allow strategic decision makers to target marketing campaigns or locate retail operations in geographic areas appropriate for their target audiences. The benefits of VGI have been further demonstrated after recent large-scale disasters, such as the Haitian earthquake in 2010, by informing disaster responders with essential information [63]. However, significant drawbacks exist with the ability to successfully interpret VGI. These drawbacks exist primarily because VGI varies in quality and accuracy. For example, one image may be tagged with the word “Paris” while another is tagged with precise geographic coordinates. Additionally, as there are few validation processes, a user can easily misidentify or intentionally provide incorrect geospatial tagging [64,65]. Additionally, Stephens [66] suggests that projects utilizing VGI contain an inherent gender bias stemming from low female participation in VGI data collection and subsequent reviews of user generated content.

2.3. User-Characteristics

In addition to task-characteristics, researchers suggest that the characteristics of the user also play a role in decision-performance. Such characteristics include context-based factors, experience level, self-efficacy, cognitive workload and spatial reasoning ability.

Several researchers have highlighted the importance of research investigating user-characteristics when using tools with geovisualization capabilities, such as SDSS and GIS (e.g., [25,27,42,46,67,68]). Slocum *et al.* [67] reported that context-based factors influence the ability to interpret geo-visualized information. For example, “expertise, culture, sex, age, sensory disabilities, education, ethnicity, physiology and anatomy, and socioeconomic status” influence the ability to interpret geospatial information [67]. Additionally, Zipf [68] posits that geovisualization must address user contexts such as pre-existing knowledge of the area presented in the map, physical impairments as well as cognitive abilities. Additionally, Zipf [68] posits that a user’s cultural context can influence the interpretation of the colors used in a map. For example, in some cultures, the color green represents parkland or forests,

while in others it represents bodies of water. In their work, Albert and Golledge [46] measured gender as a control variable. One of their conclusions was that men performed significantly better in operations involving “not” operators. Additionally, the authors found that there were no significant differences in performance scores between subjects with GIS experience *versus* those that had none. This is an essential observation as GIS and SDSS technologies are often implemented as Web-based technologies that allow users with limited experience to use geovisualization. Finally, both Zipf [68] and Slocum *et al.* [67] point out the importance of considering sensory disabilities when developing geovisualization technologies.

Speier and Morris [25] discovered that task experience, database experience, gender and computer self-efficacy were non-significant in their analysis of query interface design on decision performance. Other user-characteristics, such as measurement variables related to information learning as well as fatigue related to working through multiple tasks were controlled for by Swink and Speier [29]. Mennecke *et al.* [27] compared subjects with previous SDSS experience to subjects with limited SDSS experience to determine if experience influenced decision-performance. In their experiments, the cognitive effort required in the decision-making process was measured using a condensed version of the “Need for Cognition” (NFC) instrument. However, their research found only marginal support in that solution accuracy increased and no support in that solution efficiency was different between subject groups. Additionally, Mennecke *et al.* [27] discovered that experience only presented significant improvement on solution accuracy when working with paper maps. They also discovered that students were more efficient than professionals in solving geographic problems. While this may seem surprising, it likely can be explained in that professionals incorporate multiple levels of analysis that students with limited experience may not be able to draw upon.

Additionally, Jarupathirun and Zahedi [42] posit, that based on empirical research into the theories associated with goal setting, users who set a higher goal level will be motivated to expend more effort toward reaching the desired goals. Jarupathirun and Zahedi [42] also argue that intrinsic incentives, such as perceived effort and perceived accuracy, can influence goal commitment levels, which are known to moderate the effects of goal levels on performance [69]. Finally, in order to reduce a lack of motivation and prior experience, some researchers have provided financial incentives and tasks were often drawn from domains familiar to the subjects [28].

Additionally, self-efficacy had strong positive influences on task-technology fit and the expected outcomes, as well as a strong negative influence on perceived goal-difficulty. It is suggested that repeated, successful completion of tasks could improve self-efficacy, which could be accomplished through training and learning as well as tutorials and support systems [30].

