12-9-2013 12:00 AM

Web 2.0-based Collaborative Multicriteria Spatial Decision Support System: A Case Study of Human-Computer Interaction Patterns

Mohammadreza Jelokhani-Niaraki
The University of Western Ontario

Supervisor
Jacek Malczewski
The University of Western Ontario

Graduate Program in Geography
A thesis submitted in partial fulfillment of the requirements for the degree in Doctor of Philosophy

Web 2.0-based Collaborative Multicriteria Spatial Decision Support System: A Case Study of Human-Computer Interaction Patterns

(Thesis format: Monograph)

by

Mohammadreza Jelokhani-Niaraki

Graduate Program in Geography

A thesis submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

Abstract

The integration of GIS and Multicriteria Decision Analysis (MCDA) capabilities into the Web 2.0 platform offers an effective Multicriteria Spatial Decision Support System (MC-SDSS) with which to involve the public, or a particular group of individuals, in collaborative spatial decision making. Understanding how decision makers acquire and integrate decision-related information within the Web 2.0-based collaborative MC-SDSS has been one of the major concerns of MC-SDSS designers. This study examines human-computer interaction patterns (information acquisition behavior of decision makers) within the Web 2.0-based MC-SDSS environment. It reports the results of an experimental study that investigated the effects of task complexity, information aids, and decision modes on information acquisition metrics and their relations. The research involved three major steps: (1) developing a Web 2.0-based MC-SDSS for parking site selection in Tehran, Iran to analyze human-computer interaction patterns, (2) conducting experiments using this system and collecting the human-computer interaction data, and (3) analyzing the log data to detect information acquisition metrics.

Using task complexity, decision aid, and decision mode as the independent factors, and the information acquisition metrics as the dependent variables, the study adopted a repeated-measures experimental design (or within-subjects design) to test a number of hypotheses. Task complexity was manipulated in terms of the number of alternatives and attributes at four levels. At each level of task complexity, the participants carried out the decision making process in two different GIS-MCDA modes: individual and group modes. The decision information was conveyed to participants through common map and decision table information structures. The map and table were used, respectively, for the exploration of geographic (or decision) and criterion outcome spaces.

The study employed a process-tracing method to directly monitor and record the decision makers' activities during the experiments. The data on the decision makers' activities were recorded as Web-based event logs using a database logging technique. Concerning task complexity effects, the results of the study suggest that an increase in task complexity results in a decrease in the proportion of information searched and proportion of attribute ranges searched, as well as an increase in the variability of information searched per attribute. This finding implies that as task complexity increases decision makers use a more non-compensatory strategy. Regarding the decision mode effects, it was found that the two decision modes are significantly different in terms of: (1) the proportion of information search, (2) the proportion of attribute ranges examined, (3) the variability of information search per attribute, (4) the total time spent acquiring the information in the decision table, and (5) the average time spent acquiring each piece of information. Regarding the effect of the information/decision aids (map and decision table) on the information acquisition behavior, the findings suggest that, in both of the decision modes, there is a significant difference between information acquisition using the map and decision table. The results show that decision participants have a higher number of moves and spend more time on the decision table than map.

The study presented in this dissertation has implications for formulating behavioral theories in the spatial decision making context and practical implications for the development of MC-SDSS. Specifically, the findings provide a new perspective on the use of decision support aids, and important clues for designers to develop an appropriate user-centered Web-based collaborative MC-SDSS. The study's implications can advance public participatory planning and allow for more informed and democratic land-use allocation decisions.

Key Words: Web 2.0-based MC-SDSS, GIS-MCDA, human computer interaction, information acquisition behavior, task complexity, information aid, decision mode

Acknowledgments

My first and most sincere appreciation goes to my supervisor, Dr. Jacek Malczewski, for all I have learned from him and for his continuous help and support in all stages of this thesis. I have been amazingly fortunate to have an advisor who gave me the freedom to explore on my own, and at the same time the guidance to recover when my steps faltered. I am extremely grateful to him for being open to ideas, and for encouraging and helping me to shape my interest and ideas. His motivation, valuable suggestions, and scholarly advice added considerably to my Ph.D. experience.

I would like to express my gratitude to my supervisory committee members, Dr. Micha Pazner, Dr. Claus Rinner and Dr. Milford Green, who gave me valuable suggestions during my study. A special thanks goes to the second reader of my thesis, Dr. Marco Van de Wiel, for his time spent reading through my thesis. I'm thankful to Dr.Soheil Boroushaki for his great support through my Ph.D. program. I extend thanks to my thesis examiners for their time spent reading through my thesis. I wish to thank the staff in the Department of Geography at Western University; special thanks to Lori Johnson and Caroline Majeau for all their assistance over the duration of my study. I would like to thank all my fellow graduate students in the department: Francisco Flores de Santiago, Johnathan Osborne, Yannick Rousseau, Chris Hewitt, Hossein Hosseini, and others.

Most importantly, none of this would have been possible without the love and patience of my family. Thank you Mom, the sacrifices you have made for me and the perseverance I have seen you show always remind me never to complain and always move forward with gratefulness. I would not have been able to get this far without you. I would also like to thank my brother, Saber, and my sister, Nasrin. Saber and Nasrin, I appreciate all your love, support and encouragement. Last, but not least, I would like to dedicate this thesis to the loving memory of my late father and brother who were a constant source of inspiration. I hope they would have been proud of me.

Table of Contents

List of Tables

List of Figures

List of Appendices

List of Abbreviations

AHP	Analytic Hierarchy Process
AJAX	Asynchronous JavaScript and XML
ANOVA	Analysis of Variance
API	Application Programming Interface
GIS	Geographic Information Systems
GIS-MCDA	Geographic Information Systems based-Multicriteria Decision Analysis
GUI	Graphical User Interface
GWT	Google Web Toolkit
HCI	Human-computer interaction
LMM	Linear Mixed Model
MCDA	Multicriteria Decision Analysis
MC-SDSS	Multicriteria Spatial Decision Support Systems
MySQL	My Structured Query Language
OWA	Ordered Weighted Averaging
PGIS	Participatory GIS
SDSS	Spatial Decision Support Systems
SPSS	Statistical Package for the Social Sciences
WLC	Weighted Linear Combination

Chapter 1

1 Introduction

1.1 Background

There is some evidence to show that spatial decisions made collectively tend to be more effective than decisions made by an individual decision maker (e.g., Carver, 1999; Dragićević & Balram, 2004; Jankowski, 2009; Joerin, Desthieux, Beuze, & Nembrini, 2009; Simão, Densham, & Haklay, 2009). Thus, it is suggested that spatial planning/decision making should involve the use of a collaborative/participatory approach, where individuals with different backgrounds can be brought together to solve a decision problem (e.g., Bailey, Goonetilleke, & Campbell, 2003; Kyem, 2004; Bugs, Granell, Fonts, Huerta, & Painho, 2010). Participatory approaches provide an interactive, open, democratic, communicative, collaborative and well informed deliberative process in which both experts and non-experts communicate, negotiate, and develop solutions (Esnard & MacDougall, 1997; Klosterman, 1997). Only through such a process, it is possible to find a solution that reconciles the conflicting objectives that result from different people's opinions and the final outcome can be accepted by the majority (Sipilä & Tyrväinen, 2005; Simão et al., 2009).

An effective involvement of individuals (interest groups) in a participatory planning process requires the development of suitable methods and tools. Conventional participatory planning methods have been criticized for their limited ability to engage the public, provide useful information and tools, involve the interest groups in open and asynchronous discussions, and promote an exchange of ideas (Bugs et al., 2010; Wu, He, & Gong, 2010). Such criticism is based in part on the individuals' inability to be present at a specific time and location, as well as their unwillingness to express their views and preferences among other community members during the public meetings (Dragićević & Balram, 2004; Jankowski, 2009; Boroushaki & Malczewski, 2010b).

The concept of Web-based GIS has been proposed as an effective tool for participatory planning. The Web can be used as an information infrastructure for delivering spatial data and GIS functionalities to the general public. GIS offers a wide spectrum of visual and computational decision support tools that can be used by both planners and lay participants on the Web for selection, prioritization, and integration of decision options (Sadagopan, 2000; Tang & Waters, 2005). Studies on the use of asynchronous GIS-based approaches for participatory planning suggest that the space-time distributed environment of the Web not only provides the flexibility to work in different places and times for the convenience of the participants, but also offers equal participation opportunity (Zhu & Dale, 2001; Sikder & Gangopadhyay, 2002; Malczewski, 2006b). Web 2.0 technologies and concepts have recent been adapted to Participatory GIS (PGIS) projects (Rinner, Keßler, & Andrulis, 2008; Bugs et al., 2010; Sani & Rinner, 2011; Dessì, Garau, & Pes, 2012). The ability of Web 2.0 in advancing participation, interactivity, and collaboration has played a significant role in PGIS in general and collaborative decision making in particular. Web 2.0 technologies shift Web applications from a perceived information display medium that provides the Web content to many people through websites, to a fully interactive platform that allows collaboration. They allow two-way communication; that is, a read-write web by means of which the users are contributing as well as consuming information.

Web 2.0-based GIS is an evolution of Web-based GIS that focuses on public participation and interaction using a geo-spatial system (Ganapati, 2010). This evolution has led to the increasing usability of GIS for non-specialist users, facilitating wider community usage of GIS technologies and taking advantage of the collective intelligence of the Web, building participation-oriented and user-centric GIS platforms, and developing spatial mashups (Geo-Web services) (Ganapati, 2010; Beaudreau, Johnson, & Sieber, 2011; Karnatak, Shukla, Sharma, Murthy, & Bhanumurthy, 2012). However, the conventional Web (or Web 2.0)-based GIS approaches have very limited capabilities for supporting decision making procedures. The integration of Web 2.0-based GIS and MCDA (Multicriteria Decision Analysis) techniques can alleviate this limitation. It can offer a Multicriteria

Spatial Decision Support System (MC-SDSS) for public participation, which provides appropriate analytical tools and platforms for direct involvement of the public in the spatial planning process. A MC-SDSS integrates previously separate GIS and MCDA tool sets into a unified whole more valuable than the sum of the parts. At the most basic level, a MC-SDSS can be viewed as a decision support tool that integrates geospatial data and value judgments (the decision maker's preferences) to produce information for decision making (Laaribi, Chevallier, & Martel, 1996; Malczewski, 1999a; Joerin, Thériault, & Musy, 2001). The underlying idea behind incorporating MCDA techniques into GIS is that the MCDA capabilities can complement GIS tools during the decision making stages. Using GIS to store, manage, produce, analyze, retrieve, organize, and visualize geographically referenced and associated tabular attribute data offers the capability of efficiently developing techniques and methods for modeling spatial decision making problems. Planners can use GIS to reveal hidden information, analyze the data from different perspectives and summarize them into useful information, extract spatial patterns, analyze spatial relationship, identify problematic areas, and recommend possible computational policy solutions. As an analytical system, MCDA can serve spatial decision making process by providing a wide range of powerful techniques and approaches for structuring decision problems, designing, evaluating, and prioritizing geographic alternatives. It is in the context of the combined capabilities of GIS and MCDA that the significance of advancing theoretical and applied research on MC-SDSS becomes obvious (Malczewski, 2006a).

MCDA can facilitate the GIS-based participatory decision making process in several ways. First, the integration of MCDA techniques into GIS-based procedures allows decision makers to input their judgments with respect to evaluation criteria and/or alternatives into GIS-based decision-making procedures, and generate a variety of planning scenarios that satisfy their decision objectives. Second, the GIS-MCDA strategy can improve the participatory decision making process by providing a flexible problem-solving setting, in which those who are involved in collaborative tasks can analyze, discuss, and, if necessary, redefine a decision problem (Kyem, 2001; Hossack, Robertson, Tucker, Hursthouse, & Fyfe, 2004; Norese & Toso, 2004). The GIS-MCDA approach offers a platform for organizing data relevant to the decision and helps to select the set of criteria for assessing and prioritizing alternative courses of action. The members of the decision making group can examine the spatial characteristics (locations) of alternatives, visualize them, and evaluate them according to their preferences (Voss et al., 2004). Third, an incorporation of MCDA into GIS can assist collaborative work by providing a tool for structuring group decision-making problems and facilitating communication in a group setting (e.g., Zhu & Dale, 2001; Rosmuller & Beroggi, 2004; Mau-Crimmins, de Steiguer, & Dennis, 2005; Boroushaki & Malczewski, 2010a). Fourth, an integration of GIS and MCDA allows for minimizing conflict over the choice of the best alternative course of action by providing mechanisms for revealing participants' preferences, identifying and discussing various alternatives, and building a consensus among decision makers (Feick & Hall, 1999; Jankowski & Nyerges, 2001a; Kyem, 2001; Sharifi, van den Toorn, Rico, & Emmanuel, 2002; Boroushaki & Malczewski, 2010a). Evidence shows that MCDA for individual decision making combined with proper voting rules offers a valuable tool for group decision making in the GIS environment (Malczewski, 1996; Jankowski & Nyerges, 2001a; Norese & Toso, 2004). The incorporation of MCDA into Web 2.0-based GIS allows democratization of spatial data and spatial decision-making process by offering open accessibility and wide distribution of geospatial information. Web 2.0-based MC-SDSS tools change multicriteria decision making from a closed, place-based (fixed time and location), synchronous procedure to an open, asynchronous, distributed, and active decision making process. Such tools enable participants to input their preferences regarding the decision problem based on different time/ location of the spatial-temporal dimensionality of collaborative decision-making (Boroushaki & Malczewski, 2010a). These tools offer a broadly-distributed and optimal solution for spatial planning, as well as provide easy access to the general public for active participation in the decision making process.

The main objective of GIS-MCDA procedures in the context of Web-based GIS-MCDA applications is to enhance two areas of spatial collaborative decision-making and planning process: deliberative and analytic (Rinner, 2006; Boroushaki, 2010). The deliberative area of that process can be improved by consensus among various stakeholders and decision-makers through organizing discussion processes and facilitating negotiation and communication (Rinner, 2006; Rinner et al., 2008). The analytic area of decision-making and spatial planning process can be enhanced by providing a mechanism that enables individual decision-makers to use their value judgments about the decision issue, thereby producing a group solution that represents best the preferences of all participants (Malczewski, 1996; Feick & Hall, 1999; Jankowski & Nyerges, 2001a; Feick & Hall, 2004; Malczewski, 2006b; Simão et al., 2009).

1.2 Research problem

Over the last decade or so, significant research efforts have been made to integrate GIS and MCDA methods into the Web (or Web 2.0) environment (Rinner & Malczewski, 2002; Sikder & Gangopadhyay, 2002; Dragićević & Balram, 2004; Evans, Kingston, & Carver, 2004; Voss et al., 2004; Hall & Leahy, 2006; Chen, Jiang, & Li, 2007; Karnatak, Saran, Bhatia, & Roy, 2007; Rao et al., 2007; Jankowski, Zielinska, & Swobodzinski, 2008; Simão et al., 2009; Taranu, 2009; Boroushaki, 2010). However, the research into Web-based MC-SDSS has so far tended to concentrate on the technical questions of how to integrate GIS and MCDA (Carver, 1999; Sakamoto & Fukui, 2004; Karnatak et al., 2007). In a research agenda about geovisual analytics for decision support analysis, Andrienko et al. (2007) argue that MCDA methods are essential for supporting the involvement of humans in complex spatial problem-solving. However, they also suggest that a simple combination of geovisualization techniques and GIS methods with MCDA modelling is not sufficient for facilitating the mutual reinforcement of the abilities of humans and computers and call for research about human-computer interaction (HCI) (see MacEachren et al., 2004).

Little empirical research has been performed to understand the way decision makers, stakeholders, planners, and citizens acquire and use the relevant decision information during a collaborative GIS-MCDA process (Jankowski & Nyerges, 2001a; Meng, 2010).

Our understandings of the benefits of MC-SDSS applications are currently limited by the scarce empirical studies on the usage patterns of decision support tools. The major reason for the limited empirical critiques is that most research about MC-SDSS has focused on software design and development rather than use. This limited knowledge on how people search through and combine information to make spatial decisions leaves the design and development side without sound scientific bases for advancing the technology. Evidence shows that the effects of advanced information technologies on individuals and groups are less a function of the technologies themselves than how they are used by people (DeSanctis & Poole, 1994; Crossland, Wynne, & Perkins, 1995; Jankowski & Nyerges, 2001a). The motivation for research coming out of this conclusion is that studying the patterns of human-commuter interaction under MC-SDSS conditions is as important as developing the decision support software. Web technology provides a distinctive opportunity for studying the usage patterns of MC-SDSS by means of the online system events log data analysis.

Given the importance of understanding decision makers' information acquisition behavior, it is equally important to understand this behavior across different types of decision situations (Abdul-Muhmin, 1994). Research on human-computer interaction in the context of MC-SDSS suggests that decision situations involving different levels of task complexity and also the use of different types of geographic information aids affect decision makers' information acquisition behavior (Jankowski & Nyerges, 2001a; Speier, 2006; Meng & Malczewski, 2010). There is a large body of literature on the influence of task complexity on information acquisition strategy. Empirical studies have shown that task complexity affects information processing demands and decision strategies of the individuals (e.g., Payne, 1976; Ford, Schmitt, Schechtman, Hults, & Doherty, 1989; Conlon, Dellaert, & Soest, 2001; Klemz & Gruca, 2001; Schulte-Mecklenbeck, 2005; Queen, Hess, Ennis, Dowd, & Gruhn, 2012). Decision makers rely on simplifying or non-compensatory information search strategies as task complexity (i.e., the amount of information available by using a decision aid) increases (Minch & Sanders, 1986; Payne, Bettman, & Johnson, 1993; Malczewski et al., 2003). Compensatory search strategies involve the combination of available information and an evaluation process where high values on some evaluation criteria can compensate for low values on other criteria. Non-compensatory search strategies, on the other hand, involve various simplifying heuristics for evaluating and combining information. With a non-compensatory strategy, comparisons and combinations across evaluation criteria are avoided and evaluation may be qualitative rather than quantitative. Non-compensatory search strategies are less cognitively demanding and may result in different decisions than when compensatory strategies are used. Consequently, the decision maker is faced with a tradeoff between reduced cognitive effort and potentially less than optimal decisions (Bodily, 1985; Malczewski & Rinner, 2005).

Access to different information aids, such as tables, graphs and maps has also been found to influence the decision process and outcomes (Crossland et al., 1995; Smelcer & Carmel, 1997; Dennis & Carte, 1998; Speier, 2006; Andrienko et al., 2007). Therefore, it is reasonable to expect that the type of decision aids offered for use in the GIS-MCDA environment has an influence on the number of times they are used and the way they are brought into use. The human-computer interaction (the pattern of decision aid moves) will likely be different between maps and decision tables because of the advantages or disadvantages of information associated with each (Contractor & Seibold, 1993). Jankowski and Nyerges (2001b) examined the usage of four different types of geographic information structures including: Map, MCDA (decision table), Consensus (rank map), and Table/Text aids in a collaborative GIS-MCDA environment. In an examination of the use of map and MCDA decision aids, they found that the time that participants spend on these information aids is significantly different.

None of the previous studies has examined the effects of task complexity and information aids on the information acquisition strategies in the Web 2.0-based collaborative GIS-MCDA. There is, therefore, a need for research to provide insights into decision makers' information acquisition behaviors (human-computer interaction patterns) and the effect of task complexity and information aids on this behavior during the use of a Web 2.0-based collaborative MC-SDSS. The purpose of this dissertation is to contribute to addressing this need by carrying out an experimental study of information acquisition behavior in a collaborative GIS-MCDA process. In addition to task complexity and information aid effects, this study examines the effects of decision mode (individual versus group decision making) on the information acquisition behavior. Several studies suggest that the information acquisition strategies used by decision makers differ between the different modes of decision making process (Abdul-Muhmin, 1994; Schrah, Dalal, & Sniezek, 2006). For example, Schrah et al. (2006) suggested that decision makers employ different information acquisition strategies in the decision modes where they are provided with advice (alternative choice recommendations) and where they are not. There is no empirical study in the literature exploring how decision maker' information acquisition behavior is affected by the use of different GIS-MCDA modes. Decision makers may exhibit different information search behaviors with or without having an access to the group decision results (group choice recommendations).

Given the study's focus on describing the process leading to a decision and an interest in dynamics of human-computer-human interaction during collaborative decision making, the study will adopt a process tracing approach to measure the information acquisition metrics (Ford et al., 1989; Jankowski & Nyerges, 2001a). Process tracing is a data collection technique that allows the researchers to directly monitor and record decision maker' activities during the decision making process (Takemura & Selart, 2007). It provides a detailed understanding of what information is examined, when, how, and for how long the information is processed by tracking the steps leading to the decision (Pfeiffer, 2012). The use of process tracing technique allows for uncovering the cognitive processes that underlie how task complexity, information aid, and decision mode affect the way people deal with decision problems.

1.3 Research questions and hypotheses

The main objective of this dissertation is to examine the patterns of human-computer interaction (information acquisition behavior) in the use of a Web 2.0-based collaborative MC-SDSS for tackling a site selection problem under different decision situations. To achieve this objective, the following set of research questions and corresponding hypotheses have been formulated.

Research question 1

How does the complexity of a decision task affect information acquisition strategies in the collaborative GIS-MCDA procedure? This research question is examined using the following hypotheses:

H1a: *There is a significant relationship between task complexity in the individual decision making* (*the GIS-MCDA individual mode*) *and the proportion of information searched*. It is expected that an increased task complexity in the GIS-MCDA individual mode will result in a decrease in the proportion of information search (Payne, 1976; Ford et al., 1989; Chinburapa, 1991; Roe, Busemeyer, & Townsend, 2001; Katz, Bereby-Meyer, Assor, & Danziger, 2010; Schram & Sonnemans, 2011; Queen et al., 2012). **H1b**: *There is a significant relationship between task complexity in the group* (*collaborative*) *decision making* (*the GIS-MCDA group mode*) *and the proportion of information search*. It is anticipated that the proportion of information search in the GIS-MCDA group mode will decrease along with an increasing task complexity.

H2a: *There is a significant relationship between task complexity in the GIS-MCDA individual mode and the proportion of information searched across the attribute ranges* (*the ranges of attribute values*). It is expected that an increased task complexity in the GIS-MCDA individual mode will result in a decrease in the proportion of information searched. **H2b**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and the proportion of information searched across the attribute ranges*. It is anticipated that an increased task complexity in the GIS-MCDA group mode will decrease the proportion of attribute ranges searched.

H3a: *There is a significant relationship between task complexity in the individual decision making and the average amount of time spent on each piece of information*. It is expected that an increased task complexity in the GIS-MCDA individual mode will result in a decrease in the average amount of time spent on each piece of information (Ford et al., 1989; Klemz & Gruca, 2001). **H3b**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and the average amount of time spent on each piece of information*. It is anticipated that that an increased task complexity in the GIS-MCDA group mode will result in a decrease in the average amount of time spent on each piece of information.

H4a: *There is a significant relationship between task complexity in the GIS-MCDA individual mode and variability in the proportion of information searched per attribute*. It is expected that an increased task complexity in the GIS-MCDA individual mode will result in increased variability in the proportion of information searched per attribute (Chinburapa, 1991; Abdul-Muhmin, 1994; Bröder & Schiffer, 2003; Schmeer, 2003). **H4b**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and variability in the proportion of information searched per attribute*. It is anticipated that an increased task complexity in the GIS-MCDA group mode will result in increased variability in the proportion of information searched per attribute.

H5a: *There is a significant relationship between task complexity in the GIS-MCDA individual mode and variability in the proportion of information searched per alternative*. The anticipated result is that an increased task complexity in the GIS-MCDA individual mode will result in increased variability in the proportion of information searched per alternative (Payne et al., 1993; Abdul-Muhmin, 1994; Bröder & Schiffer, 2003; Schmeer, 2003; Carrigan, Gardner, Conner, & Maule, 2007; Glaholt, 2010). **H5b**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and variability in the proportion of information searched per alternative*. It is expected that an increased task complexity in the GIS-MCDA group mode will result in increased variability in the proportion of information searched per alternative.

H6a: *In the GIS-MCDA individual mode*, *decision makers use a more attribute-wise strategy* (*direction of search*) *than an alternative-wise strategy in the information search process*. It is expected that, in the GIS-MCDA individual mode, search will become organized by attributes rather than by alternatives. **H6b**: *In the GIS-MCDA group mode, decision makers use a more attribute-wise strategy than an alternative-wise in the information search process*. The anticipated result is that, in the GIS-MCDA group mode, search will become organized by attributes rather than by alternatives. **H6c**: *There is a significant relationship between task complexity in the GIS-MCDA individual mode and direction of search* (Payne, 1976; Abdul-Muhmin, 1994; Roe et al., 2001; Katz et al., 2010). It is expected that increased task complexity in the GIS-MCDA individual mode will result in a direction of search that is more attribute-wise than alternative-wise. **H6d**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and direction of search*. It is suggested that increased task complexity in the GIS-MCDA group mode will result in a direction of search that is more attribute-wise than alternative-wise.

H7a: *There is a significant relationship between task complexity in the GIS-MCDA individual mode and the total time spent acquiring the information in the decision table*. It is expected that an increased task complexity in the GIS-MCDA individual mode will result in increased time spent acquiring the information in the decision table (Chinburapa, 1991; Abdul-Muhmin, 1994). **H7b**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and total time spent acquiring the information in the decision table*. It is anticipated that an increased task complexity in the GIS-MCDA group mode will result in increased time spent acquiring the information in the decision table.