Another user-characteristic was that of the mental workload exhibited by subjects performing geospatial decision-making tasks. Speier and Morris [25] measured Subjective Mental Workload (SMW) using the NASA Task Load Index (NASA-TLX) after each completed task and discovered that when comparing visual- and text-based interfaces, with low- and high-complexity decisions, the use of visual interfaces carried a reduced SMW. Speier and Morris [25] suggest that research into the SMW could benefit from additional investigation and particularly the NASA-TLX measure could use additional validation, as the user-reported cognitive loads might not represent actual cognitive loads that would be measured utilizing actual physiological responses.

Finally, the significance of the spatial reasoning ability of the decision-maker must be further explored, as there are conflicting research results regarding the ability of spatial reasoning to aid in decision-making using geospatial data. Some research has presented no or conflicting evidence of the effects of spatial ability on decision performance (e.g., [22,29,30,42]). For example, Smelcer and Carmel [22] discovered no statistical significance between spatial ability and the effects of information representation, task difficulty and geographic relationships on decision performance. The researchers speculated that due to the nature of the tasks, which did not involve the need to navigate spatial problems, spatial visualization techniques were not required [22]. Swink and Speier [29] call “for more in-depth investigations of visual skills related to decision-making performance.” Additionally, while in their early work Jarupathirun and Zahedi [42] questioned whether spatial ability has any impact on system utilization and decision-making performance, they follow-up with a determination that spatial ability as measured through spatial orientation ability and visualization ability had no significant effect on the perceived task-technology fit [30]. These findings are of value as they suggest that high spatial ability is not a necessary requirement for efficient and effective decision-making using geospatial data. This is essential when developing a technology for the web, where it will be impossible to ensure that all users of a technology have a prerequisite spatial ability [30].

However, other research has discovered that there are effects between spatial ability and decision performance (e.g., [25,29,70]). For example, Swink and Speier [29] determined that increased spatial orientation produced a higher decision quality and required less decision time; however this finding was only significant for large problems with low data dispersion. Additionally, Speier and Morris [18] found that spatial reasoning ability alone had no significant effects on decision outcomes. However, when combined with interface design, spatial reasoning ability had a significant effect on decision accuracy. Research in other domains has identified a connection between spatial ability and geovisualization tools. For example, Rafia *et al.* [70] discuss the use of Web-based virtual environments to facilitate the instruction of spatial thinking skills. In their study of 98 pre-service undergraduate students, only 7 students, or about 7%, were found to have any previous spatial experience. Rafia *et al.* [70] imply that such a gap is a crucial issue and creates a hurdle for students pursuing careers that require qualitative spatial reasoning. As students with no pre-existing spatial thinking had difficulties in courses requiring spatial thinking ability, perhaps users lacking spatial thinking skills would have difficulties utilizing geovisualization tools.

Additionally, students who have participated in courses that utilize geovisualization tools, such as computerized cartography or geographic information systems, have demonstrated improvement in their spatial thinking ability [71]. In their research, Lee and Bednarz [71] point out that psychometric testing designed to assess spatial abilities, such as spatial visualization and spatial orientation, were generally focused on small-scale spatial thinking and thus were not necessarily valid to test large-scale geographic spatial abilities. However, Lee and Bednarz [71] discovered that recently, new spatial analysis tests have been developed which considered large-scale geographic spatial abilities (e.g., [72–75]). More recently, a multi-dimensional geospatial reasoning ability scale that includes measures of geospatial orientation and navigation, geospatial memorization and recall as well as geospatial visualization has been proposed [76]. This geospatial reasoning ability scale addresses the potential shortcomings that Lee and Bednarz [71] revealed in their research. Table 2 presents various user-characteristic measures found in the examined research.

Table 2. Measures of user-characteristics in examined research.

User-Characteristic Measure	Study
VZ-2 (Spatial Visualization)	[22]
Three Paper/Pencil Tests	[46]
S-1 (Spatial Orientation)	[29]
General Measure of Information Rate	[47]
NFC (modified)	[27]
S-1 (Spatial Orientation)	[25]
NASA-TLX	[25]
VZ-2 (Spatial Visualization)	
S-1 (Spatial Orientation)	[30]
Self-Efficacy	
New “Spatial Skills Test”	[71]
GRA (Geospatial Reasoning Ability)	[76]

2.4. Decision-Making Performance

Another key component of geospatial decision-making is that of decision-making performance. To determine decision-making performance, most researchers utilize the objective measures of decision-time and decision-accuracy as indicators of decision-making performance (e.g., [26,28,31]). However, in their measure of decision performance, Smelcer and Carmel [22] simply refer to decision-time. Others propose varying additional indicators such as decision-concept and regret which, among others, are discussed below (e.g., [77,78]).

While decision-time and decision-accuracy are common indicators of decision-performance, Sirola [77] posits that the use of an appropriate decision-analysis methodology will undoubtedly influence decision-performance metrics and could modify the decision maker’s perceptions of the decision-making process and result. These decision-analysis methodologies can include cost-risk comparisons, knowledge-based systems, cumulative quality function, chained paired comparisons, decision trees, decision tables, flow diagrams, pair-wise comparison, cost functions, expected utility, information matrices, multi-criteria decision aids and logical inference/simulation.

In their vignette-based research, Speier and Morris [25] identify decision-performance as decision outcomes, which consist of subjective mental workload, decision-accuracy and decision-time constructs. Their research highlights significant interaction effects between interface type (text/visual) and task complexity on SMW, as well as interface type and task complexity individually.

Jarupathirun and Zahedi [30] explored perceived decision-quality, perceived decision-performance, decision-satisfaction and SDSS satisfaction and suggest further inclusion into the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) models. Additionally, Dennis and Carte [26] discovered that when using map-based presentations, users were more likely to utilize a perceptual decision process while tabular data presentations induced an analytical decision process. In their work, time and accuracy were used as measurements of decision performance. While numerous researchers utilized perceived or objective decision performance measures to determine the results of decision-making performance, Hung *et al.* [78] suggest that perceived regret should also be considered, as many decision makers consider potential

regret when making decisions. In their study it was found that there was a significant reduction in regret for participants who utilized a DSS. Other constructs and theories, particularly those from psychology and organizational behavior, are also utilized, including research in self-efficacy, motivation, goal-setting and Image Theory. For example, Jarupathirun and Zahedi [30] introduced a perceived performance construct consisting of decision satisfaction, SDSS satisfaction, perceived decision-quality and perceived decision-efficiency. In their findings, perceived decision-efficiency was the greatest motivator for goal commitment. While decision-quality is likely more important than efficiency, the authors proposed that there might be a perception that SDSS improves decision-quality inherently. These findings are consistent with other studies in which task-characteristics have been shown to have an impact on user satisfaction as measured through task-technology fit [79].

In their study of visual-query interfaces, Speier and Morris [25] discovered that decision-making performance increased by utilizing a visual query interface when working with complex decisions. In addition, Swink and Speier [29] discovered that moderate amounts of data dispersion required longer decision times than did tasks with low data dispersion.

Based on the reviewed literature, the most common measures of decision-making performance are the objective measures of decision-time and decision-accuracy.