H8a: *There is a significant relationship between task complexity in the GIS-MCDA individual mode and time spent acquiring the information on the map*. It is expected that an increased task complexity in the GIS-MCDA individual mode will result in increased time spent acquiring the information on the map. **H8b**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and time spent acquiring the information on the map*. It is anticipated that an increased task complexity in the GIS-MCDA group mode will result in increased time spent acquiring the information on the map. **H8c**: *There is a significant relationship between task complexity in the GIS-MCDA* *individual mode and the number of moves on the map*. It is expected that an increased task complexity in the GIS-MCDA individual mode will result in a higher number of moves on the map. **H8d**: *There is a significant relationship between task complexity in the GIS-MCDA group mode and the number of moves on the map*. It is anticipated that an increased task complexity in the GIS-MCDA group mode will result in a higher number of moves on the map.

H9: *There is a significant relationship between task complexity in the GIS-MCDA group mode and the time spent viewing the group (collective) decision*. It is expected that increased task complexity in the GIS-MCDA group mode will result in increased time spent viewing the group (collective) decision. As task complexity increases, the participants may find the decision task difficult, and therefore will tend to use the group advice (e.g., group debates and ranking of the alternatives) (Schrah et al., 2006; Gino & Moore, 2007).

Research question 2

How do information acquisition and integration strategies used in the collaborative GIS-MCDA individual mode differ from strategies used in the collaborative GIS-MCDA group mode? This question is addressed by the following hypotheses:

H10a: *There is a significant difference in the proportions of information searched between the two decision modes*. **H10b**: *There is a significant difference in the proportion of attribute ranges searched between the two decision modes*. **H10c**: *There is a significant difference in the average amount of time spent on each piece of information between the two decision modes*. **H10d**: *The two decision modes are significantly different in terms of variability in the proportion of information searched per attribute*. **H10e**: *The two decision modes are significantly different in terms of the variability in the proportion of information searched per alternative*. **H10f**: *There is a significant difference in the direction of information searched between the two decision modes*. **H10g**: *The two decision modes are significantly different in terms of the total time spent acquiring the* *information in the decision table*. **H10h**: *The two decision modes are significantly different in terms of the time spent acquiring the information on the map*. **H10i**: *The two decision modes are significantly different in terms of the number of moves on the map.* I expect that the two decision modes would be significantly different in terms of: (i) the proportion of information search, (ii) the variability of information search per attribute, (iii) the variability of information search per alternative, (iv) the direction of search (sequence of information search), (v) the total time spent acquiring the information, (vi) the average time spent acquiring each piece of information, (vii) the total time spent on the map exploration, and (viii) the number of moves on the map.

Research question 3

How do the types of geographic information structures (e.g., maps and tables) affect decision makers' information acquisition behaviors? To answer this research question, the following set of hypotheses is examined:

H11a: *There is a significant relationship between the type of information aid in the GIS-MCDA individual mode and information search moves*. It is suggested that, in the GIS-MCDA individual mode, the number of moves in the decision table is significantly higher than that on the map. **H11b**: *There is a significant relationship between the type of information aid in the GIS-MCDA group mode and the number of moves*. It is expected that, in the GIS-MCDA group mode, the number of moves in the decision table will be significantly higher than that on the map (Jankowski & Nyerges, 2001b). **H11c**: *There is a significant relationship between the type of information aid in the GIS-MCDA individual mode and the time spent acquiring the decision information*. It is anticipated that the amount of time spent on the decision table in the GIS-MCDA individual mode will be significantly more than that on the map. **H11d**: *There is a significant relationship between the type of information aid in the GIS-MCDA group mode and the time spent acquiring the decision information*. The expected result is that the amount of time spent on the decision table in the GIS-MCDA group mode is significantly more than that on the map (Jankowski & Nyerges, 2001b). **H11e**: *In both the GIS-MCDA individual and group* *modes, there is a significant relationship between the time spent on the decision table and the time spent on the map*. **H11f**: *In both the GIS-MCDA individual and group modes, there is a significant relationship between the number of table moves and map moves*.

Research question 4

Is there a relationship between the time spent searching for information in the decision table/map and the time spent viewing the group decision? This question can be answered in terms of the following hypotheses:

H12a: *There is a significant relationship between the time spent on the map and the time spent viewing the group decision in the GIS-MCDA group mode*. **H12b:** *There is a significant relationship between the time spent on the decision table and the time spent viewing the group decision.* It is expected that the time spent on the decision table/map and the time spent viewing the group decision will be significantly correlated.

Research question 5

Is there relationship between the information acquisition metrics used in the decision table? This research question can be addressed using the following hypothesis:

H13: *In both of the GIS-MCDA individual and group modes, there is a significant relationship among the information acquisition metrics*. It is anticipated that there will be a significant relationship between the proportion of information search, the proportion of attribute ranges examined, the average decision time, the variability of information search per attribute, the variability of information search per alternative, and the direction of search (Abdul-Muhmin, 1994).

Research question 6

Does task complexity affect the relationship between the information acquisition in the decision table and the map? The answer to this question can be derived from the following hypotheses:

H14a: *Increased task complexity in the GIS-MCDA individual mode has an insignificant impact on the relationship between the time spent on the decision map and table*. **H14b:** *Increased task complexity in the GIS-MCDA group mode has an insignificant impact on the relationship between the time spent on the map and table*. **H14c:** *Increased task complexity in the GIS-MCDA individual mode has an insignificant impact on the relationship between the number of map and table moves.* **H14d***:* *Increased task complexity in the GIS-MCDA group mode has an insignificant impact on the relationship between the number of map and table moves.* It is expected that, in both the GIS-MCDA individual and group modes, an increase in decision task complexity will affect both the relationship between the time spent on the decision map and table and the relationship between the number of moves on the map and in the decision table (Jankowski & Nyerges, 2001b).

Research question 7

Does task complexity affect the relationship between the time spent on the decision table/ map and the time spent viewing the group decision? To examine this question, the following hypotheses have been developed:

H15a: *Increased task complexity in the GIS-MCDA group mode has an insignificant impact on the relationship between the time spent viewing the group decision and the time spent on the decision table*. **H15b**: *Increased task complexity in the GIS-MCDA group mode has an insignificant impact on the relationship between the time spent viewing the group decision and the time spent on the map*. It is anticipated that increased task complexity has significant impact on the relationship between the time spent on the decision table/ map and the time spent viewing the group decision.

Research question 8

Does the decision mode influence the relationship between the information acquisition in the decision table and the map? To answer this question, the following hypotheses have been constructed:

H16a: *The decision mode has an insignificant effect on the relationship between the time spent on the map and table*. **H16b**: *The decision mode has an insignificant effect on the relationship between the number of map and table moves*. I expect that the decision mode will influence both the relationship between the time spent on the map and table and the relationship between the number of map and table moves.

1.4 Methodology

The main focus of this research is on the examination of the set of hypotheses derived from the research questions in the context of a Web 2.0-based MC-SDSS application. To achieve the research objectives, the methodology used in the study involves a three stage procedure:

(1) Developing and implementing a Web 2.0-based collaborative MC-SDSS for tackling a site selection problem in the City of Tehran, Iran

The MC-SDSS software used in the case study consists of three modules: (i) the information aid tool is a Google Maps- and table-based representation of the decision information for exploring the decision-related information; (ii) the MCDA tool is a set of multicriteria decision procedures for evaluating decision alternatives by individuals and group of participants, and allows for ranking decision alternatives based on the user's preferences with respect to evaluation criteria; and (iii) the group decision tool consists of two sub-modules: (a) a Google Maps-based on-line discussion forum for geo-referenced discourse, which allows for two basic forms of geo-argumentative relations: argumentative relations between geographic objects and spatial relations between arguments (Rinner, 2001, 2006), and (b) a Google Maps-based tool for representing group/compromise rankings of alternatives, which are obtained by aggregating individual rankings using the Borda approach (Jankowski & Nyerges, 2001a; Boroushaki, 2010).

The system can be used in two decision modes: (i) the individual decision making mode (or GIS-MCDA individual mode) and (ii) the group (collaborative) decision making mode (or GIS-MCDA group mode) (Jankowski & Nyerges, 2001a). In the individual mode, the participants have access to the two modules. The individual decision making module (i) provides participants with a decision table and map for exploring the decision information, and allows the participants to determine the criteria preferences, and eventually evaluate the alternatives. The decision table and map have been respectively used for the representation of decision space (alternative location space) and the criterion outcome space (criterion value space) (see Malczewski, 1999b). Locations of feasible decision alternatives along with the underlying spatial relationships constitute the geographic decision space. To each of the alternative locations there is assigned a binary decision variable, which takes 1 if the corresponding location is selected, or otherwise 0. Each location in the decision space (map) has its associated criterion values in the decision outcome space (decision table or criterion outcome table). Jankowski, Andrienko, and Andrienko (2001) argue that an integrated visualization of the decision space and criterion outcome space can be useful for understanding the structure of a decision problem (see also Rinner, 2007). They suggest that the simultaneous representation of criterion and decision spaces opens a possibility of eliciting a decision maker's preferences for decision criteria not only on the basis of attribute data but also geography.

Similar to the individual mode, the collaborative MC-SDSS in the group mode allows the participants to examine the decision table and the map, express their criteria preferences, and generate the alternatives' orderings. The only difference is that, in the group mode, participants can review the other participants' comments and also group rankings of the alternatives using the group decision making module. Having examined the group decision and others' comments, the participants are able to compare their individual decisions with the group/collective decision, and therefore are able to refine their initial preferences in an effort to get their decision close to the group decision. Both the decision modes will be used for the case study of parking site selection in district # 22 of Tehran.

(2) Conducting experiments using the system and collecting the human-computer interaction data

The study makes use of a decision-making experiment involving different decision situations based on the levels of task complexity, the types of information aids and decision modes. The primary field research activities center on using the MC-SDSS by a "virtual" non-mediated group comprised of community members interacting with the MC-SDSS tools accessed via Internet. Each individual in the group is able to participate in the experiments after registering online as a user in order to track the human-computer interaction patterns. The data on the participants' activities during the experiment is recorded based on a database logging approach. The Web-based event logs (database log) provide an efficient and non-intrusive method for collecting data from the participants for the purpose of analyzing computer-human interactions. Each time a user performs an interaction with MC-SDSS, the system writes records to the database.

(3) Analyzing the event log data for testing the hypotheses

The hypotheses are tested by conducting Repeated Measures ANOVA (within-subjects ANOVA) tests, Linear Mixed Model (LMM) analyses, and Pearson correlation tests using the Statistical Package for the Social Sciences (SPSS) software (SPSS IBM., 2012). The set of hypotheses H1 to H9 are examined using the Repeated Measures ANOVA test (with Greenhouse-Geisser correction as needed). The LMM test is employed for analyzing the group of H10, H14, H15and H16 hypotheses. The three sets of hypotheses, H11, H12, and H13, are analyzed by conducting the Pearson correlation test; however, some of the H11 hypotheses will also be tested using the LMM test.

1.5 Structure of thesis

The thesis is divided into seven chapters (see Figure 1). Chapter 1 discusses the research background and outlines the research questions, hypotheses, and methodology. Chapter 2 explores the relevant literature. It gives a background on the pertinent concepts including: spatial planning, PGIS, collaborative multicriteria spatial decision analysis (Collaborative GIS-based MCDA), and Web 2.0 and Web 2.0-based collaborative GIS-MCDA. The chapter provides an overview of the research about information acquisition in the collaborative GIS-MCDA and behavioral decision making. Based upon the decision behavior literature, some general arguments about information acquisition metrics are made. Chapter 3 describes a collaborative GIS-MCDA procedure to be used in the empirical study. Chapter 4 provides a detailed discussion of the metrics used for examination of the information acquisition behavior during the use of the Web 2.0-based collaborative MC-SDSS. These metrics are used in the research hypotheses as a means of inferring decision making behavior and describing the strategies (or combination rules) used by decision makers in the collaborative GIS-MCDA. They characterize human-computer interaction patterns in the information acquisition context. In Chapter 5, the study area and experimental procedure are described. The chapter also demonstrates the development of a Web 2.0-based collaborative MC-SDSS based upon the GIS-MCDA procedure proposed in Chapter 3. Chapter 6 presents the findings of the experiments, the results of hypothesis testing, and discussion of the results. Chapter 7 gives a summary of the research and concluding remarks. Also, it discusses the limitations and outlooks for research.

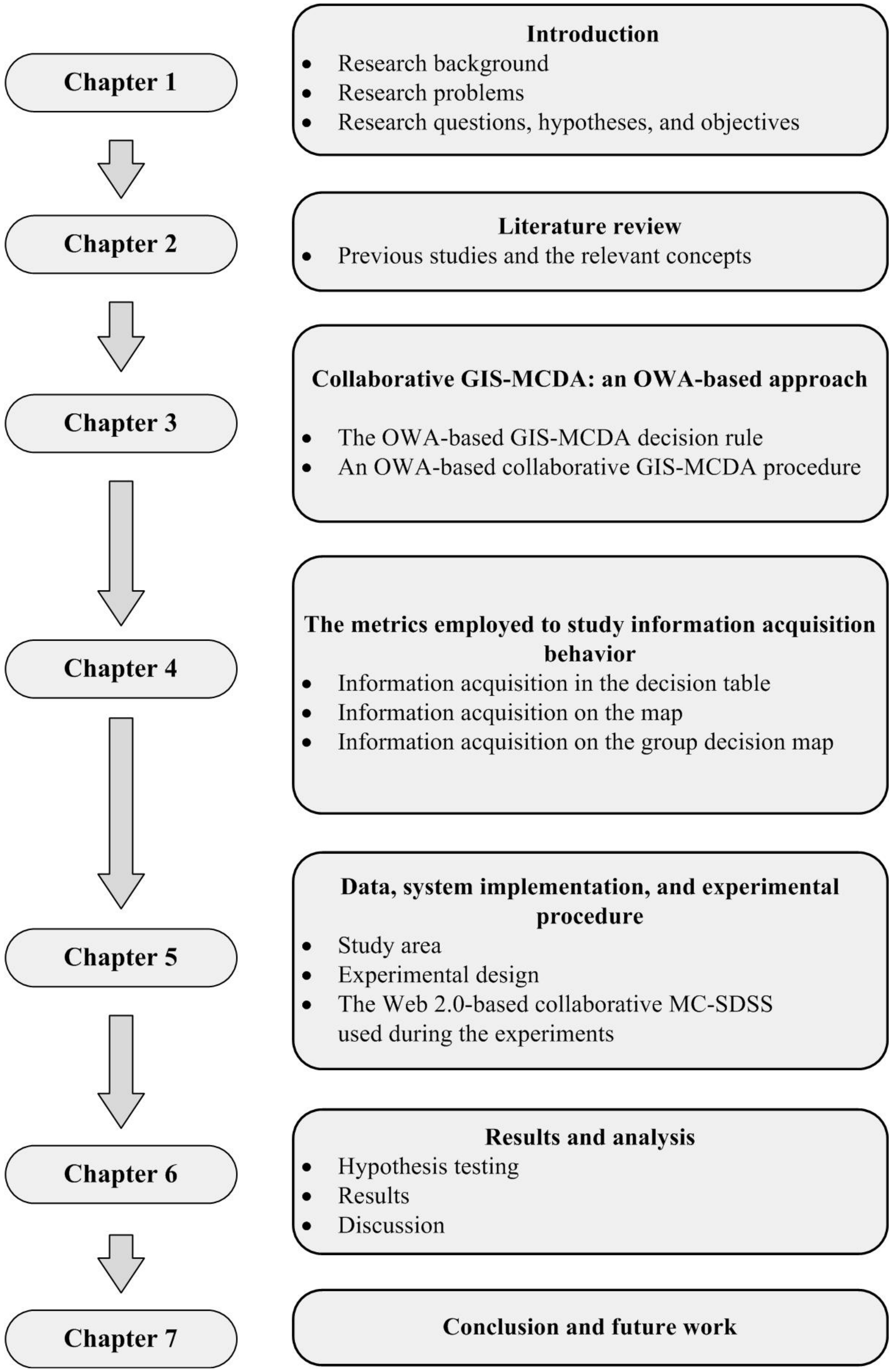


Figure 1. The structure of the thesis.

Chapter 2

2 Literature review

This chapter gives an overview of the theories, concepts, and practices that are relevant to this dissertation. It reviews the existing literature on studying information acquisition behavior in the process of decision making in general, and collaborative GIS-MCDA in particular. The chapter begins with a description of the pertinent concepts, including spatial planning, PGIS, GIS-based MCDA methods and framework, collaborative spatial multicriteria decision analysis (collaborative GIS-MCDA), and Web 2.0 and Web 2.0-based collaborative GIS-MCDA. Next, the theories and empirical studies from other areas of decision making that can contribute to a better understanding of the information acquisition/search behavior in collaborative GIS-MCDA are reviewed. The empirical studies of information acquisition in the decision making process and methodologies concerning information acquisition behavior are also examined. Attention is given to the information processing metrics commonly used in the literature, as well as how the metrics are operationalized. Finally, the theoretical and empirical perspectives on the effects of different types of decision situations (i.e., decision situations manipulated by task complexity, information aid, and decision mode) on the information acquisition metrics are reviewed.

2.1 Participatory spatial planning

One of the early definitions of spatial planning is given by the European Regional/Spatial Planning Charter (CEMAT, 1983). CEMAT defines spatial planning as follows: “Regional/spatial planning gives geographical expression to the economic, social, cultural and ecological policies of society. It is at the same time a scientific discipline, an administrative technique and a policy developed as an interdisciplinary and comprehensive approach directed towards a balanced regional development and the physical organization of space according to an overall strategy” (p.5). Spatial planning aims at creating a more rational territorial organization of land uses and the linkage between them to balance the demand for development with the need to protect the environment, and to achieve the social and economic objectives (Däne & Van Den Brink, 2007).

The approaches to spatial planning have been traditionally recognized as centralized, bureaucratic and top-down activity carried out by planning offices, planning authorities and other stakeholders (Krek, 2005). Typically, planners and professionals carry out almost all activities by themselves, starting from problem identification to plan formulation, with very little or no consideration given to the views of beneficiaries and other stakeholders[1]. Such approaches have been criticized for failing to provide an adequate solution for solving complex and wicked spatial problems, engaging diverse participants as competent stakeholders (experts and lay-persons), generating a nonconflictual decision or plan, democratizing planning process, etc. (Voss et al., 2004; Tang, 2006).

Rittel and Webber (1973) argue that planning problems are typically "complex", "wicked" and "ill-structured". The problems cannot be adequately solved by the rational comprehensive planning approaches. The contradictory issues and the number of environmental, economic, and social factors directly or indirectly influence planning, and make it a complex process (Nidumolu, de Bie, van Keulen, Skidmore, & Harmsen, 2006; Yang et al., 2008). Such planning problems cannot effectively be addressed by a centralized approach (Tang, 2006; Joerin et al., 2009).

According to Massam (1988), a generic planning problem can be defined as follows: "given a set of N plans or alternatives, and for each an evaluation on a set of M criteria, for a set of G interest groups, classify the N alternatives in such a way as to identify their relative attractiveness so that agreement among interested groups is maximized" (p. 19). This definition implies that the diverse values, objectives, and interests of the interested groups (decision-makers and the recipients of the outcome of the planning process) form an integral part of the planning process (Hodge, 2003; Tang, 2006). Tang (2006) argues

---

[1] http://www.unescap.org/ttdw/Publications/TPTS_pubs/pub_2308/pub_2308.pdf

that the main goal of planning to reconcile the diverse values, objectives, and interests into acceptable community interests may not be achieved by centralized planning approaches that rely only on planners' judgment, which is based on their knowledge, culture, and values. In other words, the conflicting interests caused by the differences as a matter of worldviews and values, experience and trust, and knowledge and expertise are not considered in the centralized approaches.

The tendency of centralized planning ignores the principles of democratic planning. In a democratic society, one of the fundamental freedoms is the right of a citizen to know and participate in a decision situation, when decisions about valued-concerns affect the welfare (taken broadly) of those people and the places in which they live (Jankowski & Nyerges, 2001a). Citizens are the key players in urban planning as they are the ones who will be affected by the consequences of planning (Simão et al., 2009; Wu et al., 2010) and they also know the reality and the issues around them better than anybody else. A democratic government based on pluralist participation must first obtain different and opposing opinions and preferences from interest groups and the public at large, analyze them and then develop a single policy platform that will reflect the will of the majority of the voters (Wohlgemuth, 1999; Pennington, 2004). Without consideration of public debate, deliberation, values and objectives in planning, citizens are treated as passive members. These challenges are the driving forces changing spatial planning paradigm from the traditional, centralized, bureaucratic, and top-down approach to a holistic, participatory, communicative, and collaborative planning practice. Participatory approaches to spatial planning are gaining increased attention among decision makers and planners, as well as with community groups and civil society (Lovan, Murray, & Shaffer, 2004; Kim, Halligan, Cho, Oh, & Eikenberry, 2005; Larson & Ribot, 2005). McCall and Dunn (2012) argue that these approaches can be interpreted as the specifically participatory methods of a more generic model of cyclic spatial planning and management with four basic phases: exploration, assessment, design of mitigation alternatives, and action. The integration of participatory approaches in spatial planning processes is expected to support good governance principles of openness, participation, accountability, effectiveness and coherence through contributions to empowerment, legitimacy, and equity (McCall & Dunn, 2012).

2.2 Participation

Participation refers to a process by which the public can express opinions and exert influence regarding political, economic, management or other decisions. Jankowski and Nyerges (2001a) argue that at least four cumulative levels of "social interaction" fall under the umbrella term of "participation": communication, cooperation, coordination, and collaboration. At a basic level of participation, people communicate with each other to share and exchange ideas, concerns, viewpoints, and knowledge as an essential process of social interaction. A cooperative interaction is defined by a set of processes which help people interact together in order to accomplish a specific goal or develop[2]. Cooperative interactions occur when a constructive change for one individual also increases the collective benefit of a group of individuals[3]. In a coordinated interaction, participants agree to cooperate, but they also agree to sequence their cooperative activity for mutual, synergistic gain (Jankowski & Nyerges, 2001a). A collaborative interaction is the process through which participants in a group agree to work on the same task simultaneously or at least with a shared understanding of a situation in a near-simultaneous manner (Roschelle & Teasley, 1995). The collaboration of people representing diverse areas of competence, political agendas, objectives and conflicting goals, scenarios, and social interests provide a synergic solution during planning. Through such a process, interested parties can have an active role from the initial stages (formulation of goals, exploration of alternatives) right up to the final stage of planning (Carsjens & Ligtenberg, 2007).

There are a number of advantages of a participatory approach to the planning process. A participatory process:

---

[2] http://www.londonmet.ac.uk/deliberations/collaborative-learning/panitz-paper.cfm
[3] http://www.thebigblob.com/competitive-and-cooperative-interactions-in-biological-inspired-ai/

- enables individuals to voice their concerns and work on a compromise solution, leading to consensus decision-making practices.

- "encompasses a group of procedures designed to consult, involve, and inform the public to allow those affected by a decision to have an input into that decision; "input" is the key phrase, differentiating participation methods from other communication strategies." (Rowe & Frewer, 2000, p.6);

- provides a rich source of updated information that helps to improve the quality of the analysis, leading to different solutions (Bugs et al., 2010);

- helps decrease the complexity level as a group of people including local or neighborhood citizens, planning experts, and government employees has more information (knowledge) to understand and tackle the decision problem;

- assures sustainability, stability and longevity of plan which stays intact over time[4];

- may improve the general sense of community and trust in government, since individuals themselves participate in planning and affect decisions (Tang & Waters, 2005);

- can avoid the problems associated with bureaucratic governance (Pennington, 2004);

- promotes the development process; the plans and decisions, which are well-designed but have not included public involvement, may face opposition which will slow or stop the project.

[4] Http: //www. lgc.org /people/public.html

2.3 Participatory GIS-based planning

2.3.1 Participatory GIS (PGIS)

GIS-based approaches have the potential to improve the quality of plans, helping planners to achieve more informed, consistent, timely, and accurate spatial decisions by producing relevant information (Fischer & Nijkamp, 1993; Esnard & MacDougall, 1997; Voss et al., 2004; Witlox, 2005; Sieber, 2006). Dai, Lee, and Zhang (2001) describe the main advantages of using GIS in planning as follows: the increase of efficiency, the automation of planning tasks, accuracy improvement, accessibility at low costs, ease of use by public, very short time for data manipulation, the possibility to explore diverse scenarios, providing decision support, and ease of handling the graphic output.

While the planners and decision-makers have full access to relevant spatial data/information and GIS tools, there are relatively few GIS-based spatial planning and decision-making tools that are available to the general public. This division has been one of the main criticisms of GIS (Pickles, 1995; Carver, 1999; Carver & Peckham, 1999; Dragićević, 2004). During the 1990s, the critiques of the uses of traditional GIS in society and calls for enhanced public participation in spatial planning have led to the use of GIS for participatory planning/decision making. GIS and its offspring spatial decision support systems (SDSS) were suggested as information technology aids to facilitate geographic problem understanding and decision making in a participatory setting (Jankowski & Nyerges, 2001a). In general, these technologies lie within the broad umbrella of what has become known as Participatory GIS (PGIS). PGIS shifts the spatial planning from a closed, expert-oriented process to an open, community-oriented process (Malczewski, 2004). There are many definitions of the concept of PGIS. For example, PGIS is defined as:

- "a variety of approaches to make GIS and other spatial decision-making tools available and accessible to all those with a stake in official decisions" (Schroeder, 1996, p.1);

- an integrative and inclusive process-based set of GIS methods and technologies amenable to public participation, multiple viewpoints, and diverse forms of information (Krygier, 2002);

- a computer-aided approach that creates an environment to facilitate analysis and deliberation in a group decision setting (Jankowski & Nyerges, 2001a), allowing participants to access and understand information, incorporate local knowledge, integrate and contextualize complex spatial information, dynamically interact with input, and analyze alternative plans (Sieber, 2006);

- a system that facilitates the meaningful introduction of appropriate forms of spatial information and analytical tools for widening public participation in the policy-making process, and promotes the goals of nongovernmental organizations, grassroots groups, and community-based organizations (Tang & Waters, 2005).

2.3.2 Collaborative multicriteria spatial decision support systems

While the mainstream GIS technology is focused on the creation of easy-to-use, ubiquitous mapping and spatial analysis tools, it has lacked a capability to collate individuals' interests and preferences to support collaborative spatial decision making (CSDM) in particular, and participatory decision making in general (Jankowski & Nyerges, 2001a). The information needs that use specialized models for description, decision analysis, assessment, and forecast in planning cannot be answered by GIS alone. Planning requires specialized decision analysis procedures that go beyond the standard database manipulation and basic functions of GIS. Collaborative Multicriteria Spatial Decision Support Systems (MC-SDSS) extend the PGIS tools to include not only the capabilities of GIS, but also Multicriteria Decision Analysis (MCDA) techniques for collaborative decision analysis. It has been argued that the synergetic capabilities of GIS (GIS database and spatial analysis) and MCDA procedures (multicriteria analytical models) can potentially enhance the collaborative decision-making processes by providing a rich collection of techniques and procedures for eliciting the decision-makers' preferences; structuring decision problems; as well as designing, evaluating, and prioritizing decision alternatives (Feick & Hall, 1999; Jankowski & Nyerges, 2001a; Kyem, 2004; Malczewski, 2006a). Marttunen (2011) summarizes the potential benefits of the use of MCDA in planning (see Figure 2).

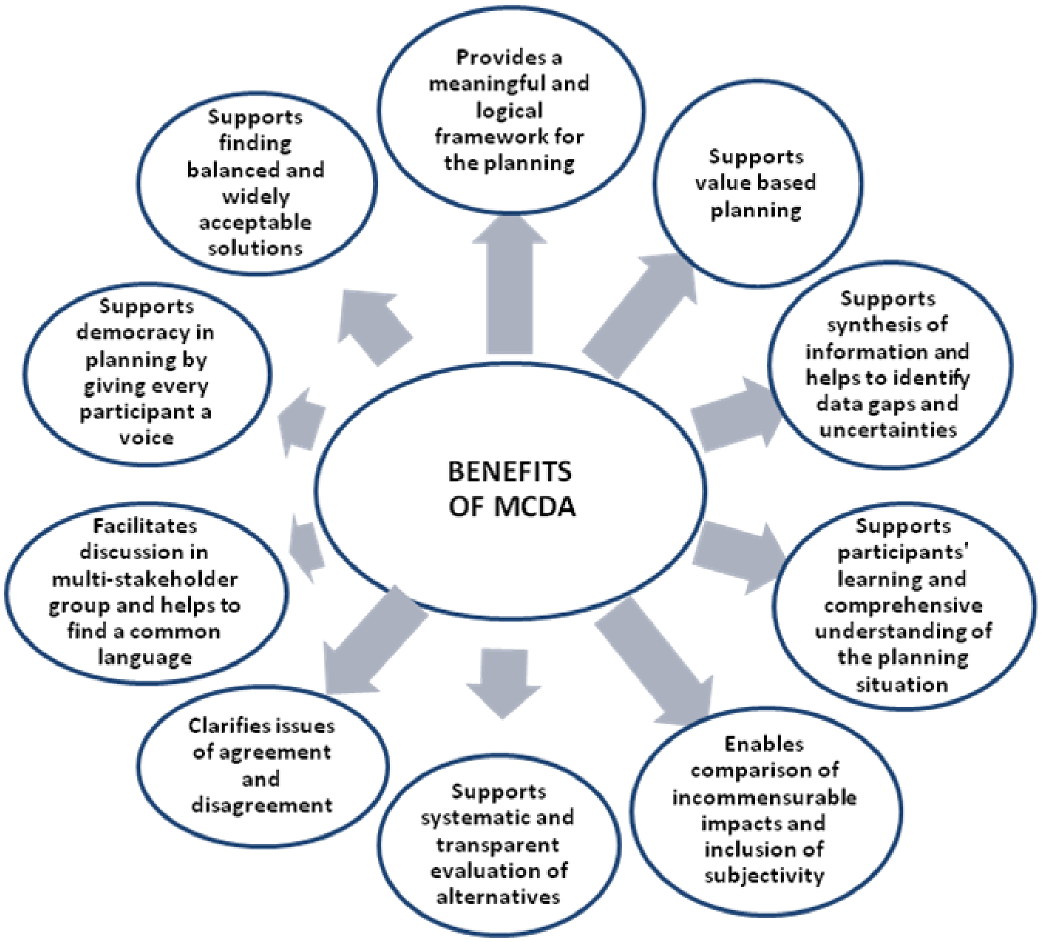


Figure 2. Benefits of MCDA in planning (Source:Marttunen, 2011).

2.3.3 GIS-based MCDA

The general aim of GIS-based MCDA techniques is to contribute to the decision making process by selecting the best alternative from the number of feasible alternatives according to multiple criteria. It involves the use of geographical data, decision maker preferences, and an aggregation function (decision rule) that combines spatial data and the decision maker's preference to evaluate decision alternatives. The main rationale behind integrating GIS and MCDA is that these two distinct areas of research can complement each other (Malczewski, 1999a; Thill, 1999; Chakhar & Martel, 2003; Malczewski, 2006a; Boroushaki, 2010). While GIS is commonly recognized as a powerful and integrated tool with unique capabilities for storing, manipulating, analyzing and visualizing geographically referenced information for decision-making, MCDA provides a rich collection of procedures and algorithms for structuring decision problems, designing, evaluating and prioritizing alternatives. It is in the setting of the synergetic characteristics of GIS and MCDA that the importance of advancing theoretical and applied research on MC-SDSS becomes obvious.

2.3.3.1 GIS-based MCDA elements

Malczewski (1999a) divided MCDA problems into six components: (1) a decision goal or a set of goals; (2) a set of evaluation criteria (attributes and objectives); (3) the decision maker's preferences or group of decision makers with their preferences; (4) the set of decision alternatives; (5) the set of uncontrollable variables (factors beyond the decision maker's control), and (6) the outcomes or consequences associated with each alternative with respect to each criterion (see Figure 3). These elements are organized in a hierarchical structure with the top level corresponding to the ultimate goal of the decision at hand. A goal essentially describes an improvement from the present state of a system toward its desirable state. A decision maker can be a single person or a group of people. An important task of the decision maker(s) is to identify their values and interests with respect to the decision problem by determining the relative importance (weights) of criteria against which the alternatives are evaluated. Two types of criteria can be defined:

objective and attribute. An objective is a statement about the desired state of the decision problem under consideration. It indicates the directions of improvement of one or more attributes. For any objective, several different attributes[5] can be defined, providing complete assessment of the degree to which the objective might be achieved. Attributes are measurable characteristics expressing the degree to which the associated objectives are achieved for a particular decision alternative (Keeney & Raiffa, 1976; Jankowski & Nyerges, 2001a). In the spatial context, an attribute describes a measurable quantity or quality of a geographic entity or a relationship between geographic entities. The procedures for selecting a set of attributes should be based on the desirable properties of attributes. Both individual attributes and a set of attributes should possess some properties to adequately represent the multicriteria nature of the decision problem. A set of attributes should be complete (the attributes should cover all aspects of a decision problem), operational (they can be used meaningfully in the analysis), decomposable (they can be broken into parts to simplify the process), non-redundant (they avoid problems of double counting), and minimal (the number of attributes should be kept as small as possible). Attribute values of the alternatives can be organized in a table format called decision matrix or decision table. The table rows and columns represent decision alternatives and attributes, respectively. A value at the intersection of row and column in the table represents the decision outcome associated with a particular alternative with respect to a given attribute.

[5] Throughout this dissertation the term attribute will be used interchangeably with the term criterion.

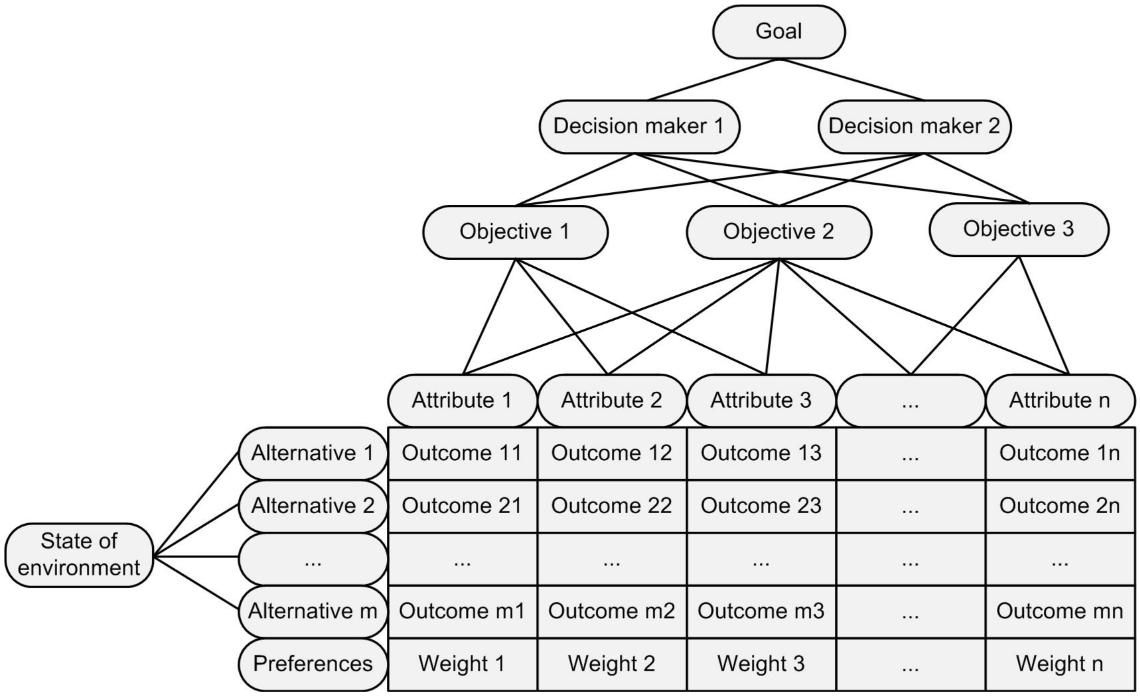


Figure 3. A hierarchical structure for the MCDA (Source:Malczewski, 1999a).

2.3.3.2 GIS-based MCDA framework

Malczewski (1999a) proposes a sequence of activities for spatial multicriteria decision analysis by synthesizing Simon's (1977) three-step decision making process (i.e., intelligence, design, and choice) and MCDA components (see Figure 4). They include: defining the decision problem, identifying evaluation criteria and constraints, determining decision alternatives, applying a decision rule, performing sensitivity analysis, and making a recommendation. A clear problem definition in spatial MCDA is the first step toward rationally selecting the best alternative. The problem definition is the result of a discrepancy between the present state of a system and the desired state. This discrepancy can be formulated as a problem calling for a decision.

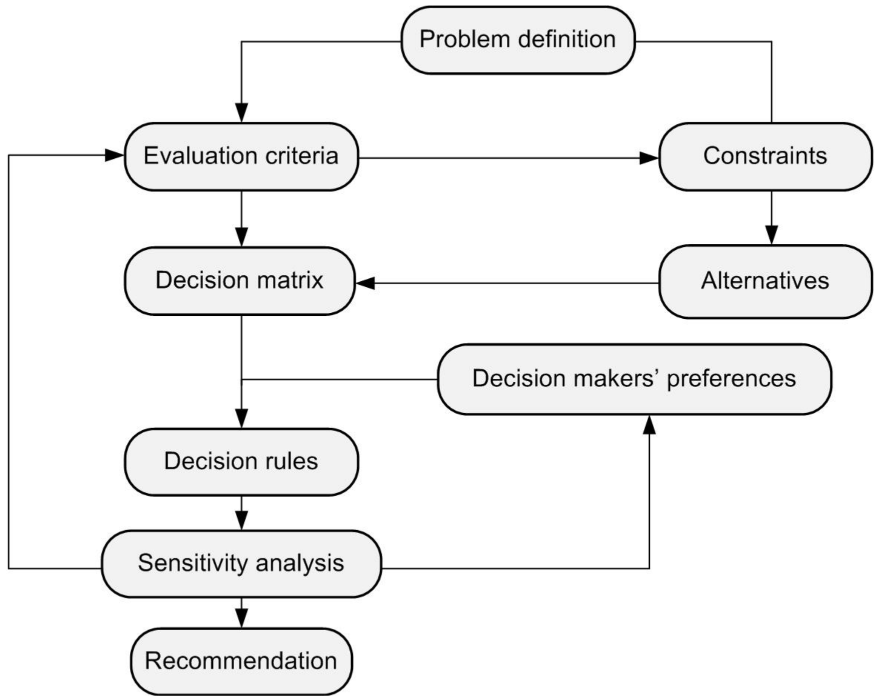


Figure 4. Framework for multicriteria analysis (Source:Malczewski, 1999a).

Articulating goals of a decision problem leads to a set of spatial and non-spatial criteria (objectives or attributes), which represent the important characteristics that an alternative should have. A constraint is the criterion that imposes limitations on the alternatives under consideration. GIS constraint maps are aimed at removing infeasible alternatives and representing only feasible ones. For example, a decision alternative to be feasible must be located within 500 meters of major road. In some cases, the constraint will be expressed as some characteristic that the final solution must possess (Eastman, Jin, Kyem, & Toledano, 1995). For example, the size of a parcel of land for development must be less than 3000 hectares.

The decision alternatives are defined geographically in terms of location, spatial pattern, and spatial interaction. A spatial decision alternative consists of at least two elements: action (what to do?) and location (where to do it?) (Malczewski, 1999a). A set of alternatives is often generated based on the spatial relationship principles of connectivity, contiguity, and proximity. Geographic alternatives can be defined using both raster- and vector-based GIS data models. In raster data layer, each cell or a collection of adjacent cells forms a decision alternative. In some cases, geographic alternatives can be defined as a spatial aggregation of cells based on a particular geometric shape. In vector data model, depending on the spatial scale of a problem, a location representing the decision option can be represented by point (e.g. site), area (e.g. county), line (e.g. water pipeline corridor) or any combination of the above such as in the case of a land use plan (Jankowski & Nyerges, 2001a). Malczewski (1999a) defines ten categories of vector-based alternatives and groups them into two types: simple and complex. These categories include point, line, polygon, point-point, point-line, point-polygon, line-line, line-polygon, polygon-polygon, and point-line-polygon. Simple decision alternatives are characterized by a single type of object such as a point for representing a site. Depending on the number of spatial units for an alternative, geographic decision problems can be categorized into two types: atomistic and holistic (Tomlin, 1990). An atomistic decision problem is one that can be addressed on a discrete and location-by-location basis, whereas a holistic decision problem considers collections of locations as an integrated area that represents a decision alternative.

Decision makers' preferences reflect the values and interests of decision makers with respect to the evaluation criteria. Decision makers are able to handle the preference judgments by means of fuzzy judgments as well as precise numerical judgment. The procedure that determines how best to evaluate alternatives or to decide which alternative is preferred to another is known as a decision rule. It integrates the data on a set of alternatives and decision makers' preferences into an overall assessment of each alternative. Sensitivity analysis is aimed at determining how the outcome of a model is affected by changes in the model inputs. Sensitivity analysis in spatial MCDA involves identifying the effects of changes in the inputs (geographical data and decision maker's preferences) on the outputs (ranking of alternatives). It can be performed to see how the decision alternatives might be ranked differently if the inputs are changed.

2.3.3.3 Choice model: decision rule

MCDA methods can be categorized into two broad classes: Multi Objective Decision Making (MODM) and Multi Attribute Decision Making (MADM) (Malczewski, 1999a). MODM considers a criterion as an objective. It can be thought of as the optimization and search of an alternative or alternatives on the bases of a set of objectives. For example, a multiobjective problem could be stated as determining a route which simultaneously optimizes both cost and environmental impact (Church, Loban, & Lombard, 1992). Decision space in MODM is continuous and alternatives are defined implicitly by a mathematical programming structure. On the other hand, MADM[6] concentrates on problems with discrete decision spaces in which alternatives are defined explicitly by a finite list of attributes. MADM is used to select an alternative from a set of predetermined alternatives based on the decision maker's preferences. Both MODM and MADM methods can be used either by an individual or a group of people. Group decision making demands the participation of multiple decision makers with conflicting preferences to solve a particular decision problem. The people who influence a decision can contribute and collaborate in a group decision making process. In the group mode, all members can make use of MCDA models and methods to evaluate decision alternatives based on their preferences. A number of MCDA methods, such as weighted linear combination (WLC), ideal point methods, concordance analysis, analytical hierarchy process (AHP), value/utility function approaches, and ordered weighted averaging (OWA), have been developed that can be used for both of the above mentioned MCDA categories (for an overview see Malczewski, 1999a). The process of applying these methods in the spatial context is concerned with how to appropriately combine the relevant criteria values (spatial data) and decision maker's preferences to determine the overall evaluation scores (ratings and rankings) for the decision alternatives.

[6] Throughout this dissertation, the term MCDA will be used to refer to a MADM-based approach.

2.3.3.4 Collaborative GIS-based MCDA

Although GIS-based MCDA approaches have traditionally focused on the MCDA techniques for individual decision making, substantial efforts have been made to integrate GIS with MCDA for participatory/collaborative/group decision making (Malczewski, 1996; Jankowski, Nyerges, Smith, Moore, & Horvath, 1997; Feick & Hall, 1999; Andrienko & Andrienko, 2001; Feick & Hall, 2001; Jankowski & Nyerges, 2001a; Kyem, 2001; Bailey et al., 2003; Kyem, 2004; Phua & Minowa, 2005; Simão et al., 2009; Taranu, 2009; Boroushaki, 2010). In general, collaborative GIS-based MCDA approaches cover many of the features of a single-user GIS-based MCDA (see Section 2.2.1). The specific features of a collaborative GIS-based MCDA are intended to support: alternative generation, selection of the evaluation criteria (objectives and attributes), criterion weighting, expressing individual preferences, combination of the individual judgments into a single collective preference, final ordering of alternatives so that a compromise alternative can be selected, and cartographic display functions for group decision-making problems (see Limayem & DeSanctis, 2000; Jankowski & Nyerges, 2001a; Malczewski, 2006b; Boroushaki, 2010). In addition to the principal components of conventional GIS-based MCDA frameworks (data and analysis module, MCDA module, and interface), a collaborative GIS-based MCDA should contain communication capabilities and allows for voting, ranking, and rating for developing a consensus. Communications technologies available within collaborative decision support systems include: electronic messaging, local- and wide-area networks, and teleconferencing. Jankowski and Nyerges (2001a) present generic methods and tools for collaborative GIS-based MCDA by synthesizing Renn et al. 's (1993) three-step public-participation decision process with Simon's (1977) three-step process for the macro level of a macro-micro decision strategy (see Table 1). The decision strategy consists of three macro-phases: intelligence on criteria, design of options set, and choice of options. Each phase is composed of four micro activities: gather, organize, select, and review.

Table 1. Methods and tools for collaborative decision making derived from macro-micro decision strategy (Source:Jankowski & Nyerges, 2001a).

	Macro-decision strategy phases		
Micro-decision strategy activities	*1.* ***Intelligence*** *about values, objectives and criteria*	*2.* ***Design*** *of a feasible option set*	*3.* ***Choice*** *about decision options*
A. Gather...	participant input on values, goals and objectives using **information management** and **structured-group process techniques**	**data and models** (GIS and spatial analysis, process models, optimization, simulation) to generate options	values, criteria and feasible decision options using **group collaboration support methods**
B. Organize...	goals and objectives using **representation aids**	an approach to decision option generation using **structured-group process techniques** and **models**	values, criteria and feasible decision options using **choice models**
C. Select...	criteria to be used in decision process **using group collaboration support methods**	decision options from outcomes generated by **group process techniques** and **models**	goal- and consensus achieving decision options using **choice models**
D. Review...	criteria, resources, constraints, and standards using **group collaboration support methods**	decision options and identify feasible options using **information management** and **choice models**	recommendation(s) of decision Options using **judgment refinement techniques**

Jankowski & Nyerges (2001a) and Boroushaki (2010) presented a Web-based analytic-deliberative tool, called *ParticipatoryGIS,* for a collaborative GIS-based MCDA. They argue that the ultimate goal of the GIS-based MCDA procedures is to tackle two distinct dimensions of spatial collaborative decision-making and planning: (i) the deliberative dimension of spatial planning by building a consensus, on the solution set of alternatives, among various decision-makers and interest groups through organizing and facilitating communication (Jankowski & Nyerges, 2001a; Rinner, 2006; Rinner et al., 2008) and (ii) the analytical dimension of spatial decision-making by generating a collective group solution that best represents the preferences of all participants (Malczewski, 1996; Feick & Hall, 1999; Feick & Hall, 2004; Malczewski, 2006b).

The deliberative aspect of collaborative GIS-based MCDA involves discussion processes, arguing in favour or against decision alternatives, negotiation, and consensus-finding methods that seek input from community members and take into account their preferences and opinions. The paramount goal of the deliberation is to reach a high degree of consensus among the decision-makers (Herrera-Viedma, Herrera, & Chiclana, 2002; Ben-Arieh & Chen, 2006). A consensus can be attained through the exchange of information and opinions, and through deliberation and rational arguments, which are expected to facilitate a convergence of the decision-makers' opinions (Boroushaki & Malczewski, 2010a).

Boroushaki and Malczewski (2010a) proposed a generic structure for the analytical dimension of the collaborative GIS-MCDA process involving the use of two decision rules (see Figure 5): individual and group (collective) decision rules. They distinguished two approaches: (i) prior articulation of preferences; where the preferences and judgments (e.g., criterion weights) of decision-makers are first aggregated into a collective group preference, and in the second step, the group judgment is used within MCDA decision rule, and (ii) aggregation of individual solutions, which involves two stages: first, each decision-maker solves the decision problem individually to obtain a set of individual solutions, by assigning different weights for the evaluation criteria, and in second stage, the individual solutions are aggregated using a collective choice rule to obtain a group solution.

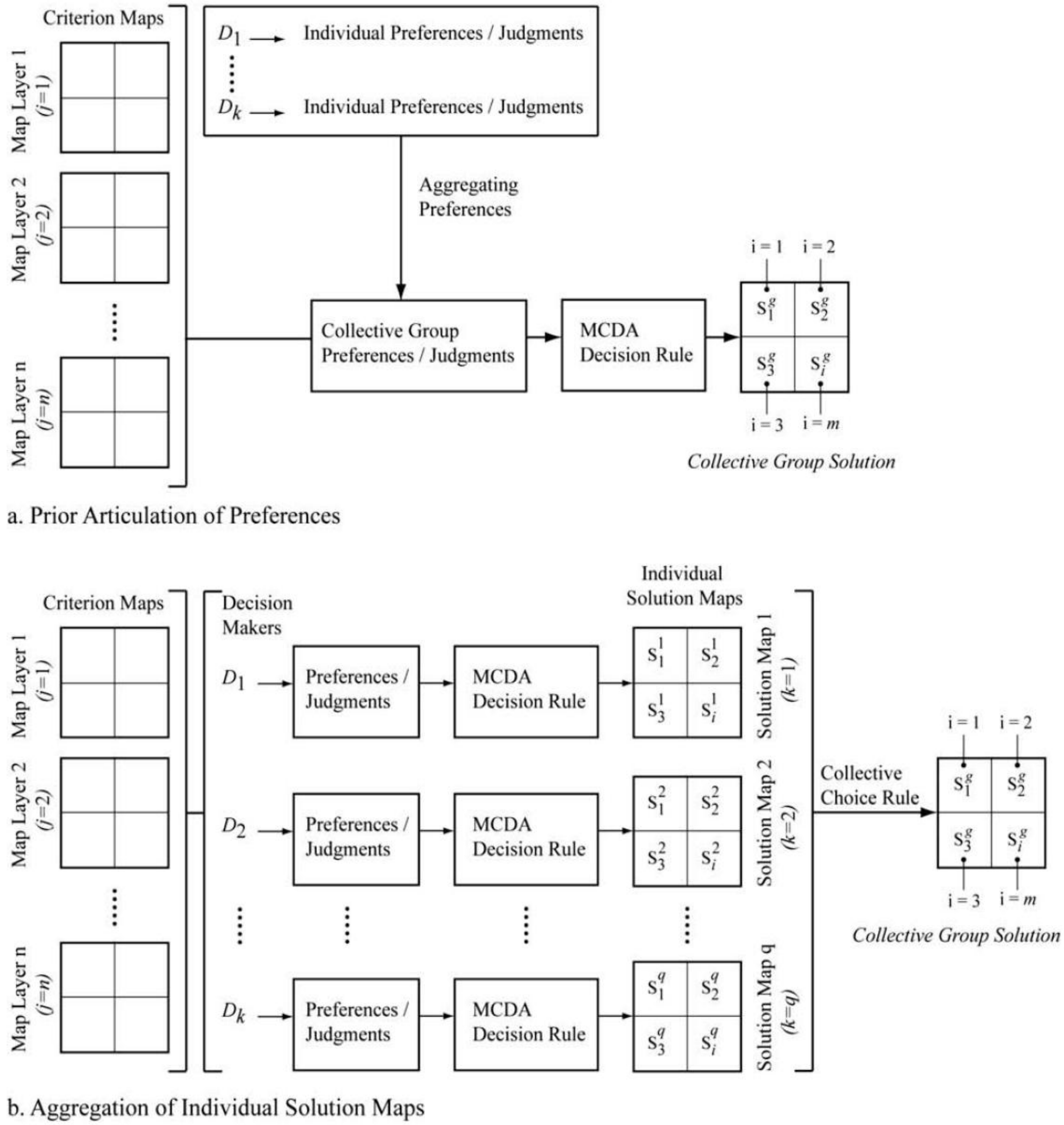


Figure 5. Structure of a collaborative GIS-MCDA process (Source:Boroushaki & Malczewski, 2010a).