3. Conceptual Model

Based on the reviewed literature and associated theoretical frameworks, a conceptual model of business decision-making using geospatial data is proposed. This model consists of four distinct constructs, including information presentation, task-characteristics, user-characteristics and decision-performance. Information presentation was determined to be a key antecedent of decision-performance as suggested through Vessey's [4] Cognitive Fit Theory. Literature has shown that different information presentation methods may be required based on the geospatial problem being solved. Additionally, task-characteristics have demonstrated an impact on decision-performance. Specifically, task complexity, problem type, data dispersion, group decision-making and data quality have been shown to define task-characteristics. In addition to information presentation and task-characteristics, user-characteristics have also been shown to influence decision-performance. Such user-characteristics include age, gender, prior experience, culture, sensory ability, education, self-efficacy, task motivation, goal-setting, mental workload, and geospatial reasoning ability. Finally, while decision-accuracy and decision-time were the most common measures of decision-performance, decision-satisfaction, decision-regret and decision-methodology could be valid measures of decision-performance.

The relationships between these constructs are presented through the following three propositions:

Proposition P₁: Information presentation effects decision-performance.

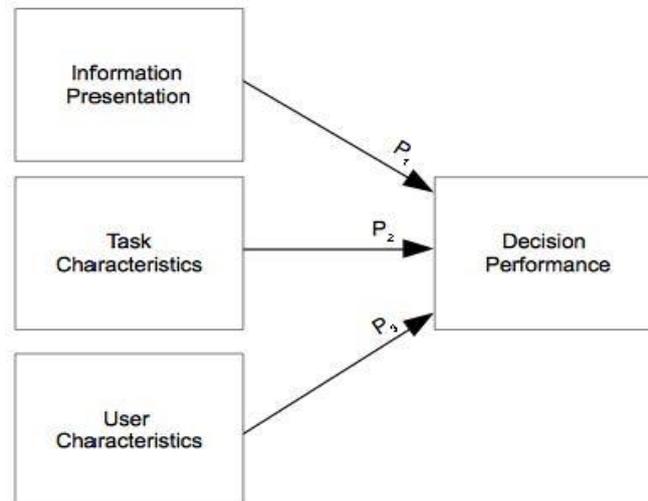
Proposition P₂: Task-characteristics effect decision-performance.

Proposition P₃: User-characteristics effect decision-performance.

Figure 1 presents this conceptual model visually. It is suggested that future research should further explore this model empirically and identify key antecedents and measures for each of the constructs. Specific measures of information presentation, task characteristics, user characteristics and decision-performance were purposefully abstracted, as it is our goal to provide researchers with a

high-level and unbiased model that can be applied to all research exploring geospatial decision-making scenarios involving individuals.

Figure 1. Conceptual geospatial decision-making model.



4. Discussion

This literature review highlights key measures and constructs suggested for future experiments and to test the conceptual model and determine its antecedents. Future research should further explore the design of relevant measurement instruments and the development of laboratory experiments to test the proposed conceptual model and propositions.

4.1. Limitations of Reviewed Literature

Four key limitations were discovered in the reviewed literature, including (1) the choice of research subjects; (2) the selection of task types; (3) the motivation of subjects to successfully complete the problem solving experiment and 4) a lack of experiments testing the full conceptual model.

First, in the majority of the reviewed literature, undergraduate students were utilized as research subjects (see Table 3), which may not accurately represent business decision makers who utilize geospatial data (e.g., [22,25,29]). However, research conducted by Mennecke *et al.* [27] discovered that there were few differences between the results of university students and business professionals when performing their study. Jarupathirun and Zahedi [30] cited Mennecke *et al.* [27] in their research as a strong validation that university students are a valid proxy for professionals. However, Jarupathirun and Zahedi [30] suggest that as many university students are of a younger population, they may have been more likely to have had previous experiences with Web-based SDSS, such as automated banking kiosk locators and online mapping tools, such as Google Maps [9], providing them with prior SDSS experience. Thus, it is recommended that future studies, which elect to use student populations, provide a justification of the sample choice and clearly discuss limitations of generalizability per the recommendations of Compeau *et al.* [80].

Table 3. Research population groups.