Malczewski (2004) suggested that the potential for advancing the role of GIS-based MCDA in the participatory decision making can be stimulated by focusing on the way in which different interest groups use GIS-based techniques. This poses an important question: how can broader and more effective use of GIS-MCDA tools by the general public be attained in participatory planning? It has been argued that effectiveness of GIS-MCDA tools in participatory planning depends on the time that shared information is sent and received and on the location of group members (Jankowski & Nyerges, 2001a). In this regard, four approaches to the use of GIS-MCDA for group decision making have been distinguished: (i) same place-same time (conventional face-to-face meeting), (ii) same place-different time (storyboard meeting), (iii) different place-same time (conference-call meeting), and (iv) different place-different time (distributed meeting) (Desanctis & Gallupe, 1987; Malczewski, 2006b). The first three types of these approaches received some criticism, based on the limited ability to effectively provide decision support data and functionalities in a distributed environment, sufficiently engage the public in an open and asynchronous session, and to promote an exchange of ideas (Dragićević & Balram, 2004; Jankowski, 2009; Boroushaki, 2010; Bugs et al., 2010). They have been criticized for the failure to represent some interest groups and the inability to provide a platform for active participation and collaboration, due to their closed, synchronous and place-based nature (Alexander, 2000).

Since the early 1990s, the use of GIS-based MCDA methods in the World Wide Web (Web) environment has been one of the substantial shifts in the light of such critiques (Menegolo & Peckham, 1996; Andrienko & Andrienko, 2001; Zhu & Dale, 2001; Zhu, McCosker, Dale, & Bischof, 2001; Rinner & Malczewski, 2002; Sikder & Gangopadhyay, 2002; Dragićević & Balram, 2004; Evans et al., 2004; Sugumaran, Meyer, & Davis, 2004; Voss et al., 2004; Hall & Leahy, 2006; Chen et al., 2007; Karnatak et al., 2007; Rao et al., 2007; Jankowski et al., 2008; Simão et al., 2009; Taranu, 2009; Boroushaki, 2010; Markieta & Rinner, 2012). Web technologies opened new possibilities for the use of GIS-MCDA in a participatory environment, shifting the paradigm of participatory planning process from a closed, place-based (fixed time and location), and synchronous process to an open, asynchronous, distributed, and active decision making process. The space and time distributed environment of the Web offered not only flexibility of using GIS-MCDA in different space and time for the convenience of individuals, but also provided better access to spatial information and enhanced benefits from its use. Access to the relevant GIS-MCDA data and tools anywhere (any location that has the Internet access), anytime (24 hours a day, seven days a week), and through any PCs or handheld devices (e.g., PDA, smart phones) and networks (wired or wireless technologies) has remarkably enhanced the level of community participation in spatial planning (Chang, 1997; Sadagopan, 2000; Kingston, 2002; Tang & Waters, 2005).

While the early Web facilitated the collaborative GIS-MCDA by providing online geographic information and decision analysis tools, there was little in the way of user interaction, communication, and contribution in the collaborative process. The goal of the collaborative GIS-MCDA to support the users in contributing, sharing and exchanging their opinion/preferences with respect to the decision criteria, alternatives, etc. was not adequately achieved by the early Web. Recent endeavourers have adopted Web 2.0 technologies and concepts to PGIS related projects. The ability of Web 2.0, which is the next envisioned iteration of the Web, in advancing participation, interactivity, contribution, and collaboration have had significant role in PGIS in general, and collaborative decision making in particular.

2.4 Web 2.0, Web 2.0-based GIS, and Web 2.0-based collaborative GIS-MCDA

2.4.1 Web 2.0

The term "Web 2.0" was first coined by DiNucci (1990). DiNucci emphasized that the Web will be "understood not as screenfuls of text and graphics but as a transport mechanism, the ether through which interactivity happens" (p.32). Musser and O'Reilly (2006) defined Web 2.0 as "a set of economic, social, and technology trends that collectively form the basis for the next generation of the Internet-a more mature, distinctive medium characterized by user participation, openness, and network effects" (p. 4). It is a new trend of the Internet that shifts the Web into an interactive, read-write (two-way communication), and participatory platform, in which people not only consume content but also contribute and produce new content. Web 2.0 does not make a fundamental change to the software/hardware infrastructure of the Internet; rather, it is a shift in the nature of how the Web is used and perceived.

The shift from the Web to Web 2.0 can be viewed from both social and technical perspectives. The essence of the social aspect of Web 2.0 is that it supports interaction and communication of users, content generation by users, collective intelligence exploitation, collaboration, knowledge sharing, etc. (Usluel & Mazman, 2009). The technological shift of Web 2.0 was focused on supporting Web sites, such as Web-based communities, social-networking sites, wikis, and blogs that incorporate Web 2.0 features. AJAX (Asynchronous JavaScript and XML) was the most significant turning point that altered the nature of Web 1.0. It is a standards-based programming technique designed to make Web-based applications more responsive, interactive, and customizable. The key of AJAX is the asynchronous interaction between browser clients and Web servers, which implies that multiple requests can occur in parallel. It allows for updating the content of Web pages instantly when a user performs an action (unlike an HTTP request during which users must wait for a whole new page to load). This capability of AJAX permits the development of highly interactive Web 2.0 applications featuring more responsive user interfaces. Another important technological development of Web 2.0 was focused on building the mashups. A mashup is an interactive Web application that combines content and functionality to create entirely new and innovative services. Central to the mashups are the easy-to-use, publicly accessible, free, and AJAX-based application programming interfaces (APIs) that are made available at no cost to Website designers. Thousands of different API libraries have been written for the user-driven Web.

2.4.2 Geospatial Web 2.0 (GeoWeb)

The rise of Web 2.0 and its related technologies has had significant impact on the recent evolution of GIS and PGIS. This advancement has led to the development of Geospatial Web 2.0, which is an evolution of Web GIS that focuses on public participation and interaction in geo-spatial system (Ganapati, 2010). Characterizing this evolution was increasing usability for non-GIS specialists, facilitating wider community usage of GIS technologies and taking advantage of the collective intelligence of the Web, building participation-oriented and user-centric GIS platforms, and developing spatial mashups

(Geo-Web services), etc. (Ganapati, 2010; Beaudreau et al., 2011; Karnatak et al., 2012). This trend has given rise to concepts like spatial mashups and argumentation mapping.

2.4.2.1 Spatial mashups

The Web 2.0 technologies have an important role in developing user-driven spatial mashups (rich geographic Websites). The AJAX-based spatial APIs can be adopted for interactive and fast accessing of geo-spatial data and services. Google Maps is a prominent example of the AJAX-based spatial APIs that has been made available to users to incorporate Google Maps into their spatial mashups. For example, the Web page "housingmaps.com" has employed the Google Maps API to display the real estate information on a Google Map. The Google Maps example essentially demonstrates the realization of what researchers had primarily theorized about in reference to the concept of PGIS (Leahy, 2011). Goodchild (2007) describes the Google Maps phenomenon as the "democratization of GIS", because it has opened some of the more straightforward capabilities of GIS to the general public. That is, non-GIScientists are now able to "read, write, alter, store, test, represent information in ways that they desire and in formats and environments they understand" (Miller, 2006, p.188). According to Macdonald (2008), there were 1740 spatial mashups in August 2008 (see http://www. programmableWeb.com/tag/mapping/) and the number has risen to 2153 in February 2010. By mid-2007, there were over 50,000 new Websites that were based on Google Maps (Tran, 2007). In the previous era of the Internet mapping, the number of mapping Websites was significantly smaller due to technical and financial barriers (Haklay, Singleton, & Parker, 2008).

2.4.2.2 Argumentation mapping

The ability of Web 2.0 to facilitate person-to-person communications has been adopted for developing online argumentation mapping as a specific type of PGIS. Argumentation mapping is the concept proposed by Rinner (2001) as a map-centered communication tool to support geographically referenced discussions and deliberations. This concept was developed as a method for organizing debates on spatial issue in asynchronous online discussions (Rinner, 2001; Sidlar & Rinner, 2007), where it proposes to structure the arguments, argument locations, and their many-to-many relationships. An argument can refer to multiple locations, a location can be referenced by multiple arguments, an argument can be logically related to a number of other arguments, and locations can be spatially related. Such a model provides the theoretical foundations for PGIS tools that support the deliberative aspects in spatial decision-making.

By clicking on the map, individuals can reference their contributions about different dimensions of the decision problem to geographic locations. It enables participants to hold conversations in the form of posted messages on the map, which allows for graphical submission, compilation, tracking of geographic proposal via annotated map. The participants who view the same map at a later time are able to read comments and view the geographical locations to which they are linked, and can develop argumentation and discourse further with other participants. This essentially facilitates a level participant-to-participant communication that closer approximates the kinds of discussion that take place during in-person meetings, with the added ability to have statements in the discussion linked explicitly to associated spatial features on the map (Leahy, 2011).

Most of the Web 2.0-based argumentation mapping tools (mashups) have been deployed using the free-of-charge geospatial data and functionalities provided by Google Maps APIs (e.g.,Sidlar & Rinner, 2007; Simão et al., 2009; Boroushaki & Malczewski, 2010b; Sani & Rinner, 2011). The ease of use of Google Maps plays a key role in the success of such systems as the target group is the general public with no familiarity with GIS functionalities (Rinner et al., 2008). There were already a number of Google Maps-based mashups in existence; therefore, a reasonable number of the general public and non-GIS experts could be expected to be familiar with this particular user interface.

2.4.3 Web 2.0 and collaborative GIS-MCDA

The collaborative GIS-based MCDA capabilities matured as the Web and Web-based GIS became more advanced, social, and user-oriented. Recent trends in Web 2.0 development overcome some of the obstacles associated with technical and social challenges that were faced by early Web-based GIS-MCDA applications. The concern of accessibility to GIS-based MCDA methods for the general public is far less challenging in the current era then it was previously. Large amounts of data are freely available to the public through commercial service, and from official and/or user-generated data repositories. Although existing data sources available to the public may fail to fully support what an individual requires, the tools for individuals to create their own data sets are readily accessible through various Web 2.0 services (Leahy, 2011).

Using the AJAX-based technologies, many interactive GIS-MCDA interfaces and mashups have been developed for the collaborative decision making environment (e.g., Boroushaki, 2010; Markieta & Rinner, 2012). These technologies allow the integration of analytical and deliberative parts of GIS-MCDA in a single Web page with a set of tools and functionalities that resemble a desktop GIS (Boroushaki & Malczewski, 2010b). Such AJAX-based GIS-MCDA frameworks enable participants to have continuous and seamless interaction with GIS-MCDA systems. For instance, Markieta and Rinner (2012) developed an AJAX-based interactive GIS-MCDA tool that enables users to generate on-the-fly weighting schemes for any combination of criterion map layers. Using these tools, even a non-technical user can actively interact and contribute to the decision making process.

A number of collaborative GIS-based MCDA applications have specifically used the Google Maps-based argumentation mapping techniques to support the deliberative aspect of collaborative decision making (e.g., Boroushaki, 2010). Using this capability, individuals can deliberate and exchange information regarding the decision alternatives on Google Maps. Such tools empower participants to share their opinions about the current alternatives; to propose inclusion of one or more locations as the new alternatives in a decision problem or exclusion of alternative(s); to collaborate on design and refinement of the alternatives; and to assist in giving voice to social, health, environmental, economic, and safety concerns related to a particular place. This makes Google Maps an appropriate candidate to be the base of any collaborative GIS-MCDA development.

2.5 Information acquisition in collaborative GIS-MCDA

Any informed decision involves the acquisition and integration of information about decision problems. Researchers in collaborative decision-making have long recognized the importance of information acquisition as a determinant of decision quality (e.g., Janis, 1989; Saunders & Miranda, 1998; Paul, Saunders, & Haseman, 2005; Meng, 2010). Janis (1989) suggests that information acquisition by decision makers early in the decision-making process likely leads to a high-quality decision since it is assimilated and processed with little bias. Saunders and Miranda (1998) argue that relevant information needs to be collected and assimilated in the early stages of the decision-making process to form a strong preference for the decision solution.

The process of information search and acquisition is critical to collaborative GIS-MCDA. It refers to the process by which a decision maker seeks information about decision alternatives and criteria. This includes an examination of information aids (e.g., decision table and maps), what pieces of information are acquired, the pattern in which information is acquired, etc. Typically, decision makers in the collaborative GIS-MCDA process need to seek the decision information as a basis for assigning criteria preferences/weights. During specification of the criteria preferences, one may take into account the preferred range of attributes values (a particular range), the least-preferred and the most-preferred value for a given attribute, compare a change from the least-preferred to the most-preferred value for an attribute to a similar change in another attribute, and so on.

Researchers suggest that the weights a decision maker assigns to criteria typically reflect: (1) the changes in the range of variation for each attribute (the extent to which alternatives vary on that attribute), and (2) the different degrees of importance being attached to these ranges of variation (subjective evaluation of importance of that attribute) (Keeney & Raiffa, 1976; Anderson & Zalinski, 1988; Mellers & Cooke, 1994; Malczewski, 2000; Pöyhönen, Vrolijk, & Hämäläinen, 2001; Parnell et al., 2007; Ligmann-Zielinska & Jankowski, 2012). According to range sensitivity principal, a weight value is dependent on the range of criterion values; that is, the difference between the minimum and maximum value for a given criterion. A weight can be made arbitrarily large or small by increasing or decreasing the range value. The general rule is that one is concerned with the perceived advantage of changing from the maximum level to the minimum level of each attribute, relative to the advantages of changing from the worst to the best level for the other attributes under consideration. In other words, the weights assigned to attributes should be derived by asking the decision maker to compare a change from the least-preferred to the most-preferred value on one attribute to a similar change in another attribute.

The decision table and map are two fundamental categories of decision aids for representing and organizing the information about spatial decision problems. These two information aids enable decision makers to explore the decision space (spatial alternatives) and criteria outcome space (the criteria values associated with the alternatives). Within the collaborative GIS-MCDA context, a number of studies have explicitly developed a decision support tool that represent the decision information on the map or in the table format (e.g., Jankowski et al., 1997; Jankowski & Nyerges, 2001a; Boroushaki, 2010). For example, Spatial Group Choice, a collaborative GIS-MCDA tool developed by Jankowski et al. (1997), used both the table and map as aids for representing the decision information. Using this system, a decision maker is able to explore and compare the attribute data associated with alternatives contained in a decision table, and to examine the spatial distributions of alternatives and attributes on a thematic map. In a similar attempt, Boroushaki (2010) developed a Web 2.0-based collaborative

GIS-MCDA tool called PGIS for solving a parking site selection problem. Within this system, the collaborating participants are able to access the decision alternatives displayed on a map, examine the criteria values associated with the alternatives by clicking on each alternative, prioritize the criteria, and evaluate the alternatives according to their individual preferences.

2.5.1 Decision strategies and information acquisition metrics

Decision strategies are typically characterized as compensatory or non-compensatory. In compensatory strategies, the low values on some attributes are compensated for by the high values on other criteria (Koele & Westenberg, 1995; Schmeer, 2003; Pfeiffer, 2012). In other words, compensatory strategies involve trade-offs among criteria. Non-compensatory strategies, on the other hand, avoid compensation or trade-offs between criteria and only consider a subset of available information. Compensatory decision-making processes are more complex, require greater cognitive effort, and are more difficult to apply than non-compensatory procedures (Chinburapa, 1991; Bettman, Luce, & Payne, 1998; Schmeer, 2003; Katz et al., 2010). Decision makers often choose non-compensatory decision strategies, especially when the decision to be made is complex (Payne et al., 1993; Katz et al., 2010).

There is a link between decision strategies and information acquisition metrics. Decision behavior researchers have made remarkable efforts in operationalizing information acquisition and integration variables as a means of inferring the strategies used by decision makers (e.g., Payne, 1976; Svenson, 1979). In order to identify the information search variables, Chestnut and Jacoby (1976) carried out a principal components analysis on a sample of 28 information acquisition variables and found three main factors (cited in Abdul-Muhmin, 1994). These include: proportion (depth), content, and sequence (direction) of information search. The proportion and direction of information search are the two variables that have been considered as the basic distinction between compensatory and non-compensatory decision strategies. The proportion of information search refers to the extent to which all or some of the available information is utilized by the decision maker prior to arriving at a decision (see also Payne, 1976; Ford et al., 1989; Roe et al., 2001; Katz et al., 2010; Schram & Sonnemans, 2011; Queen et al., 2012). A higher proportion in the amount of available information searched is indicative of a compensatory strategy, while a lower proportion reflects a non-compensatory approach. The sequence of a search is concerned with the specific order in which various information values are searched (see also Payne, 1976; Abdul-Muhmin, 1994; Roe et al., 2001; Katz et al., 2010). Typically, the search sequences are alternative-wise (where an alternative is selected and attributes are searched for that alternative) and attribute-wise (in which case an attribute is selected and alternatives are searched for that attribute). An attribute-wise pattern of information search represents the use of a compensatory strategy, while an alternative-wise search pattern indicates a non-compensatory strategy.

Along with the search proportion and direction, Payne (1976) suggested an examination of the variability of information searched per alternative, arguing that this variable differs for compensatory (low variability) and non-compensatory (high variability) strategies (see also Payne et al., 1993; Abdul-Muhmin, 1994; Bröder & Schiffer, 2003; Schmeer, 2003; Carrigan et al., 2007; Glaholt, 2010). For compensatory strategies, a constant and equal amount of information is searched for each alternative, while for non-compensatory strategies a variable pattern of information search across alternatives is used (Schmeer, 2003). Klayman (1985) argued that in addition to variability in search per alternative, the extent of variability in amount of information searched per attribute should also be examined (see also Chinburapa, 1991; Abdul-Muhmin, 1994; Bröder & Schiffer, 2003; Schmeer, 2003). He suggested that a distinction between the two different forms of variability would enable decision makers to identify the sources of total variability; e.g., whether the search is attributable to unsearched alternatives or unsearched attributes.

Payne et al. (1993) suggested that total time spent acquiring information and average time spent per item of information acquired provide the evidence whether decision makers use non-compensatory or compensatory processing strategies (see also Ford et al., 1989; Dhar, Nowlis, & Sherman, 2000; Klemz & Gruca, 2001). As a compensatory process requires more cognitive effort, it is assumed that the average time spent per piece of information acquired is greater when decision makers use the compensatory strategy than when decision makers use a non-compensatory decision-making process (Chinburapa, 1991).

2.5.2 Task complexity and its effect on the information acquisition metrics

2.5.2.1 Task complexity

The impact of task complexity on decision making behavior has been the focus of much research. Campbell (1988) argues that any structural characteristic of a decision task that places high cognitive demands on the decision maker can be perceived as a factor representing task complexity. In the literature on decision making processes, information overload has been considered to be a particular type of task complexity, where an increase in the amount of information available to the decision maker is viewed as representing a relevant complexity factor (Jacoby, Speller, & Kohn, 1974; Shields, 1980; Koele & Westenberg, 1995; Lee & Lee, 2004; Wang & Chu, 2004). Accordingly, decision researchers measure task complexity by: (i) the number of alternatives available to the decision maker (e.g., Payne, 1976; Payne et al., 1993; Schmeer, 2003; Stafford, 2007; Pfeiffer, 2012) and (ii) the number of attributes that describe those alternatives (e.g., Payne, 1976; Abdul-Muhmin, 1994; Takemura & Selart, 2007; Pfeiffer, 2012; Queen et al., 2012). Both the number of alternatives and attributes are the major variables that affect the information acquisition behavior (decision strategy) during the decision making process.

2.5.2.2 Task complexity effects

Task complexity effects lead to a better understanding of the direction in which changes in the number of alternatives and attributes, affect how decision makers choose various strategies to accomplish the decision task (Abdul-Muhmin, 1994). There is a large body of literature about the influences of task complexity on decision strategy. Empirical studies have shown that task complexity affects information processing demands and decision strategies of individuals (e.g., Payne, 1976; Ford et al., 1989; Bettman, Johnson, & Payne, 1991; Payne, Bettman, Coupey, & Johnson, 1992; Abdul-Muhmin, 1994; Conlon et al., 2001; Klemz & Gruca, 2001; Schulte-Mecklenbeck, 2005; Queen et al., 2012). Payne (1982) reviewed the literature on the effects of task complexity on the use of decision strategies. He concluded that the hypothesis that changes in task complexity result in changes in decision-making strategies tends to be strongly supported when task complexity is manipulated via alternatives (cited in Chinburapa, 1991).

Previous studies have found a tendency for individuals to use simplified decision strategies when task complexity increases. It is suggested that an increase in task complexity results in the use of non-compensatory decision strategies in order to reduce information processing demands and cognitive efforts (Payne et al., 1992; Conlon et al., 2001; Pfeiffer, 2012). As the alternatives become more numerous and/or vary on more attributes, people are more likely to reduce their information search and adopt simplifying strategies which require less cognitive effort than a complete cost-benefit analysis of the available alternatives (Vandenberghe, 2011). In a complex decision situation, decision makers have to consider more information for making a decision; thus they experience information overload and use a strategy that is low in effort and turn to less demanding strategies, i.e., non-compensatory ones. In other words, they might neglect information rather than use more effortful compensatory strategies (Pfeiffer, 2012). The empirical studies on the effects of task complexity on information search metrics have consistently demonstrated that an increase in task complexity results in: (i) a decrease in the proportion of available information searched, (ii) an increase in the variability of information search per alternative or attribute, (iii) a decrease in mean search time, and (iv) an attribute-wise search pattern.

2.5.3 The effect of task complexity, information aids and decision modes in spatial decision making

As indicated in the previous section, there are a number of studies that have focused on studying the effects of task complexity on information acquisition behavior within the realm of non-spatial decisions. However, the research efforts examining task complexity effects in the field of spatial decision making in general and GIS-MCDA in particular have been rather limited. Crossland et al. (1995) examined the effects of task complexity on decision time and accuracy during the use of a spatial decision support system. The complexity of decision problem was manipulated on two levels. The first level required subjects to rank five facility sites based on three spatial criteria. The second level required ranking ten facility sites based on seven spatial criteria. The findings of this study suggested that an increase in task complexity resulted in an increase in decision time and a decrease in decision accuracy. Jankowski and Nyerges (2001a) employed a process tracing technique to study the influence of task complexity on dynamics of human-computer interaction (social-behavioral data analysis strategies) during a collaborative GIS-MCDA. They investigated how an increase in task complexity influences the use of information aids (e.g., maps, tables, diagrams) by decision participants, group work, and group conflict. In this effort, the task complexity was increased as a variation in both the number of spatial alternatives and criteria, with the simplest task involving eight sites and three evaluation criteria versus the most complex task being a choice among twenty sites based on eleven criteria. Results in this study demonstrated that the maps were used more in the simple task than the complex task by about twice as much.

As for the effect of information aids on decision making, it has been suggested that access to different tables, graphs and maps has an influence on the decision process and outcomes (Crossland et al., 1995; Smelcer & Carmel, 1997; Dennis & Carte, 1998; Speier, 2006; Andrienko et al., 2007). Speier (2006) argues that visualized data allows the decision-maker to shift some of the cognitive processing burden to perceptual operations that typically occur automatically and results in significantly lower mental workload that accelerate the speed and depth at which large amounts of data can be absorbed and comprehended. Therefore, it is reasonable to expect that the character of decision aids offered for use in the GIS-MCDA environment will have an influence on the number of times they are used and the way they are brought into use. The human-computer interaction (the pattern of decision aid moves) will likely be different between maps and decision tables because of the advantages or disadvantages of information associated with each (Contractor & Seibold, 1993). In an empirical study of socio-behavioral dynamics of using decision aids, Jankowski and Nyerges (2001b) examined the usage of four different types of geographic information structures including: map, MCDA (decision table), consensus (rank map), and table/text aids in a collaborative GIS-MCDA environment. In examination of the use of map and MCDA decision aids, they found that participants spent more time on exploring the MCDA aid than the map during the collaborative spatial decision making process. Dennis and Carte (1998) investigated the effect of map-based and tabular presentations on decision accuracy and speed. The study found that when data were presented in a map-based form and decision makers needed to consider the relationships among the geographic areas, the use of the map-based presentation led to both faster and more accurate decisions.

However, none of these studies has gone further to examine the effects of task complexity and information aids on the information acquisition metrics discussed above within the Web 2.0-based collaborative GIS-MCDA context. Also, these research efforts have not examined effect of decision mode (individual vs. group) on the information acquisition metrics. There is no empirical study exploring how decision makers' information acquisition behavior can be affected by the use of different GIS-MCDA modes. There is, therefore, a need for further research to examine: (i) information acquisition metrics as a means of inferring the behaviors and strategies used by participants within the realm of collaborative spatial multicriteria decision making and (ii) the effect of task complexity, information aids and decision modes on the information acquisition metrics.

Chapter 3

3 OWA-based approach for collaborative GIS-MCDA

This chapter presents a collaborative GIS-MCDA procedure to be used in the empirical study. The procedure involves two stages: (i) each decision maker solves the problem individually, and (ii) the individual solutions are aggregated to obtain a group solution. The first stage is operationalized by an OWA (ordered weighted averaging)-based decision rule for the generation of individual solutions. The second stage employs a Borda-based method for aggregating the individual solutions into a consensus solution. During the process of individual decision making, decision makers have access to the decision information represented by means of a decision table or map. They are able to acquire and integrate decision-relevant information, specify their preferences, and arrive at a decision.

3.1 The OWA-based GIS-MCDA decision rule

3.1.1 The OWA operator

The procedure that determines how to evaluate alternatives or to decide which alternative is preferred to another is known as decision rule. The decision rules in the GIS-MCDA context involve combining the relevant spatial data (attribute values) and preferences set by the decision participants to provide an overall assessment (ratings /ordering) of the decision alternatives. The Boolean overlay operations (non-compensatory combination rules) and the weighted linear combination (WLC) methods (compensatory combination rules) are the two fundamental, most often used classes of the decision rules in GIS-MCDA (Eastman, 1997; Heywood, Cornelius, & Carver, 2002; O'Sullivan & Unwin, 2003). These two types of combination rules can be generalized within the framework of OWA (Jiang & Eastman, 2000; Makropoulos, Butler, & Maksimovic, 2003; Malczewski et al., 2003; Malczewski, 2006c; Boroushaki, 2010).

The concept of the OWA operator was proposed by Yager (1988) to describe a class of multicriteria aggregation methods. For a given set of n attributes (criteria), an OWA operator can be defined as a function $F: I^n \rightarrow I$ that has an associated set of order weights $V = [v_1, v_2, \ldots, v_n]$; $v_j \in [0,1]$ for $j = 1, 2, \ldots, n$ and $\sum_{j=1}^{n} v_j = 1$. Given a set of standardized attribute values $A_i = [a_{i1}, a_{i2}, \ldots, a_{in}]$ for $i = 1, 2, \ldots, m$, where $a_{ij} \in [0,1]$ is the j-th attribute associated with the i-th alternative, the OWA operator is defined as follows:

$$OWA_i(a_{i1}, a_{i2}, \ldots, a_{in}) = \sum_{j=1}^{n} v_j z_{ij} \qquad (1)$$

where $z_{i1} \geq z_{i2} \geq \ldots \geq z_{in}$ is the sequence obtained by reordering the attribute values a_{i1}, $a_{i2}, \ldots, a_{in}$. The reordering process is central to the OWA operator. It involves associating a weight, v_j, with a particular ordered position of the attribute values $a_{i1}, a_{i2}, \ldots, a_{in}$ for the i-th alternative. The first order weight, v_1, is assigned to the highest attribute value for the i-th alternative, v_2 is associated with the second highest value for the same alternative, and so on with v_n assigned to the lowest attribute value. It should be noted that a particular value of a_{ij} is not associated with a particular weight v_j but rather the weight is assigned to a particular ordered position of a_{ij}.

3.1.2 Attribute value standardization

As mentioned earlier, the OWA-based GIS-MCDA requires that the attribute values be commensurate. To do so, a standardization of the attribute values is required. Many approaches can be used to make the attribute values commensurate. Here, we adopt a standardization procedure that uses the minimum and maximum values of an attribute as scaling points. Depending on whether the attribute is to be maximized (i.e., the larger the raw value, the better the performance) or minimized (i.e., the lower the value, the better the performance), Equations 2 and 3 can respectively be used to convert the raw attribute values into standardized values (comparable units).

$$a_{ij} = \frac{S_{ij} - S_j^{\min}}{S_j^{\max} - S_j^{\min}} \qquad (2)$$

$$a_{ij} = \frac{S_j^{\max} - S_{ij}}{S_j^{\max} - S_j^{\min}} \qquad (3)$$

where S_{ij} is the raw value for the i-th alternative and the j-th attribute, $S_j^{\min}$ represents the minimum value for the j-th attribute, $S_j^{\max}$ is the maximum value for the j-th attribute, a_{ij} is the standardized value for the i-th alternative and the j-th attribute. The standardized attribute values range from 0 to 1.

3.1.3 Deriving the order weights

The OWA aggregation operator in Equation (1) exclusively focuses on the order weights. It ignores the fact that most of the GIS based decision-making problems require a set of different weights to be assigned to criteria. To overcome this problem,Yager (1997) proposed an attribute weight modification approach for generating the order weights based on inclusion of the attribute weights into the OWA operator as follows:

$$v_j = \left(\frac{\sum_{l=1}^{j} u_l}{\sum_{l=1}^{n} u_l} \right)^{\alpha} - \left(\frac{\sum_{l=1}^{j-1} u_l}{\sum_{l=1}^{n} u_l} \right)^{\alpha} \qquad (4)$$

where u_j is the reordered j-th attribute weight, w_j, according to the reordered attribute value z_{ij}. The attribute weight w_j is assigned to j-th attribute for all locations to indicate the relative importance of the attribute according to the decision maker's preferences. This weight reflects the values and interests of a decision participant with respect to the decision attribute, representing a priority that can be assigned to each attribute. All locations for the j-th attribute are assigned the same weight of w_j. The order weights, v_j, are associated with the attribute values on a location-by-location basis. They are assigned to the i-th location's attribute values in decreasing order without consideration of with which attribute they are associated. In the GIS-based multicriteria evaluation procedures, the attribute weights typically have the following property: $\sum_{j=1}^{n} w_j = 1$. Accordingly, $\sum_{j=1}^{n} u_j = 1$ and Equation (4) can be written as follows:

$$v_j = \left(\sum_{l=1}^{j} u_l\right)^{\alpha} - \left(\sum_{l=1}^{j-1} u_l\right)^{\alpha} \qquad (5)$$

Given the sets of attribute weights, w_j, and the order weights, v_j, the OWA operator can be defined as:

$$OWA_i = \sum_{j=1}^{n} \left(\left(\sum_{l=1}^{j} u_l\right)^{\alpha} - \left(\sum_{l=1}^{j-1} u_l\right)^{\alpha} \right) z_{ij} \qquad (6)$$

The value of α is related to ORness (or degree of risk) according to Equation (7) (Yager, 1996). The measure of ORness ranges from 0 to 1. It shows the degree to which an OWA operator is similar to the logical OR in terms of its combination behaviour (Malczewski, 2006c).

$$ORness = \frac{1}{\alpha + 1} \qquad \alpha \geq 0 \qquad (7)$$

The degree of ORness indicates the position of the OWA on a continuum between the AND or OR combination rules. With different ORness values (or α parameter) one can generate different sets of the OWA weights and, in turn, a variety of GIS-based map combination strategies ranging from a minimum-type (logical AND) combination through all intermediate types (including the conventional WLC) to a maximum-type (logical OR) combination (see Yager, 1988; Jiang & Eastman, 2000; Malczewski et al., 2003) (see Table 2). The AND and OR operators represent the extreme cases of OWA. The ORness value of 0 ($\alpha = \infty$) represents the strategy corresponding to the MIN operator. The order weights associated with the MIN operator are: $v_n = 1$, and $v_j = 0$ for all other weights. Given the order weights, $OWA_i(MIN) = MIN_j(a_{i1}, a_{i2}, \ldots, a_{in})$. The ORness = 1 ($\alpha$=0) represents the strategy corresponding to the MAX operator. The following weights are associated with the MAX operator: v_1=1, and v_j= 0 for all other weights, and consequently $OWA_i(MAX) = MAX_j(a_{i1}, a_{i2}, . . ., a_{in})$. If ORness = 0.5 ($\alpha$ =1), then the strategy corresponds to the conventional WLC, which is situated at the mid-point on the continuum ranging from the MIN to MAX operators. The order weights associated with the ORness value of 0.5 correspond to the attribute weights, which indicates the use of the WLC strategy. In the extreme cases of OR and AND (ORness = 0 and 1), there is no trade-off between evaluation criteria.

By identifying a particular value of ORness, one can control the level of decision risk and provide a low- or high- risk solution for the decision problem. The ORness parameter guides the decision makers along the continuum ranging from the pessimistic to optimistic decision strategies. The decision makers can specify their own preferred ORness value to put emphasis on the higher (better) values or the lower (worse) values in a set of the attributes associated with the *i*-th alternative. Both theoretical and empirical evidence show that decision makers with optimistic (or risk-taking) attitudes tend to be more concerned with the good properties (better values) of alternatives, while pessimistic (or risk-averse) decision-makers tend to concentrate more on the bad properties (worse values) of alternatives (Bodily, 1985; Mellers & Chang, 1994).

The strategy associated with the ORness = 0 (the Boolean AND operator) is referred to as the pessimistic strategy (extremely pessimistic) (see Table 2); it is the decision situation in which only the lowest attribute value of each location is considered in the evaluation process. If the lowest value is met, it means that all of the other attribute values (i.e., the higher values) are met as well. This implies that the AND operator is a very conservative or risk averse operation, where an alternative location is considered suitable only if all criteria have been met (Eastman, 2006). Conversely, the extreme optimistic strategy can be found at the opposite end of the risk continuum (ORness = 1, the Boolean OR operator). This strategy assigns an order weight of 1 to the highest value at each location. Under this strategy, the decision maker is characterized by optimistic attitudes represented by the best possible outcome, that is, only the highest possible value is selected at each location.While the Boolean AND require all attributes to be met for an alternative to be called suitable, the Boolean OR requires that at least one attribute (i.e., the highest attribute value) be met (Eastman, 2006). Such a decision strategy is too risky because, for any suitable alternative location, all except the one attribute could be unacceptable.

Table 2. The order weights and the corresponding decision/combination strategies for specific ORness values (or α parameter).

α	ORness	OWA weights (vj)	Combination strategy	Decision strategy
$\alpha \to 0$	1.0	$v_1 = 1$; $v_j = 0$ for others	Logic OR (MAX)	Extremely optimistic
α=0.1	0.9	*	*	Very optimistic
α=0.5	0.6	*	*	Optimistic
α=1	0.5	$v_j = w_j$ for all j	WLC	Neutral
α=2	0.3	*	*	Pessimistic
α=10	0.1	*	*	Very pessimistic
$\alpha \to \infty$	0.0	$v_n = 1$; $v_j = 0$ for others	Logic AND (MIN)	Extremely pessimistic

Note: *These measures are case-dependant.

Table 3 presents the set of order weights for the six evaluation attributes according to the specified ORness values. It is evident from the table that, as the ORness measure increases from 0 to 1, the value of v_1 increases from 0 to 1 at the expense of decreasing values of v_6 from 1 to 0. This means that, by increasing the ORness degree, the higher attribute values associated with an alternative become relatively more and more important and the lower values become relatively less and less important in evaluating the alternative. In other words, greater and greater order weights are assigned to the higher attribute values at a given location at the expense of assigning smaller weights to the smaller attribute values at that location. This implies that, as the ORness degree increases, a more optimistic and high-risk decision strategy is being taken in the decision making process.

Table 3. The order weights (v_j) of the six attributes for particular ORness values.

	ORness degree										
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
v_1	0.000	0.000	0.007	0.054	0.153	0.286	0.434	0.585	0.731	0.870	1.000
v_2	0.000	0.001	0.045	0.123	0.176	0.190	0.176	0.143	0.100	0.051	0.000
v_3	0.000	0.047	0.209	0.279	0.275	0.238	0.189	0.138	0.089	0.042	0.000
v_4	0.000	0.101	0.169	0.155	0.125	0.095	0.070	0.048	0.029	0.013	0.000
v_5	0.000	0.100	0.110	0.087	0.065	0.048	0.034	0.023	0.014	0.006	0.000
v_6	1.000	0.750	0.460	0.302	0.206	0.143	0.098	0.064	0.038	0.017	0.000

3.2 OWA-based collaborative GIS-MCDA

The proposed OWA-based collaborative GIS-MCDA procedure involves four major steps: (i) acquiring the decision information, (ii) specifying the attribute weights and the ORness value, (iii) deriving the individual alternative's orderings, and (iv) deriving the group orderings of decision alternatives (see Figure 6). Information acquisition (i.e., information search) is the first stage in the collaborative GIS-MCDA. In this step, a decision maker searches for the information on the alternatives, attributes, and attribute values. Exploring the decision information enables the decision makers to recognize the decision situation, and specify their preferences with respect to the evaluation attributes. There are two steps for deriving the orderings of decision alternatives from the decision makers' preferences: (i) the individual judgments are converted into an ordering using an OWA-based decision rule, and (ii) the individual orderings of the alternatives are then combined into the group orderings by means of the Borda method (e.g., Malczewski, 1996; Jankowski & Nyerges, 2001a; Feick & Hall, 2004; Boroushaki, 2010).

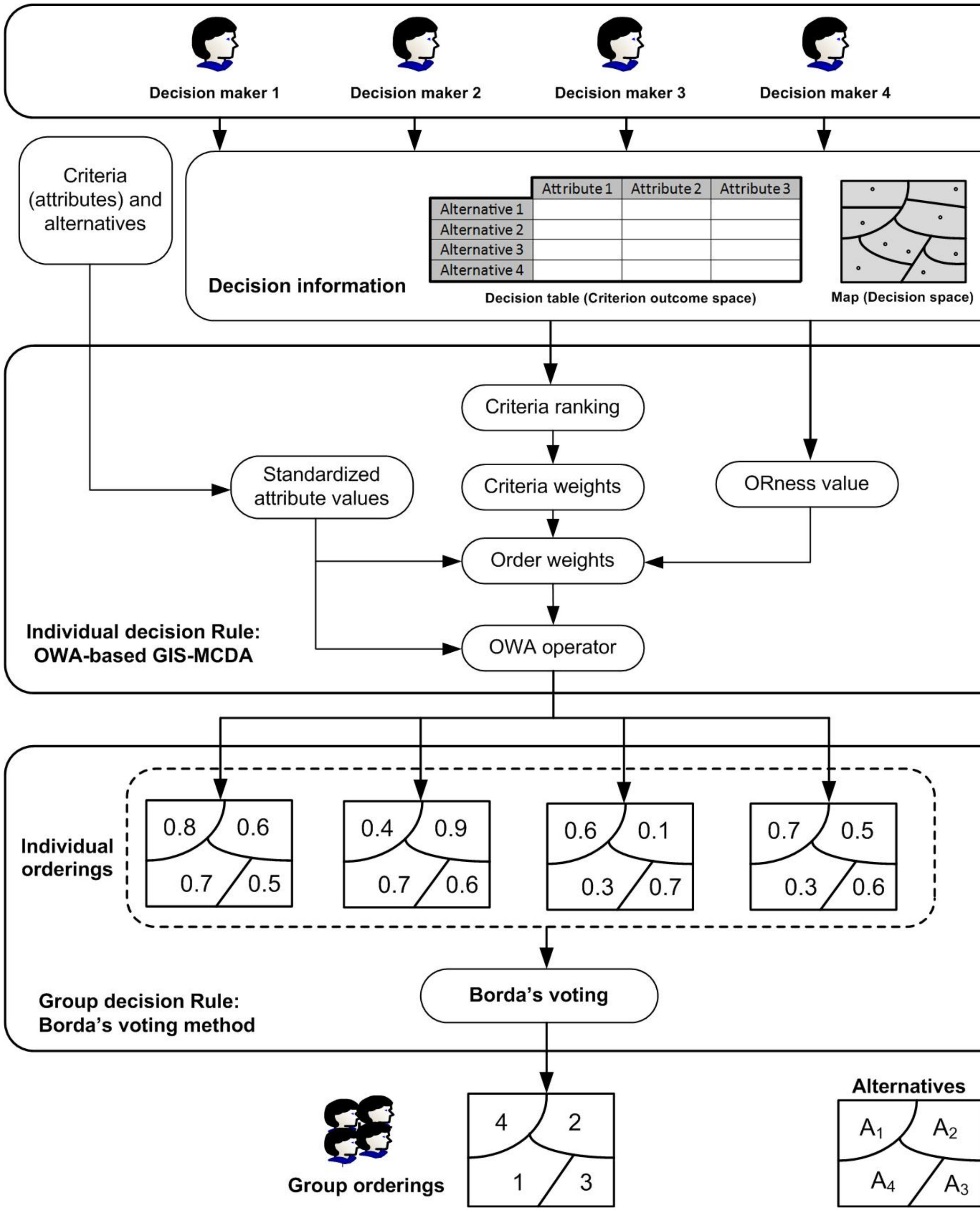


Figure 6. The collaborative GIS-MCDA procedure.

3.2.1 Information acquisition

Any decision-making process begins with searching and acquiring the decision information. In the setting of GIS-MCDA, information acquisition is concerned with the examination of decision information including the spatial alternatives, attributes, and attribute values associated with the alternatives using the information aids. The information available for the collaborative decision can be conveyed to participants through two distinct forms of information structures: the decision table and map (Dennis & Carte, 1998; Malczewski, 1999b; Jankowski et al., 2001; Jankowski & Nyerges, 2001b). The decision table represents the decision information in an alternative × attribute matrix (see Table 4). It consists of a set of values associated with each alternative-attribute pair. The rows of the matrix represent alternatives, the columns represent attributes, and the cells contain the measured values of the attributes associated with the alternatives. In addition to the alternative-attribute values, the table includes the range values of the attributes in the last row. The map is a complementary information source to the decision table. Using the map, the decision makers are able to explore the alternatives and also the spatial distribution of the geographic entities based on which attributes are defined. Malczewski (1999b) suggests that the main purpose of using maps in GIS-based MCDA should be the consideration of alternative locations during the exploration of tradeoffs among the decision criteria and the search for the best (compromise) solutions to the decision problem. The dualistic map-table information view provides a better understanding of the decision problem by allowing the decision makers to explore the basic relationships between the non-spatial attribute values of decision alternatives (criterion outcomes) and the spatial patterns of alternatives (decision space) (Jankowski et al., 2001; Rinner, 2007).

As was discussed in Chapter 2, specification of the individual preferences (attribute weights and ORness value) is the fundamental motive behind examining the available information within the GIS-MCDA context. To determine the attribute weights, one might need to look at the changes in the range of variation for each attribute, i.e., the range of the attribute values across the alternatives, and the minimum and maximum value for a given attribute. A weight value is dependent on the range of the attribute values, that is, the difference between the minimum and maximum value for a given attribute. An attribute weight can be made arbitrarily large or small by increasing or decreasing the range. For example, if all alternatives to be evaluated were characterized by the "land cost" between $10,000 and $10,100, the attribute would be less important than in the case where the attribute values range from $1 to $10,000. As another example, let us consider the values of the attribute "proximity to main road" ranging from 1 m to 100 m, and the values of the attribute "land size" ranging from 1000 to 10,000 square meters. Since the values of "land size" cover a wider range than the values of the "proximity to the main road", the attribute "land size" might likely be deemed as more important, and hence receive a higher weight.

Acquiring the decision information allows decision makers to take into account their preferred range of attribute values (a particular range), least-preferred and most-preferred value for a given attribute, etc. during the specification of criteria weights. For example, one decision maker may prefer a range of 200 m for the attribute "proximity to main road" with the least-preferred value of 100 m and the most-preferred value of 300m. Accordingly, this stresses the need for the decision makers to examine the decision table, and look at the attribute values when they assign their attribute preferences.

Table 4. The decision table: matrix of alternatives and the associated attribute values.

	Attribute $_1$	Attribute $_2$	Attribute $_3$	…	Attribute $_n$
Alternative$_1$	S_{11}	S_{12}	S_{13}	…	S_{1n}
Alternative $_2$	S_{21}	S_{22}	S_{23}	…	S_{2n}
Alternative $_3$	S_{31}	S_{32}	S_{33}	…	S_{3n}
…	…	…	…	…	…
Alternative $_m$	S_{m1}	S_{m2}	S_{m3}	…	S_{mn}
Range of attribute	RA_1	RA_2	RA_3	…	RA_n

Note: S_{ij} is the raw value of the i-th alternative with respect to the j-th attribute (i = 1,2, ... , m; j = 1,2, ... ,n); RA_j is the range value of the j-th attribute.

3.2.2 Specifying attribute weights and ORness value

The decision makers should specify their preferences with respect to the relative importance of attributes and the values of ORness based on examination of the relevant decision information. There are a number of methods for estimating the attribute weights from the individual preferences. An appropriate method for estimating attribute weights can be based on an ordering of the evaluation criteria; that is, every attribute under consideration is ranked in the order of the decision maker's preference (see Stillwell, Seaver, & Edwards, 1981;Malczewski, 2006c). Stillwell et al. (1981) have shown empirically that, in many situations, the rank-order approximation is a satisfactory approach to the attribute weight assessment. This method is simple, reliable, and requires less time to specify preferences (Bakhsh, 2008). It provides an effective way to elicit judgments about the relative importance of criteria in participatory decision making frameworks. Formally, the j-th attribute weight can be calculated as follows:

$$w_j = \frac{n - r_j + 1}{\sum_{k=1}^{n} n - r_k + 1} \qquad (8)$$

where r_j is the rank position of the j-th attribute denoting (the most important attribute ranks first ($r_j = 1$), the second most important attribute ranks second ($r_j = 2$), and so on; the least important attribute is assigned a rank of $r_j = n$); and n is the number of attributes.

3.2.3 Deriving individual orderings using the OWA-based MCDA decision rule

Given the standardized attribute values, the ORness value, and the attribute weights, individuals can utilize the OWA-based decision rule to determine the individual orderings of the alternatives. With different values of ORness, individuals can generate a wide range of OWA operators and, in turn, a wide range of the individual alternative orderings. An example of the OWA operator for ORness = 0.5 ($\alpha = 1$) is illustrated in Figure 7. Considering a spatial decision-making problem with a set of standardized attribute values at the i-th location as a_{ij} = [0.3, 0.5, 0.1, 0.8, 0.4, 0.6] for six attributes j= [1, 2,…, 6], the procedure involves: (i) ranking the attributes according to the individual preferences; (ii) determining the attribute weights according to Equation (8), w_j = [0.04, 0.23, 0.14, 0.28, 0.09, 0.19]; (iii) ranking the attributes according to their standardized values, and so the fourth attribute (j = 4) ranks first and the third attribute (j = 3) ranks sixth; (iv) ordering the attribute values, and so z_{ij} = [0.8, 0.6, 0.5, 0.4, 0.3, 0.1]; (v) reordering the attribute weights according to z_{ij}, and so u_j =[0.28, 0.19, 0.23, 0.09, 0.04, 0.14]; (vi) calculating the order weights according to Equation (5) , and so v_j = [0.28, 0.19, 0.23, 0.09, 0.04, 0.14]; and (vii) calculating OWA according to Equation (6), which would yield the result of 0.53 for ORness = 0.5.