Population	Study
University Students (including graduate, undergraduate as well as business, psychology and geography students)	[22,25–31,46,78]
Professionals	[27]

Second, the problem types examined by existing research have presented some additional limitations. While some researchers chose real estate/home finding as their task method (e.g., [25]), others chose more domain specific tasks. This is a concern as, for example, the task of locating an automated banking kiosk would reflect a fundamentally different problem than determining properties that may be impacted by a natural disaster. It is suggested that future research carefully select problem types to facilitate comparison of research results.

Third, the motivation for completing the research tasks accurately can be questioned. To address this issue, some researchers provided monetary incentives to participants plus additional monetary incentives for higher decision performance [78]. Furthermore, simulated experiments may not adequately reveal how individuals make “real world” decisions, as the motivations might be different. Additionally, group decision-making may have different motivations than individual decision-making.

Finally, few studies measured task- and user-characteristics simultaneously with information presentation to determine moderating impacts of each construct. Thus, it is suggested that the entire conceptual model be tested empirically to determine the effects of each antecedent construct on decision-performance.

In addition to the addressing these limitations, numerous future research opportunities have presented themselves in the course of this literature review.

4.2. Future Research

It is suggested that additional research be performed to test the conceptual model proposed in Section 3. For example, Swink and Speier [29] suggest that complexity levels could be increased to determine if their findings still hold true. Albert and Golledge [46] call for more research into specific tasks and how groups of individuals are able to make-decisions using geovisualization.

In their work, Jarupathirun and Zahedi [30] measured effects of perceptual constructs including perceived efficiency and perceived accuracy; however, a comparison to objective measures was not made and the authors suggested such an experiment as future research. Additionally, the authors suggested that user perceptions could be measured over time to develop a more comprehensive understanding. Crossland *et al.* [31] suggest that future research should assess “decision-maker confidence, user process satisfaction, and individual level of motivation”.

The surveyed literature suggests numerous future research possibilities within the four research themes presented within this paper. These themes include information presentation, task characteristics and user characteristics and their effects on decision performance. Potential research questions related to decision-making using geospatial data include:

Which geovisualization techniques improve decision-performance?

Which specific user-characteristics impact decision-performance?

Can specific geovisualization techniques overcome user-characteristics that negatively impact decision-performance?

Which specific task-characteristics impact decision-performance?

Can specific geovisualization techniques overcome task-characteristics that negatively impact decision-performance?

To answer these questions, it is suggested that future geospatial decision-making research emphasize the importance of including measures for each of the three antecedent constructs (information presentation, task-characteristics, user-characteristics) to determine their combined effects on decision-performance. Future research into decision-making using geospatial data should continue to validate existing theory as well as provide business decision-makers with sound best practices and tools for decision-making. Furthermore, an understanding of the importance of geospatial decision-making could lead design science researchers to develop refined geovisualization tools which may overcome potential negative task- and user-characteristics a user's geospatial ability.

5. Conclusions

As organizations collect large amounts of geospatial data, there is a need to effectively utilize the collected data to make strategic and organizational decisions. However, literature describing the best techniques to make decisions using geospatial data as well as the best approaches for geovisualization is limited. This literature review revealed that existing research provides a strong foundation for future exploration of how business decision-making using geospatial data occurs. Additionally, a conceptual model for the study of effects of geovisualization on decision-performance is presented and defined through existing theory. The conceptual geospatial decision-making model proposes that information presentation, user-characteristics and task-characteristics together impact decision-performance. More specifically, we feel that this model can be applied to individual business decision-making when utilizing geospatial data. Along with the conceptual model, numerous applicable research methods, existing constructs, potential limitations, validity concerns and potential future research questions were presented.

Based on discrepancies of previous research into the effects of geospatial reasoning ability on decision-performance, it is suggested that problem solving using geovisualized information must be explored further in order to ensure that businesses and individuals are able to make better decision using geographic data. Continuing this important area of IS research will allow practitioners to more effectively utilize geovisualization tools to organize and present large quantities of geospatial data.

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Conflicts of Interest

The authors declare no conflict of interest.

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