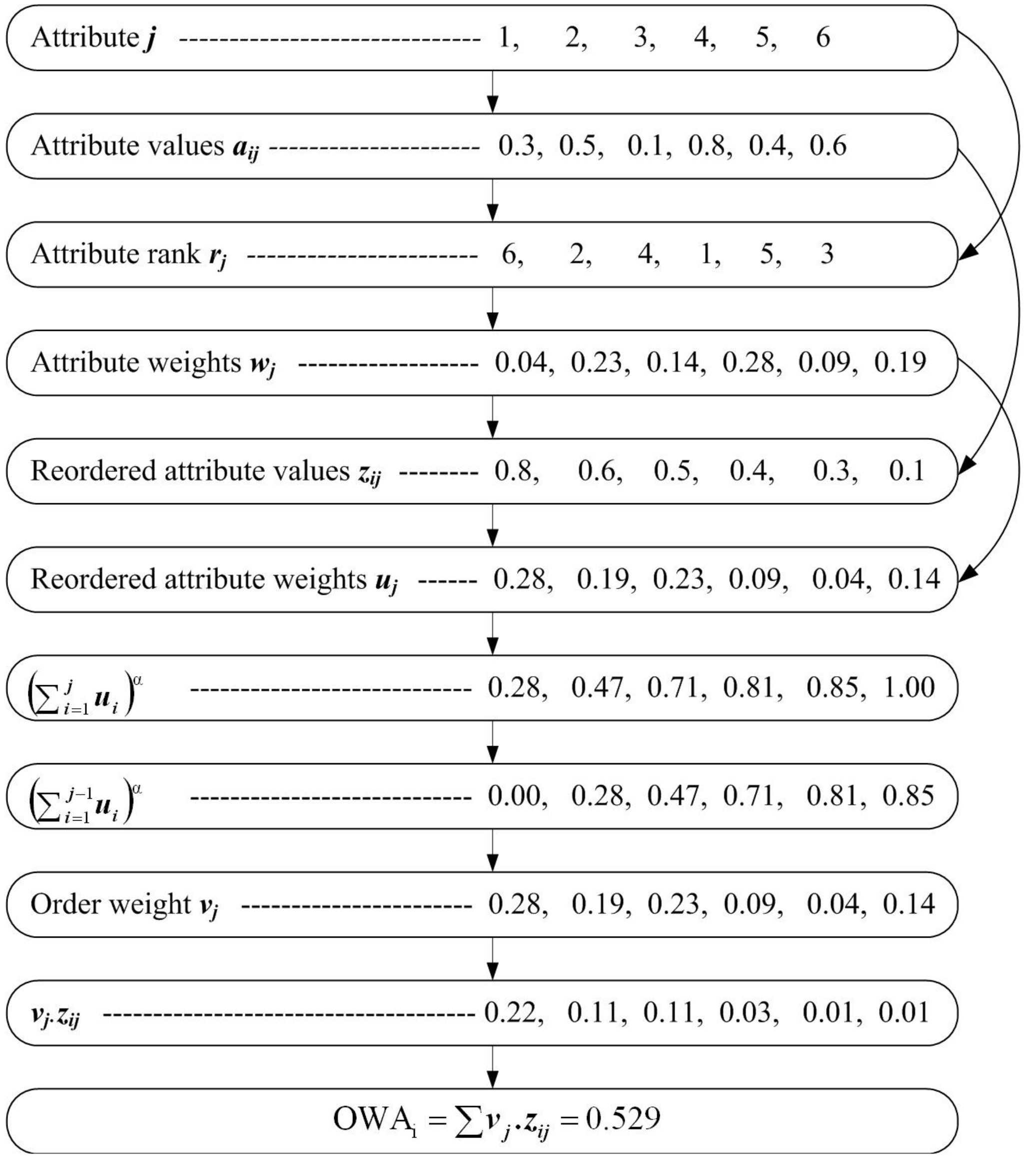


Figure 7. Example computation of the OWA for the *i*-th location and ORness = 0.5.

3.2.4 Deriving group orderings using the group decision rule

The group/collective decision rule takes the format of aggregating the individual preferences into a group preference so that the consensus or compromise solution can be identified (Feick & Hall, 2004). Specifically, a group decision rule is defined as a function $F: IO_1 \times IO_2 \times, \ldots, \times IO_k \rightarrow GO$. This function associates the individual orderings IO_k to a group ordering, GO, in such a way that there is one and only one group solution relation for a set of individual orderings. There are many possible approaches to identify the group ordering of decision alternatives (e.g., Jankowski & Nyerges, 2001a; Boroushaki & Malczewski, 2010c). Evidence shows that a combination of MCDA for individual decision making with voting techniques provides an effective tool for collaborative decision making in the GIS environment (Malczewski, 2006b). Their simplicity and comprehensibility are central advantages of the voting approaches for collaborative decision making. Here, a vote aggregation function based on the Borda count method (Borda, 1781) is used as the collective decision rule. This approach requires deriving the total of the individual orderings for each alternative as assigned by the individuals involved in the decision making process.

Given the individual orderings, IO (I_k, A_i), one can derive the individual preference set based on the pairwise comparisons. In each of the individual preference sets, for any alternative A_i and A_p, either individual k prefers A_i to A_p, or he/she prefers A_p to A_i, or he/she is indifferent between A_i and A_p. The A_i gets 1 point if it is preferred over A_p; the A_p gets 1 point, if it is preferred over A_i; and each one gets 0.5 points if an individual is indifferent between the two alternatives. For each pair A_i and A_p, there are two group preference scores indicating how many individuals prefer one of the paired alternatives over the other alternative. The group score G (A_i, A_p) represents the number of individuals who prefer the alternative A_i to A_p, whereas the second score G (A_p, A_i) indicates the number of individuals who have the opposite preference. A set of group scores presenting the total points obtained by A_i against A_p (and vice versa) are displayed in a table $m \times m$; where m is the number of alternatives (see Table 5). This table is inversely symmetric:

$G(A_i, A_p)$ = the total number of individuals - $G(A_p, A_i)$. The group overall score for the i-th alternative is calculated by summing the group scores for that alternative; that is:

$$G(A_i) = \sum_{p=1, p \neq i}^{m-1} G(A_i, A_p) \qquad (9)$$

The best (consensus) alternative is that with the highest Borda score. If there is a tie among pairs of alternatives, decision makers may arbitrarily break the tie in favour of one or the other in the pair. Figure 8 illustrates the Borda method using an example of four decision makers and the individual orderings for five candidate sites. Once all the individual orderings have been determined, the group ordering for each of the alternatives is obtained (see Table 5). The results indicate that A_2 is evaluated as the best alternative with a Borda score of 12, meaning that the majority of individuals prefer A_2.

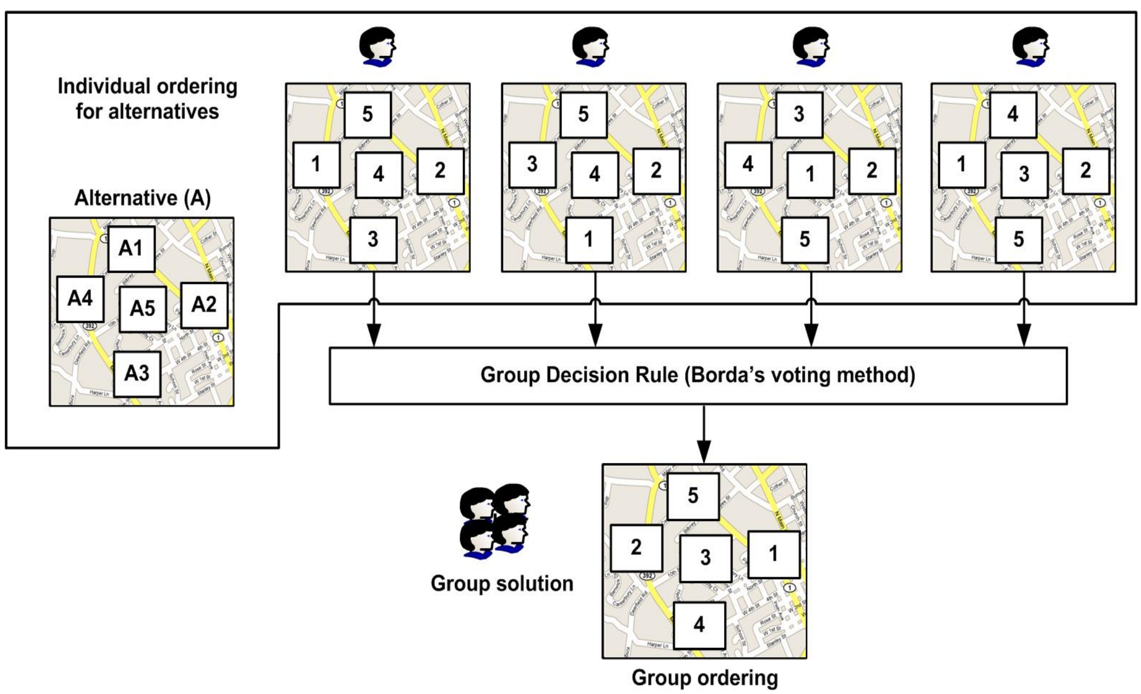


Figure 8. Deriving the group alternative orderings from the individual orderings.

Table 5. The Borda score and group ordering of the five alternatives.

	A_1	A_2	A_3	A_4	A_5
A_1	0	4	2	3	4
A_2	0	0	1	2	1
A_3	2	3	0	3	2
A_4	1	2	1	0	1
A_5	0	3	2	3	0
The Borda score	3	12	6	11	8
Group ordering	5	1	4	2	3

Chapter 4

4 The metrics of information acquisition

In this chapter, the metrics used for studying information acquisition behavior in the collaborative GIS-MCDA process will be presented and discussed. Based on the research hypotheses stated in Chapter 1, and the literature review in Chapter 2, a conceptual framework of the metrics to be investigated is presented in Figure 9. This framework has been used as the theoretical basis for examining information acquisition in the present study. Depending on the information source (or information aid) used in the context of collaborative GIS-MCDA (see Chapter 3), the metrics for the information search fall within three broad categories: the decision table, map, and group decision metrics. The decision table metrics refer to the information search characteristics derived from the decision table. The metrics include: (i) the proportion of information search, (ii) the variability of information search per attribute, (iii) the variability of information search per alternative, (iv) the direction of search (sequence of information search), (v) the total time spent searching for information, and (vi) average time spent acquiring each piece of information. The map metrics represent the information search variables concerned with exploring information on the map. In this study, the two information acquisition metrics suggested by Jankowski and Nyerges (2001a) have been used to investigate decision making behavior on the map. These include (i) the total time spent on the map exploration and (ii) the number of moves on the map. The third metric is concerned with acquiring information from the other decision makers in the collaborative decision making process. This metric is operationalized in terms of the time spent exploring the group decision, deliberations, and discussions. Obviously, examining the information provided by the other individuals is the key to the collaborative GIS-MCDA.

Differences along both the decision table and map metrics will be investigated for three sets of decision situations. The first set concerns the differences among the decision situations involving different levels of task complexity in the GIS-MCDA individual mode. The second set focuses on the differences among the decision situations with different levels of task complexity in the GIS-MCDA group mode. In the individual mode, the system allows the participants to evaluate the alternatives without knowing of the group decision. While in the group mode, individuals are able to review the group solution (i.e., the group ordering of the alternatives) and the other participants' map-based comments, and then conduct the decision making process. The third set addresses the differences between the decision situations in the GIS-MCDA individual mode and the group mode. In addition to these three sets of the differences, the differences between the decision table and map, and also the differences in the time spent examining the group decision among the decision situations involving different levels of task complexity will be examined. The set of dash arrows denote that the metrics would be different between the two decision modes, the decision table and the decision map, and the decision situations involving different levels of the task complexity in both of the two decision modes (see Figure 9). In addition to the differences, the relationships between the metrics will be examined in each of the decision modes.

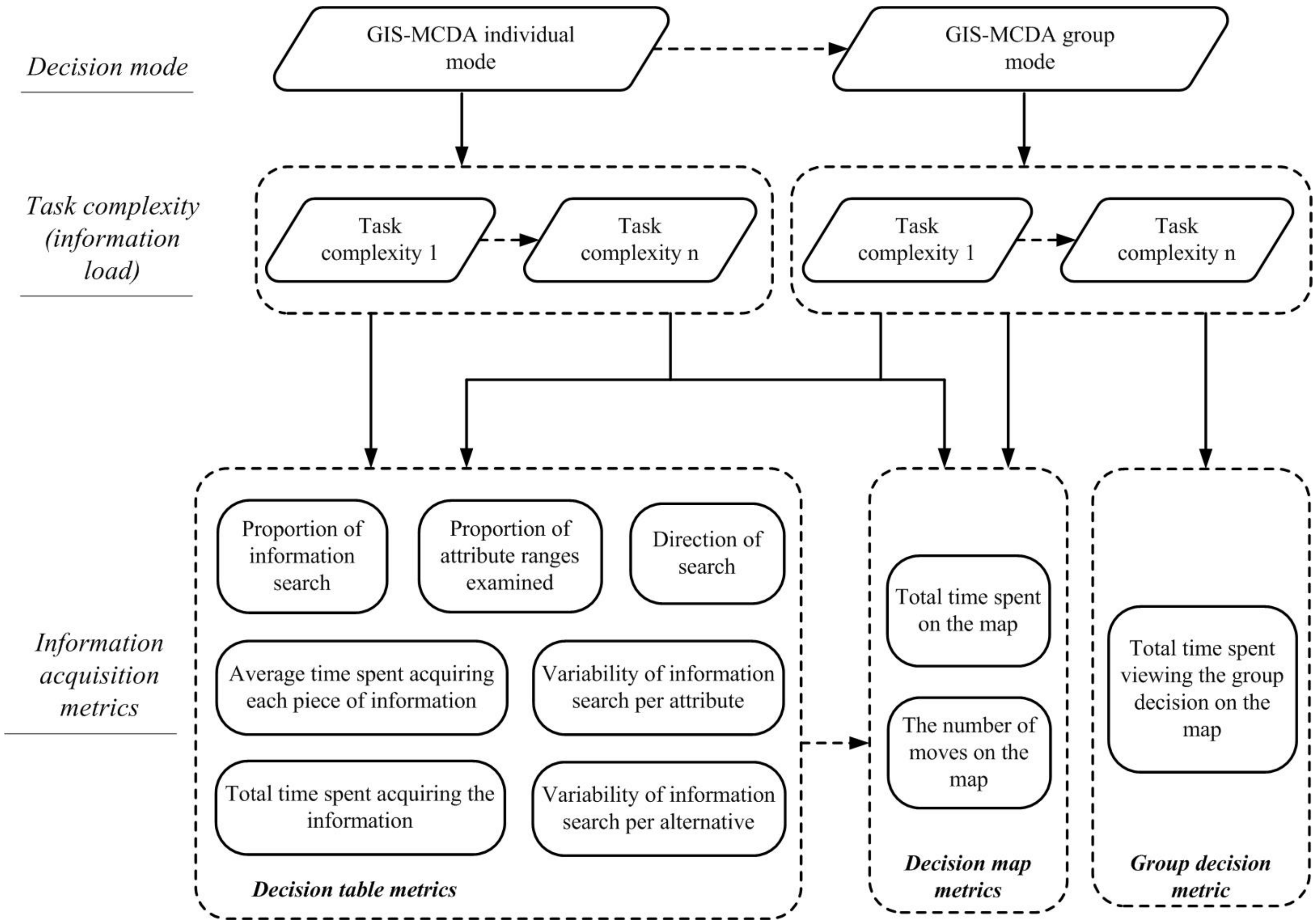


Figure 9. A conceptual framework of the information acquisition metrics to be studied in the empirical study.

4.1 Information acquisition in the decision table

4.1.1 The proportion of information search

The proportion of information search refers to the amount of information searched or the amount of available information actually considered in making a decision (see Payne, 1976; Ford et al., 1989; Roe et al., 2001; Redlawsk, 2004; Katz et al., 2010; Schram & Sonnemans, 2011; Queen et al., 2012). According to Payne (1976) and Klayman (1983), the proportion of information search is measured as the number of information pieces (cells containing the attribute values associated with alternatives) that a decision maker examines divided by the total number of information pieces. For instance, in a decision problem involving 5 attributes and 10 alternatives, there are 50 cells containing different pieces of information that can be examined. Investigation of a decision maker's search can easily reveal whether all or only a portion of these 50 pieces of information were actually searched. The proportion of information search can then be calculated as the number of cells examined divided by 50. This measure varies from 0 to 1, with 1 indicating all of the available information pieces are examined (i.e., all attributes available for every relevant alternative is examined), and 0 indicating none of the information pieces are examined.

However, the decision makers may look at the same piece of information more than once. One may reopen some of the information cells after initial viewing as an effort to make a precise decision. If a decision maker examines the entire decision matrix in such a context then, his/her score on this metric would be greater than 1. In addition, where a decision maker looks at some pieces of information more than once but does not search the entire table, his/her score on this variable may be quite high in spite of the fact that he/she has an incomplete information search (Abdul-Muhmin, 1994). To overcome this problem, the proportion of information search is calculated based on the first time information acquisition. Examination of a larger proportion of information (deep search) could be an indication of a more compensatory strategy, whereas a lower proportion (shallow search) suggests little effort to compare attribute values and few tradeoffs, therefore the hallmarks of non-compensatory search strategy.

4.1.2 The direction of search

The direction (or pattern) of search in the decision table is the sequence in which the information cells are examined (Bettman & Jacoby, 1976; Payne, 1976; Harte & Koele, 2001; Roe et al., 2001; Schrah et al., 2006; Stafford, 2007; Katz et al., 2010; Queen et al., 2012). This metric represents the transitions from the acquisition of one piece of information to the next one. The direction can be determined by examining the alternative and attribute associated with the *D*-th + 1 piece of information searched by a decision maker as a function of the alternative and attribute associated with the *D*-th piece of information searched (Payne, 1976). Different types of transitions are distinguished with respect to whether the information cell searched as the next one regards the same or a different alternative and the same or a different attribute (Stokmans, 1992; Riedl, Brandstätter, & Roithmayr, 2008) (see Figure 10). If the *D*-th + 1 piece of information searched is within the same alternative but involves a different attribute, then the search constitutes an instance of an alternative-wise search pattern. In other words, when decision makers tend to consider first several attributes of the same alternative before proceeding to the next alternative, the search direction is alternative-wise (Pfeiffer, 2012). On the other hand, if the *D*-th + 1 piece of information searched is within the same attribute, but a different alternative, then that search constitutes an instance of an attribute-wise search direction. Attribute-wise information acquisition is a search pattern in which a decision maker picks one attribute, compares its attribute levels across the alternatives, and then moves to the next attribute. If the *D*-th + 1 piece of information searched is neither within the same alternative or the same attribute as the *D*-th piece of information, then that is considered to be a shift in the direction of search. When the *D*-th + 1 piece of information acquired is within the same alternative and attribute as the *D*-th piece of information, then the search is considered a re-acquisition strategy. If a decision maker examines *C* information cells before making a decision, there are a total of *C*-1 transitions in the decision maker's search matrix (Abdul-Muhmin, 1994). For each decision maker, these *C*-l transitions are classified into each of the four categories in order to determine the total number of each transition type in the matrix.

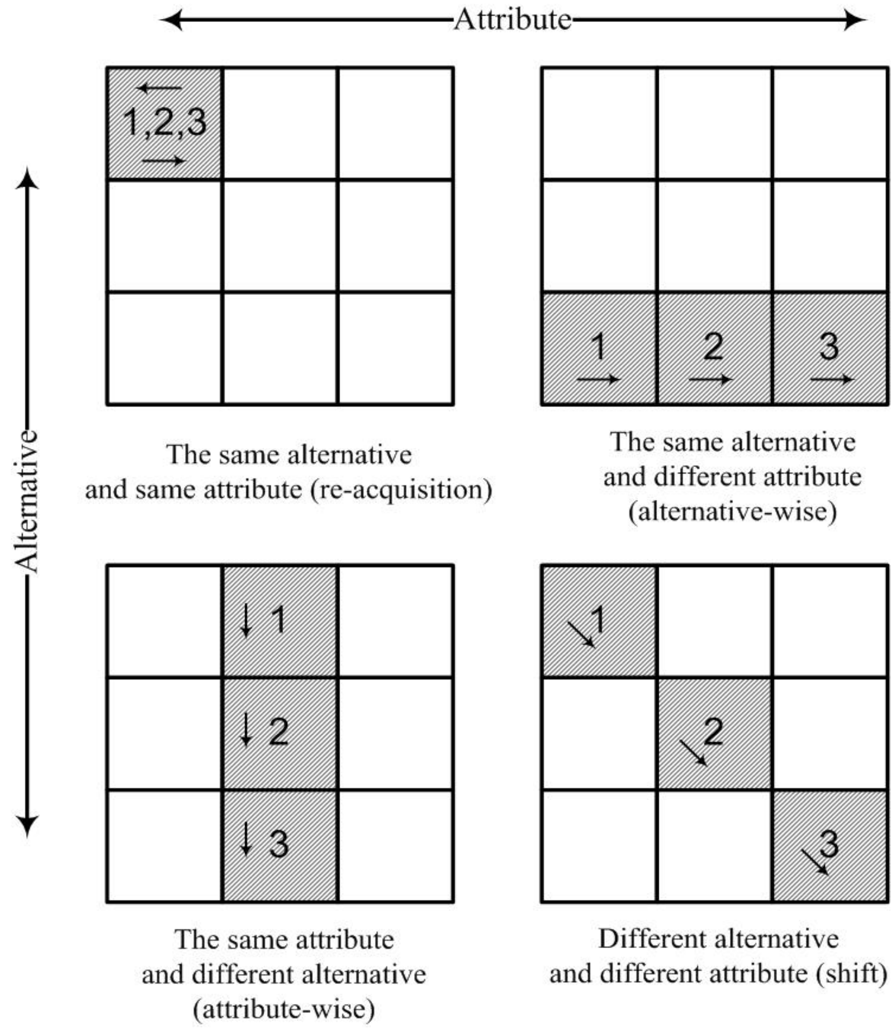


Figure 10. Examples of the transitions for the four search patterns.

Depending on whether the information search direction is the alternative- or attribute-wise, one can determine whether the decision maker employs a compensatory or non-compensatory search strategy to arrive at the decision. An alternative-wise direction involves trade-offs among attribute values, and thus, suggests a compensatory acquisition strategy, while the attribute-wise ignores the trade-offs, and therefore, presents a non-compensatory strategy. To measure whether the direction of search is alternative- or attribute-wise, Payne (1976) developed a search index (*SI*). This index is defined as a ratio of the number of alternative-wise transitions minus the number of dimension- or attribute-wise transitions over the sum of those two numbers as shown in the following equation:

$$SI = \frac{r_{alt} - r_{att}}{r_{alt} + r_{att}} \qquad (10)$$

where r_{alt} denotes the alternative-wise transition frequency and r_{att} the attribute-wise transition frequency. The value of SI varies from -1 to +1. The search direction is classified as alternative-wise if this index has a positive value and as attribute-wise if it has a negative value. A direction consisting of only alternative-wise transitions and shift transitions would have a value of + 1.00. A direction consisting of only attribute-wise transitions and shifts would have a value of −1.00. Figure 11 shows examples of the search directions of alternative-wise or attribute-wise search strategies.

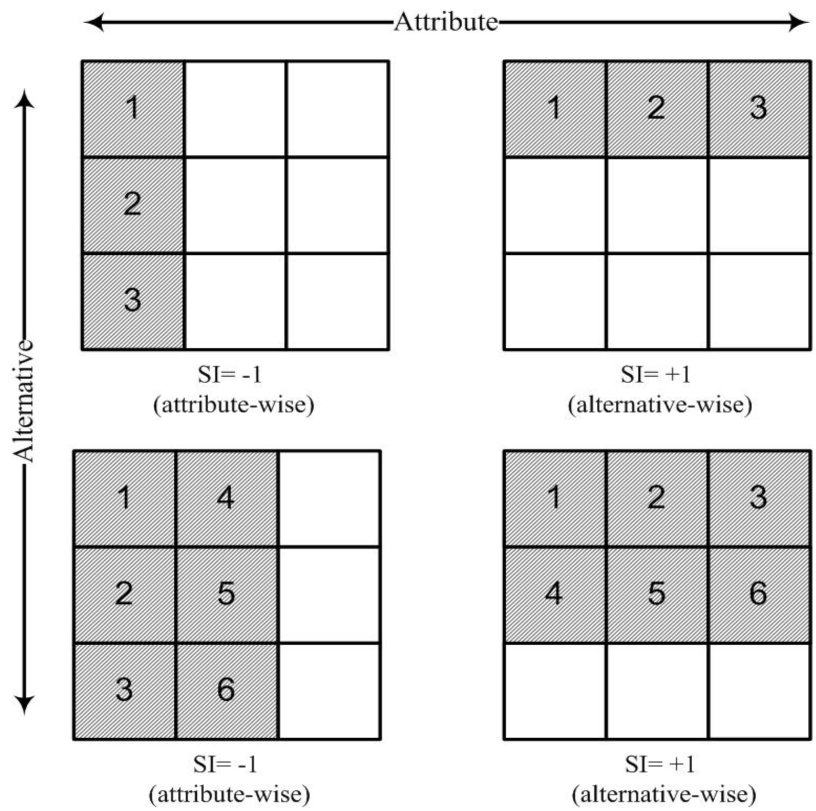


Figure 11. Examples of the information search for the attribute- and alternative-wise patterns.

Payne's *SI* has been criticized by Böckenholt and Hynan (1994). They showed that the index is biased towards alternative-wise processing if the number of attributes exceeds the number of alternatives and towards attribute-wise processing if the number of alternatives exceeds the number of attributes. This bias reflects the fact that the probability of an alternative-wise transition is greater in the case where number of attributes exceeds the number of attributes, and the probability of an attribute-wise transition is greater when the number of alternatives exceeds the number of attributes. To overcome this problem, Böckenholt and Hynan (1994) proposed a strategy measure (*SM*), which is defined as:

$$SM = \frac{\sqrt{t}\,((m\frac{n}{t})(r_{alt} - r_{att}) - (n - m))}{\sqrt{m^2(n-1) + n^2(m-1)}} \tag{11}$$

where m denotes the number of alternatives, n the number of attributes, and t the number of transitions. The value of *SM* is not constrained to the interval between -1 and +1, rendering its interpretation difficult (Pfeiffer, 2012). $SM < 0$ indicates an attribute-wise search, while $SM > 0$ indicates an alternative-wise search, and the higher the SM, the more alternative-wise is the search.

4.1.3 The variability of information search

The variability of search refers to the degree to which the amount of information searched per attribute or alternative is consistent. This measure indicates whether a decision maker searches a constant or variable amount of information per alternative and/or per attribute. The variability of information search per alternative is defined as the standard deviation of the number of information pieces searched per alternative based on the first acquisition (Payne, 1976; Schmeer, 2003; Riedl et al., 2008). This metric measures the extent to which the same or unequal amounts of information are searched for each of the available alternatives in a decision. The variability is equal to 0, if the same number of the cells for each of the alternatives is examined, and it is greater than 0, if a different number of cells per alternative is viewed.

The variability of information search per attribute is measured as the standard deviation of the number of information pieces searched per attribute. It indicates the extent to which different attributes receive different amounts of search. It equals 0, if the same number of alternatives is searched for each attribute, and it is greater than 0, if a different number of alternatives are searched for each attribute.

Both the variability of search per alternative and attribute have been linked to the type of decision strategy employed. Payne (1976) argued that the level of variability in the amount of information searched per alternative can help distinguish between compensatory and non-compensatory decision strategies. For compensatory strategies, a constant and equal amount of information will be searched per alternative, whilst for non-compensatory strategies a variable amount of information search per alternative will be observed. If a decision maker acquires the same amount of information for all alternatives, the processing is termed consistent and is assumed to reflect a compensatory strategy (Carrigan et al., 2007). On the other hand, a high variability in information searched per alternative implies that the decision maker searches unequal amounts of information for each of the available alternatives, and is an indication that the decision maker is using non-compensatory decision processes.

A similar argument can be derived for variability of search per attribute. If the variability of search per attribute is high the decision maker is assumed to have employed a non-compensatory strategy, where the number of information items searched for each attribute varies. A low variability of search is consistent with a compensatory strategy, where the decision maker trades off attributes against each other, and therefore searches a similar number of alternative values for each attribute. Although the two measures are not completely independent, they are not completely redundant either (Klayman, 1983; Schmeer, 2003). Klayman (1983) argues that the two variability metrics may be used to determine where a high variability of search comes from. Figure 12 illustrates that the two types of variability are not redundant, where the sources of variability can be distinguished by the distinction between the two variability values.

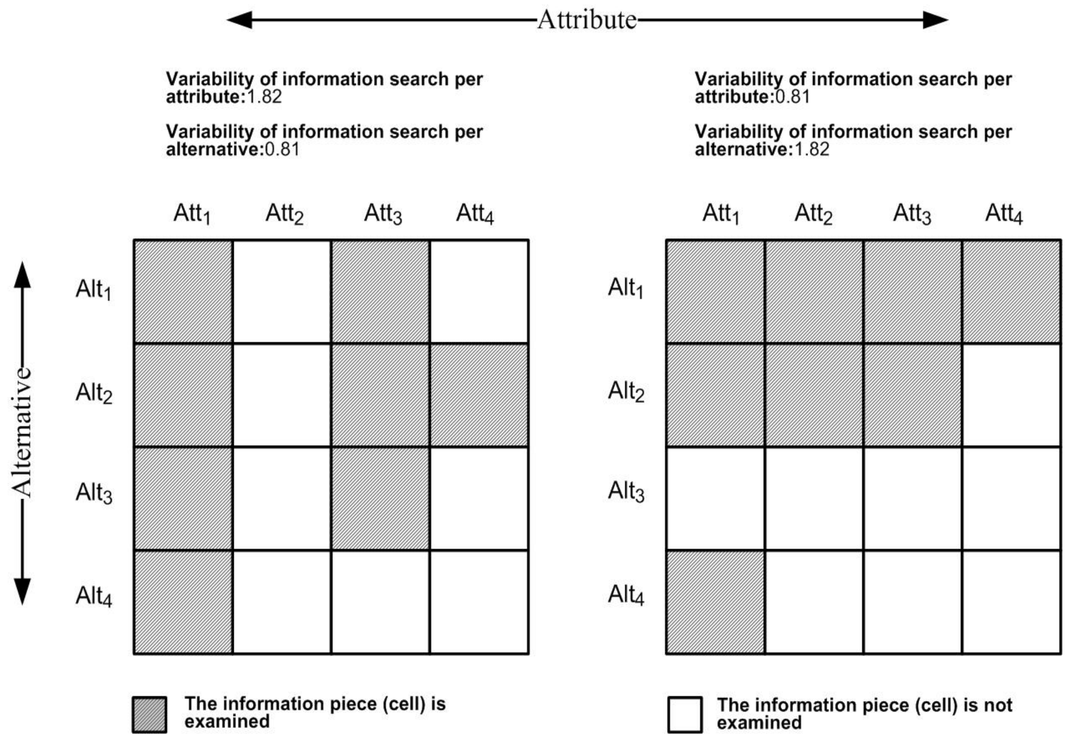


Figure 12. Illustration of the distinction between variability of search per attribute and variability of search per alternative (modified from Klayman, 1983).

4.1.4 The time spent acquiring information

In addition to the above metrics, the time spent acquiring information in the decision table is also one variable that is typically used as an information acquisition metric in decision research (Chinburapa, 1991; Riedl et al., 2008; Queen et al., 2012). This metric serves as an indirect measure of the amount of effort and deliberation required to make the decision. In this study, the time spent acquiring the information has been measured in terms of two variables. These include: (i) the total time spent examining the pieces of information in the decision table, and (ii) the average time spent per item of information acquired (Ford et al., 1989; Klemz & Gruca, 2001). The total time is measured by the length of time during which a decision maker examines the decision table. The average time is calculated by dividing the total time spent examining all acquired pieces of information by the number of acquisitions. Since a compensatory decision making process is considered to be more complex and requires more cognitive effort than a non-compensatory process, it is assumed that the average time spent per item of information acquired is greater when subjects use a compensatory than when subjects use a non-compensatory decision-making process (Chinburapa, 1991).

4.1.5 Proportion of attribute ranges

It has been argued that the tradeoffs among attributes depend on the range of the attribute values; that is, the difference between the maximum and minimum values for a given attribute (Malczewski, 2000; Pöyhönen et al., 2001; Ligmann-Zielinska & Jankowski, 2012). Taking this into account, the proportion of attribute ranges examined by the decision maker is an indication of using compensatory or non-compensatory strategy. This metric is calculated as the number of attribute ranges searched divided by the total number of attributes. The larger the proportion, the more tradeoffs among the attributes. This can be considered as an indication of a more compensatory strategy. On the other hand, a lower proportion suggests little effort to compare attributes and few tradeoffs, and is an indication of a non-compensatory strategy.

4.2 Information acquisition on the map

The map-based presentation of the decision information is a complementary source to the decision table. While the table provides a structured form of the decision information (i.e., alternative-attribute values), the map offers a graphical means for exploring the decision information in the decision (geographic) space. Representing decision alternatives in the decision space, one can explore the spatial patterns of alternatives and spatial relationships. The map functionalities allow the individuals to switch between different map views, zoom in to certain alternatives, features, and places on the map, and so on. Similar to the decision table, the number and time of acquisitions could be used as the information acquisition metrics on the map. In this study, the total time spent on the map exploration and the number of map moves, have been employed to examine the decision maker' interaction with the map (Jankowski & Nyerges, 2001b). The total time is calculated as the length of time during which the decision makers interact with the map. The number of map moves is determined as the sum of the decision maker's interactions with the map, including the map clicks, zoom-ins or zoom-outs, switches between different map views, etc.

4.3 Information acquisition on the group decision map

In addition to acquiring the information from the decision table and map, an examination of the group solution and information provided by other individuals is also critical to collaborative decision making (Jankowski & Nyerges, 2001b; Boroushaki, 2010). In the present study, the time spent exploring the group decision map has been considered as the information acquisition metric on the group decision map (Jankowski & Nyerges, 2001b; Meng, 2010). Decision makers can explore the group decision map and acquire the information on the collective solution (group ordering of alternatives). A decision maker may review the group decision, and find out that there exists a great discrepancy between his/her solution and the group solution. In this case, he/she might want to adjust and update his/her initial criterion preferences in an effort to obtain a higher degree of consensus. In addition, the decision makers may review the others' comments and suggestions regarding the inclusion of one or more locations as a new feasible alternative or exclusion of alternative(s) from the set of options on the group decision map.

Chapter 5

5 Data, system implementation, and experimental procedure

The problem of parking site selection in District # 22 of Tehran, Iran, was selected as the case study. This chapter begins with an overview of the study area, describing the geographic context, population, and decision problem. This is followed by a brief description of the alternative locations and criteria used for evaluating the decision alternatives, and an outline of the experimental design used in the empirical study. Next, the strategy used for developing and implementing the Web 2.0-based collaborative MC-SDSS, specifically targeted for the experimental study, is presented. The integration of Web 2.0 concepts into Web-based GIS applications provides the foundation for user-friendly online collaborative spatial decision-making tools (see Chapter 2). The system has been developed based on the collaborative GIS-MCDA procedure proposed in Chapter 3. Finally, the method used for collecting the human-computer interaction data is discussed.

5.1 Study area: District # 22 of Tehran

Tehran is the fastest growing city in Iran. It is divided into 22 municipal districts, each with its own administrative center (see Figure 13).The population of Tehran increased from 1,512,082 people in 1956 to approximately 7,705,036 in 2006 (Statistical Center of Iran, 2006) with an expected increase to 8,429,807 by 2013 (see Table 6). The rapidly changing pattern of urban growth of Tehran, Iran, accompanied by the growth of population, has led to a shortage of basic urban facilities. As there is a severe shortage of parking spaces and traffic congestion in the city, the availability of public parking has emerged as an area of serious concern. In recent years, urban planners and municipality departments have taken some measures to increase the number of public parking facilities in different districts of Tehran.

The proposed collaborative GIS-MCDA procedure has been used to solve the problem of parking site selection in the center of District # 22 (see http://collaborativesdss.com). The district is surrounded by the Central Alborz Mountain in the north, the Kan River in the east, the Tehran-Karaj freeway in the south, and the Vardavard forest area in the west. Comparing the area of District 22 with the other 21 districts of Tehran shows that at least 8.4 percent of Tehran's services space belongs to this region which is an indication of the significant position of this area in the western region of Tehran. According to policies of the Supervisory Council of Tehran and Comprehensive Development Plan of District 22, the district should cover all service shortages in the western area of Tehran. One of the critical problems is the shortage of public parking space.

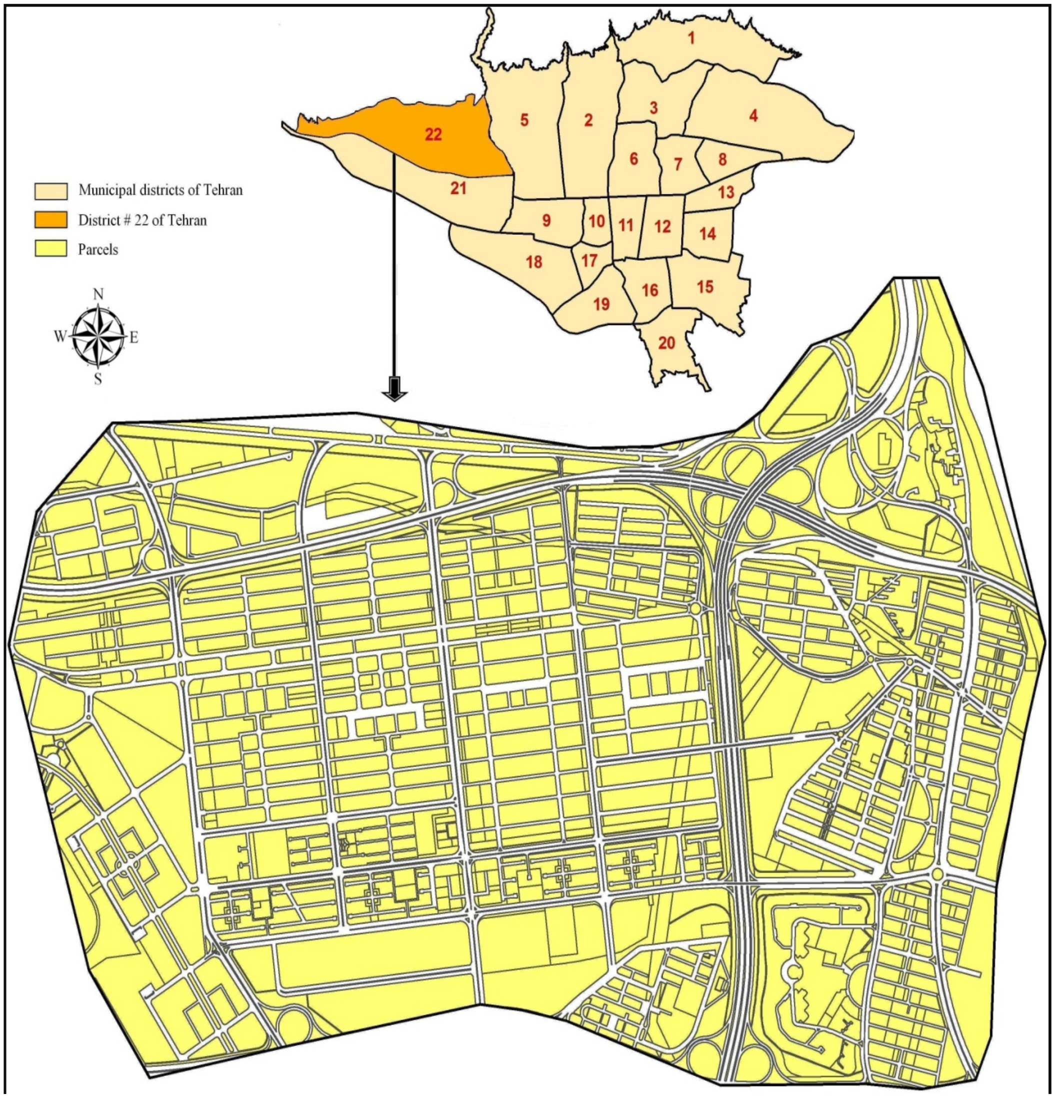


Figure 13. District # 22 of Tehran, Iran.

Table 6. The population and urban growth in Tehran from 1921 to 2006 (Source: Roshan, Zanganeh, Sauri, & Borna, 2010).

Year	1956	1966	1976	1986	1996	2000	2006
Population (million)	1.51	2.71	4.50	6.04	6.70	7.02	7.71
Area (hectare)	10000	19000	32000	62000	73950	78900	80000

5.2 Alternative sites and evaluation criteria

A set of 20 feasible candidate sites (decision alternatives) have been identified in this study (see Figure 14). The feasible alternatives have been generated taking into consideration the constraints and evaluation criteria for public parking sites. The parking site selection literature was consulted to identify the attributes (evaluation criteria) relevant for locating the parking facilities (e.g., Jiaxi, 2003; City of Dover Inc, 2008; Karimi, Ebadi, & Ahmady, 2009; Matkan, Shakiba, Pourali, & Ebadi, 2009; Boroushaki, 2010; Farzanmanesh, Naeeni, & Abdullah, 2010; Ghanbari & Ghazi Asgar, 2011). Based on the literature review, a set of eight distinct attributes for evaluating the suitability of feasible parking locations has been identified (see Table 7). The set of criteria include: two benefit (maximization) criteria and six cost (minimization) criteria. The benefit criteria include: (1) adjacent population to a candidate site, and (2) the size of the candidate site. The adjacent population reflects the demand for the candidate site; it is measured as the number of people within 500 m from the site. These two criteria are of the maximization type. The larger the size of the land and the adjacent population around the candidate site, the better the candidate site. The cost criteria are as follows: (1) distance to main roads, (2) average distance to recreational services, (3) average distance to administrative centers, (4) average distance to commercial centers, (5) average distance to transportation stations, and (6) cost of land acquisition. The smaller the values of distance and land cost, the better the candidate site.

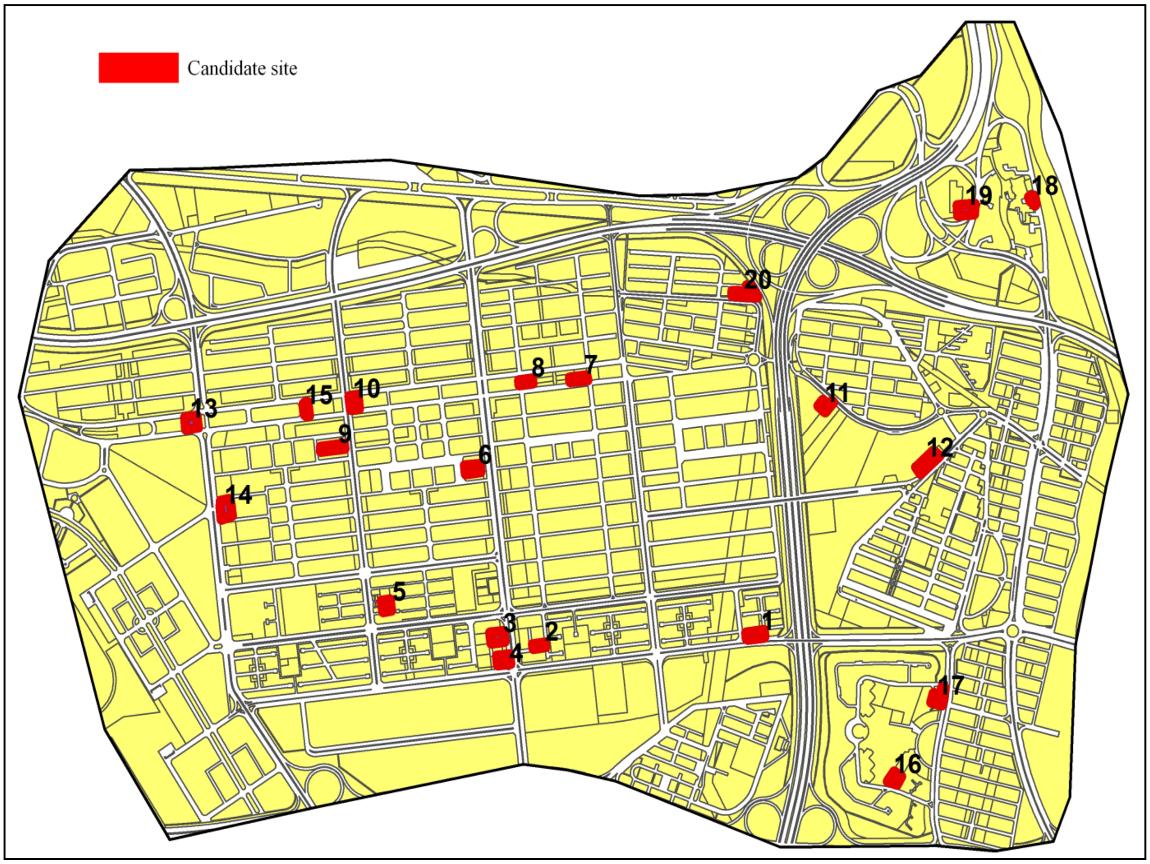


Figure 14. The candidate sites for new parking in District # 22.

Table 7. Evaluation criteria for parking site location.

#	Criteria	Description	Measurement unit	Criterion type
1	Adjacent population to a candidate site	Adjacent population is the number of people residing within 500 meters of a candidate site.	Number of residents	Maximize
2	Land size	Size is the total area of a candidate site.	Square Meter	Maximize
3	Land cost	The cost of land is obtained by multiplying the land size and the land cost per square meter.	Iranian Toman	Minimize

4	Distance to roads	Distance to main road is the nearest distance from a candidate site to a main road. The parking site is targeting users who park their cars in the downtown and look for services. Main roads are the community's main shopping areas with various amenities. Parking plays a key role to limit traffic congestion in the main roads.	Meter	Minimize
5	Average distance to recreation centers	For all recreation centers including sport, leisure and entertainment centers (e.g., cinemas, museums and visitor attractions), it will be necessary to provide a reasonable amount of parking space.	Meter	Minimize
6	Average distance to administrative centers	The availability of adequate parking space is essential for employee and also non-employee visitors doing business with large public buildings such as administrative services centers, educational centers, community centers, etc.	Meter	Minimize
7	Average distance to commercial centers	With regard to retail shopping centers, it is recognized that people come to such locations to buy goods and it may be difficult to carry them back on public transport. Hence, there will be a need for parking space at such locations. Further, markets attract short, medium and long duration parking. Shoppers will need short term parking and shop-owners will need long duration parking.	Meter	Minimize
8	Average distance to transportation stations	Public parking availability and access are essential for transportation stations such as subway stations, bus terminals, etc. Some people may prefer to park their cars in the vicinity of the stations and use the public transport services (multi-modal transportation).	Meter	Minimize

5.3 Experimental design

Using task complexity, the type of decision aid, and the decision mode as the independent factors, and the information acquisition metrics as the dependent variables, this study adopts a repeated-measures experimental design (or within-subjects design) to test the hypotheses advanced in Chapter 1. A within-subjects-design is an experiment in which the same individuals participate in all of the experimental sessions. As the subjects are exposed to each treatment in turn, the measurement of the dependent variables (i.e., information acquisition variables) is repeated. There are two fundamental advantages of using the within-subjects design (Kantowitz, Roediger III, & Elmes, 2009; Valente et al., 2011). First, a within-subjects design does not require a large pool of participants as compared to a between-subjects design that would require more participants (different people for different experiments). Second, the conditions are always exactly equivalent with respect to individual differences since the participants are the same in different conditions. Therefore, a within-subjects design leads to a reduction in error variance associated with individual differences.

The task complexity was manipulated at four levels (treatment levels): (i) five alternatives and two attributes; (ii) ten alternatives and four attributes; (iii) fifteen alternatives and six attributes; and (iv) twenty alternatives and eight attributes (see Table 8). Each increase in the number of alternatives and attributes incorporated the previous available attributes as a subset. That is, an increase in the task complexity from "five alternatives and two attributes" to "ten alternatives and four attributes" involved just adding five alternatives and two attributes to the original ones. In this way, the procedure ensured that even the most limited information load would involve at least some attributes which would seem necessary to making a realistic choice, e.g., land cost (Payne, 1976). To avoid carryover or order effects in the experiment (that is, a subject may get better at the task over time because of practice or the subject will become worse at the task over time because of fatigue) the order of presentation of the decision situations (task complexity) was counterbalanced across the participants. In other words, decision situations were presented to each participant in a different order in such a way that each condition was given in each sequential position an equal number of times. Figure 15 shows an example of the counterbalancing of the decision situations across four participants.

At each level of task complexity, the participants carried out the decision making process in the two different GIS-MCDA modes: individual and group mode (see Table 8). In the individual mode, the system allows the participants to evaluate the alternatives without knowing the group decision, while in the group mode, the members can review the group solution (i.e., group ordering of alternatives) and other participants' map-based comments, and then conduct the decision making process.

Table 8. The decision situations (or experimental treatments) according to the task complexity and the decision mode.

Experiment #	Decision situation (alternatives × attributes)	Decision analysis mode
1	5×2	Individual
2	5×2	Group
3	10×4	Individual
4	10×4	Group
5	15×6	Individual
6	15×6	Group
7	20×8	Individual
8	20×8	Group

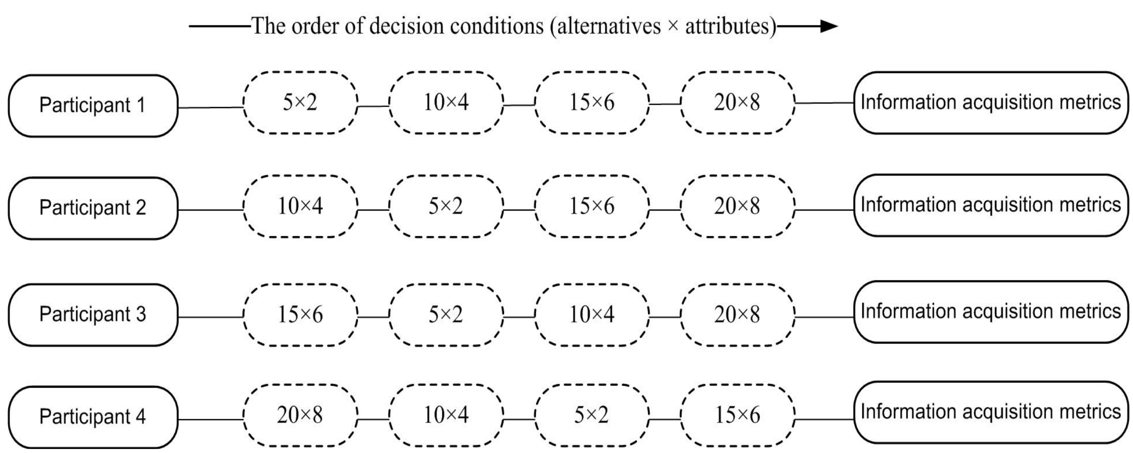


Figure 15. An example of counterbalanced decision situations for four participants.

5.4 The Web 2.0-based collaborative MC-SDSS

5.4.1 System development

The MC-SDSS applications use many different strategies to integrate GIS capabilities with MCDA models. In this study, the Web 2.0-based collaborative GIS-MCDA is developed based on the tight coupling approach. This type of coupling strategy results in a full integration of the MCDA capabilities into GIS, a shared data base, and a common user interface (Jankowski, 1995). The system is developed using the Web 2.0 Application Programming Interfaces (APIs) (Google Web Toolkit and Google Maps APIs) and MySQL database in the Java IDE environment IntelliJ IDEA 10.5 (see Appendix A). The Web 2.0 technologies provide the foundation for user-friendly online tools for collaborative spatial decision-making. The Web 2.0 APIs are easy-to-use and public domain software allowing programmers to combine geo-services and resources into so-called mashups that meet specific user needs (Rinner et al., 2008; Bugs et al., 2010). Google Web Toolkit (GWT), an AJAX (Asynchronous JavaScript and XML) development tool, is one of the best existing frameworks to build Web 2.0 applications in Java. The AJAX-powered MC-SDSS allows for seamless interaction between the users and the system; it provides a more interactive platform for collaborative decision making.

Google Maps, a Web mapping service application and technology provided by Google, is an AJAX-based spatial API that has been made available to users to incorporate Google Maps into their spatial mashups. The launch of the Google Maps service allows the Internet users around the world to have free access to browser-based WebGIS functionalities and high quality geospatial data (http://maps.google.com). It offers easy-to-use and free-of-charge WebGIS tools for both novice and expert users (Miller, 2006; Udell, 2008; Boroushaki & Malczewski, 2010b). This illustrates the realization of what researchers had primarily theorized about in reference to the concept of Participatory GIS (Leahy, 2011). Goodchild (2007) describes the Google Maps phenomenon as the “democratization of GIS,” due to its potential to open some of the more straightforward capabilities of GIS to the general public. Thanks to Google Maps, non-GIS scientists are now able to “read, write, alter, store, test, represent information in ways that they desire and in formats and environments they understand” (Miller, 2006, p.188). This makes Google Maps a valuable tool to build the groundwork for any collaborative WebGIS development. The Google Maps API was utilized in the collaborative MC-SDSS to empower decision participants with a visual framework that represents alternative locations, individual and group orderings of alternatives, and to support geographically referenced argumentations using visual access to the geo-referenced debates in the decision problem domain.

The architecture of the collaborative MC-SDSS is illustrated in Figure 16. It is based on a thin client approach (Peng & Tsou, 2003), where the user interface components (a Web browser) run on the client (user) machine but data elements (MySQL database), the application logic (decision analysis functionalities), and the Google Maps service remain on the server (Rinner & Jankowski, 2002; Boroushaki & Malczewski, 2010b). The user interface of the system consists of a user registration form and three main Web pages including “Instruction”, “GIS-MCDA individual mode”, and “GIS-MCDA group mode”. The MySQL database stores two types of data: decision data and user interaction data (log data). The decision data includes: (i) user registration information; (ii) alternatives’ locations (geographical coordinates); (iii) the criteria values associated with the alternative; (iv) criteria ranks according to each user’s preferences; (v) the final score and rank of each alternative according to each individual judgment; (vi) the score and rank of each alternative based on the majority of participants (group preference); (vii) the ORness value; and (viii) geo-referenced arguments and their locations (geographical coordinates). The log data (computer-human interaction event log data) are the records of participants’ activities during the use of the system. Each time a user performs an interaction with the MC-SDSS, such as clicking on the information items contained in the decision table, the system writes records to the database describing the nature of the action. Tracking the user’s every move makes it possible to obtain highly detailed and useful information about the participants’ information acquisition behavior in the decision making process.

The decision analysis component of the MC-SDSS applies the GIS-MCDA decision rules. It involves computing individual and group solutions using the OWA-based MCDA and the Borda score approaches, respectively (see Chapter 3). Given the individual preferences set by the decision participants, the decision analysis component generates the orderings of alternatives. Then, the set of individual orderings is combined into a compromise (group) solution and displayed on Google Maps.

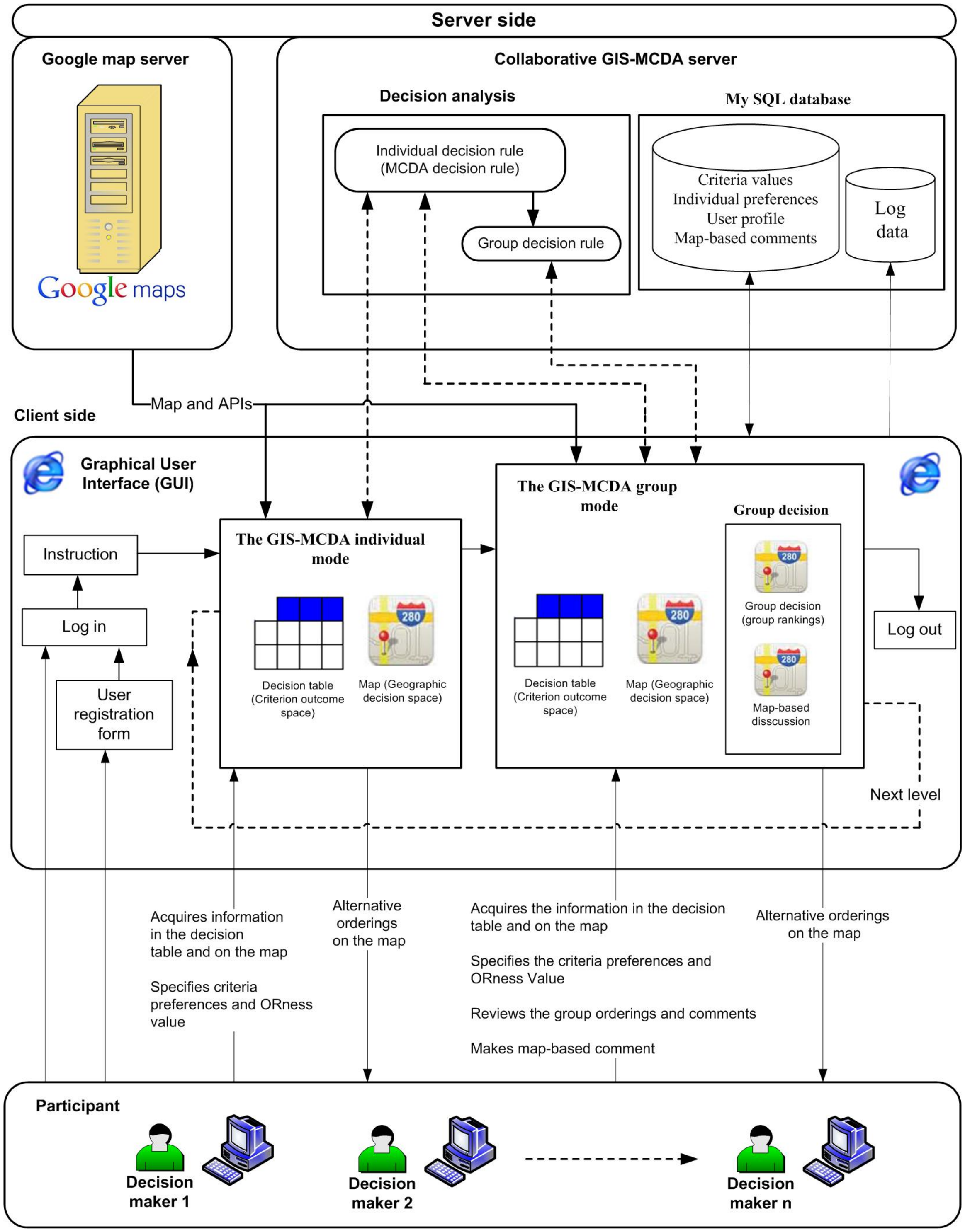


Figure 16. The architecture of the proposed Web 2.0-based collaborative MC-SDSS.

5.4.2 System description

5.4.2.1 User registration

User registration is the first stage of the collaborative decision making procedure. Each individual participating in the parking site selection process must complete and submit the registration form individually (see Figure 17). The anonymous information that individuals provide in this page includes: age, education, gender, experience with the Internet, and experience with GIS. A drop-down list of predefined entries for each of the user characteristics is provided. For example, two characteristics, "experience with internet" and "experience with GIS", include three entries ("low", "medium", and "high") from which users choose the appropriate one. By completing the registration, users are then redirected to the "instruction" page. Returning users can log into the system using the "log in" Web page.

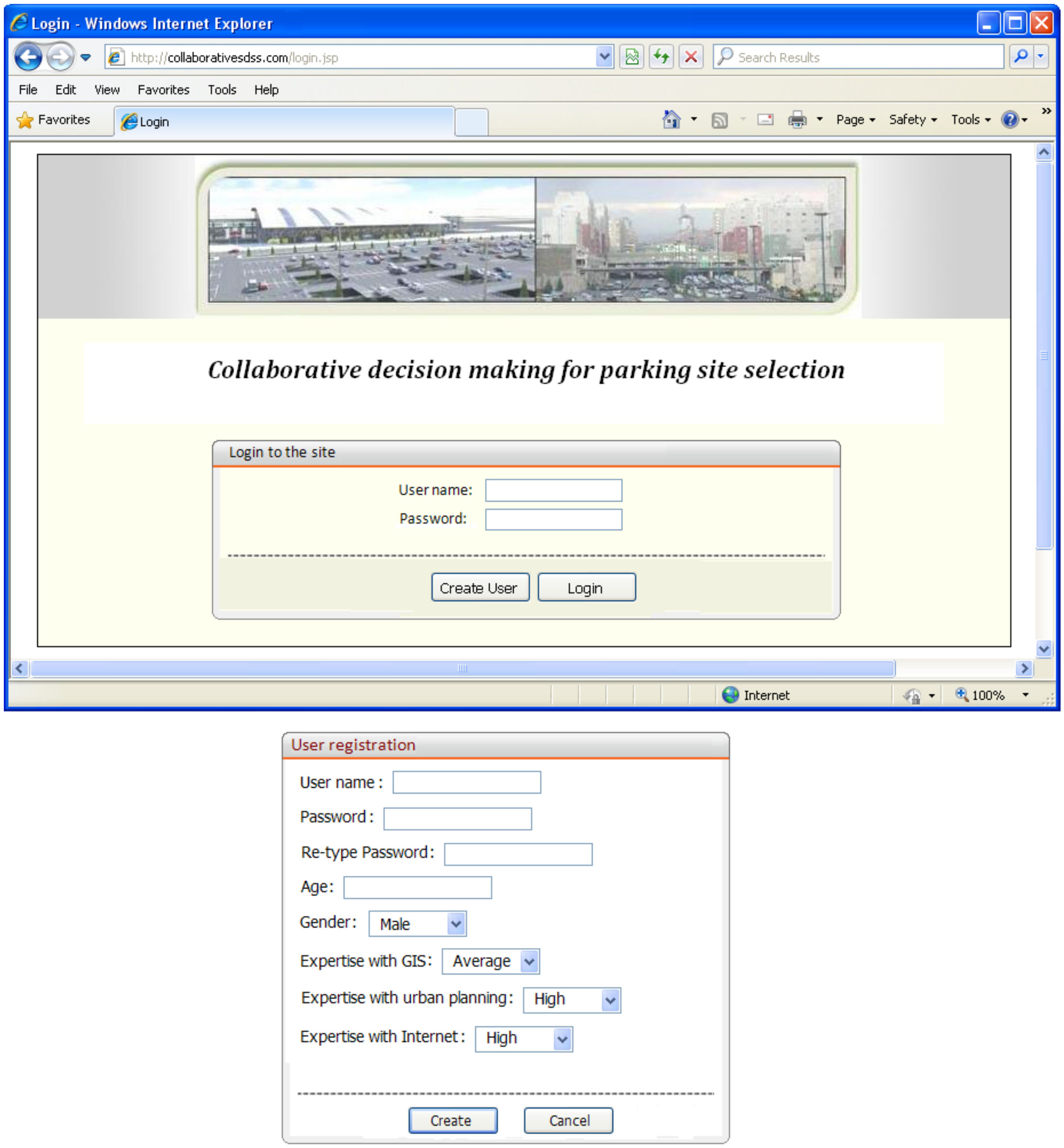


Figure 17. The user registration form.

5.4.2.2 Instruction

The instruction page describes the goal and objectives of the spatial decision problem at hand and provides a detailed explanation of the attributes and characteristics of the decision alternatives. The definitions of the evaluation criteria and their units of measurement are given in the "instruction" page as well. In addition, the page provides a step-by-step tutorial that familiarizes users with the system. It presents a walkthrough on how to use the Website for selecting the preferred location, and how to complete the experimental tasks (see Appendix B).

5.4.2.3 Decision analysis

5.4.2.3.1 The GIS-MCDA individual mode

In the individual mode, the collaborative MC-SDSS has tools to assist an individual in the evaluation of decision alternatives. It provides participants with a decision table and a map for exploring the criteria outcome and geographic decision space. It allows the participants to determine the criteria preferences (criteria ranks) and ORness value, and evaluate the decision alternatives (see Chapter 3). Figures 18 and 19 show the examples of the Web pages for the individual decision making (see Appendix C). These pages include both the decision table and the map relevant for the decision situation. The information cells in the decision table contain the measured values of attributes associated with alternatives as well as the range values of the attributes. In the beginning, only attribute and alternative labels are visible, and all the attribute values and their ranges are hidden in the cells (Lurie & Swaminathan, 2009; Katz et al., 2010). To access and examine the information in each cell, the participant needs to move the mouse cursor into the cell and click on it. The information in the cell immediately appears and remains visible until the cursor is moved out of the cell. When the participant clicks on another cell, the information in the previous cell disappears and the new cell's value comes into view. Therefore, each participant can open only one cell at a time. In this way, the system keeps track of the order in which cells are opened, the amount of time and frequency that each cell is opened, and so on.

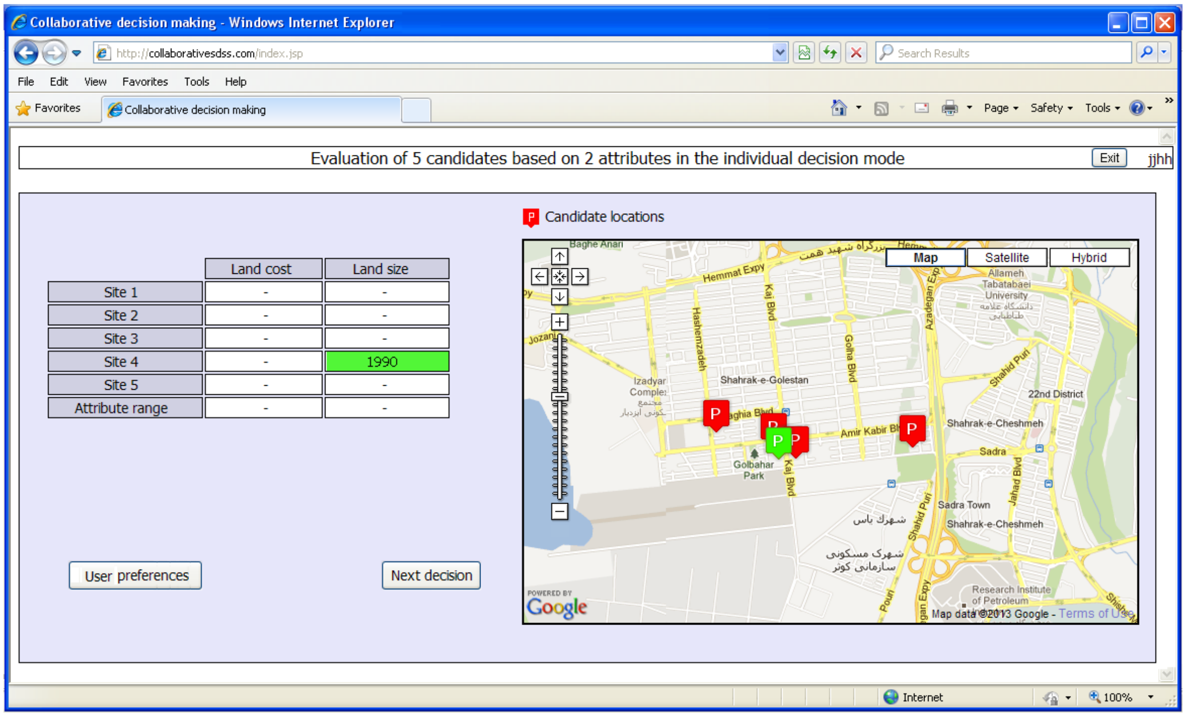


Figure 18. The GUI for the GIS-MCDA individual mode in decision situation “5×2”.

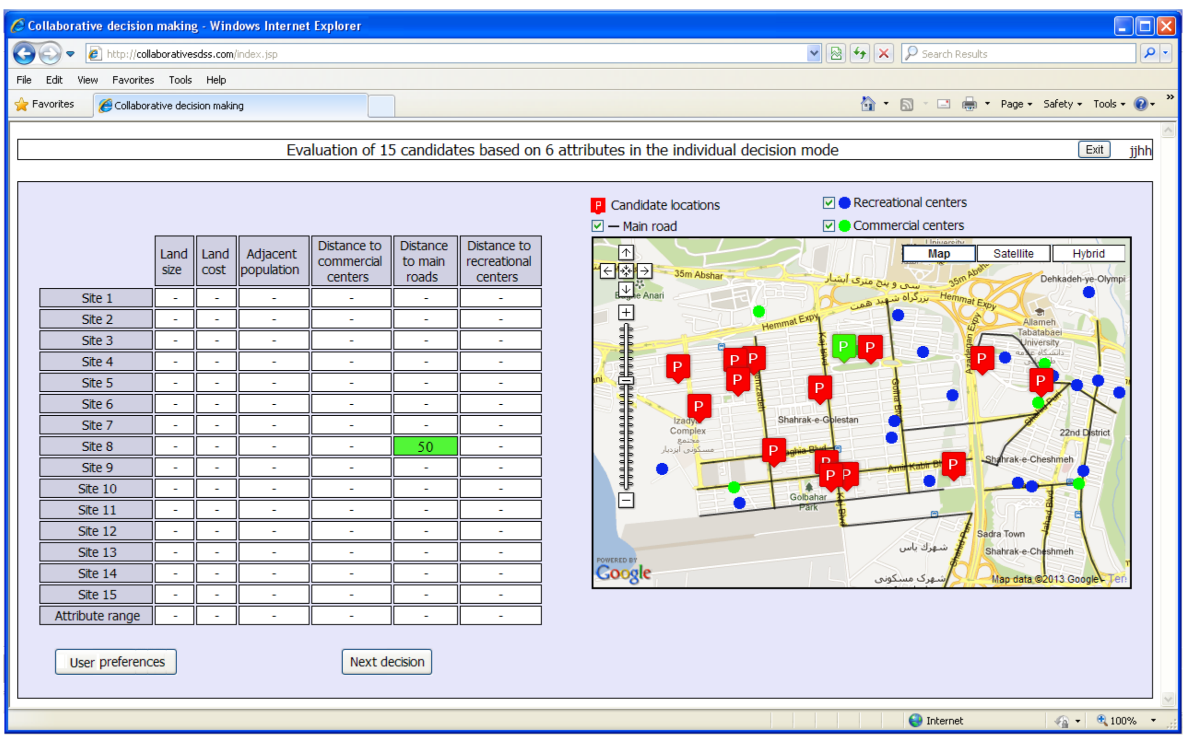


Figure 19. The GUI for the GIS-MCDA individual mode in decision situation “15×6”.

The system provides a dynamic and interactive linkage between the decision table and map views where the search moves in one view are immediately propagated to the other view (Jankowski et al., 2001). It allows the participants to locate on the map any decision alternative selected in the decision table or to assess an alternative selected on the map by examining its multi-attributes characteristics in the decision table. When the participant clicks on a particular alternative (parking site) on the map, the respective alternative on the map and the corresponding information cells (entire row) in the decision table become highlighted (see Figures 18 and 19). And vice versa, by clicking on a particular information cell in the decision table, the system highlights the corresponding alternative on the map. Such a level of interactivity allows the concurrent exploration of the candidate sites in the geographic decision space and the decision outcome space (see Chapter 1), thus facilitating information acquisition during the collaborative site selection process.

Participants can use the map to explore the alternatives, and also the spatial distribution of the geographic entities on the base of which criteria are defined. The system allows switching between different map views, turning the map layers on and off on the Google Maps, and using the Zoom slider on the on the Google Maps to zoom in to certain alternatives, features, and places on the map. In decision situation 1 (5×2), there is only one layer of alternatives on the map, as the criteria in this experiment involve only the alternatives (see Figure 18). In the more complex decision situations (2, 3 and 4), the set of criteria involve some other geographic entities in addition to the alternatives, such as main roads, recreational centers, administrative centers, etc. The participants are able to explore the spatial distribution of these entities by turning the map layers on and off on the top the map (see Figure 19).

The system enables the participants to determine the attribute ranks during or after examining the decision table or map. Using the Up/Down arrow keys, the participants assign a higher rank to the selected attribute by moving it up or assign a lower rank by moving it down (see Figure 20). After identifying the attribute priorities, the participants have to specify the value of ORness by dragging the slider between 0 and 1. The decision participants can generate the range of decision strategies based on either pessimistic or optimistic attitudes towards risk by adjusting the ORness parameter. Evidence shows that an individual with a tendency to avoid risks (pessimist decision maker) would typically specify the lower ORness value compared to an individual with high risk-taking propensity (optimist decision maker) (Mellers & Chang, 1994; Malczewski et al., 2003). Once the individual preferences and the ORness value have been specified, the system computes and represents the alternative orderings (individual solution) on Google Maps. The map is dynamically updated in response to changes in criterion preferences and the value of ORness. When the user changes the slider value, the system generates a new set of order weights, and accordingly the scores and ranks of the decision alternatives are re-calculated and represented on the map.

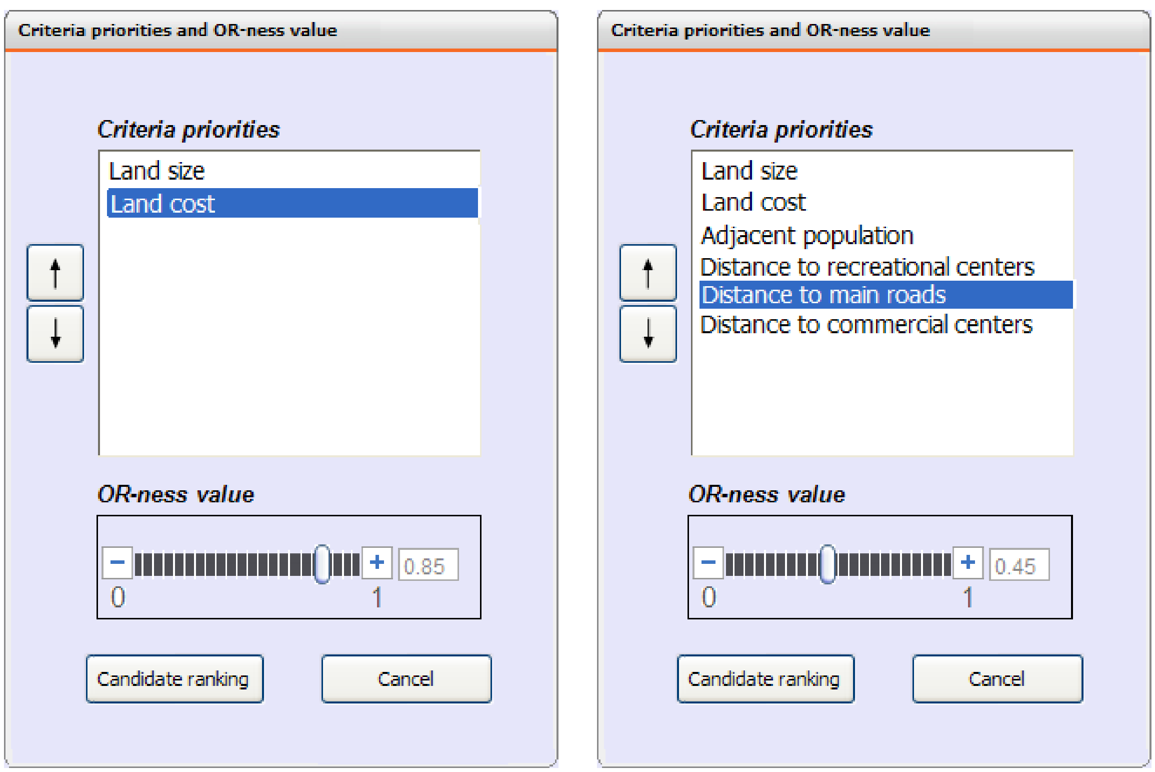


Figure 20. The windows for specifying the criteria priorities and ORness value in decision situations “5×2” and “15×6”, respectively.

5.4.2.3.2 The GIS-MCDA group mode

As with the individual mode, the collaborative MC-SDSS in the group mode allows the participants to examine the decision table and map, and determine the criteria preferences (criteria ranks) and ORness value for generating the alternatives' orderings of alternatives (see Figures 21 and 22). The only difference is that in the group mode, participants can review the other participants' comments as well as the group rankings of the alternatives during the decision making process. By reviewing the others' decisions and comments, the participants are able to compare their decision with the decisions made by other users, and refine their decision.

Similar to the individual orderings, a participant can observe the group rates/orderings by clicking on the group decision button, showing the score and ordering of each alternative location based on the preferences of all the participants who have finished the site selection procedure. Clicking on the checkbox "individual comment" in the group decision window, participants are able to review others' geo-referenced comments, make comments, and hold conversations in the form of posted messages on the map (Rinner et al., 2008; Simão et al., 2009). This tool allows for graphical submissions, compilations, and tracking of geographic proposals via an annotated map. Clicking on the map, the individuals input their contributions about different dimensions of the decision problem on the particular geographic locations (see Figures 23 and 24). They can deliberate and exchange information regarding the parking decision problem on the map.

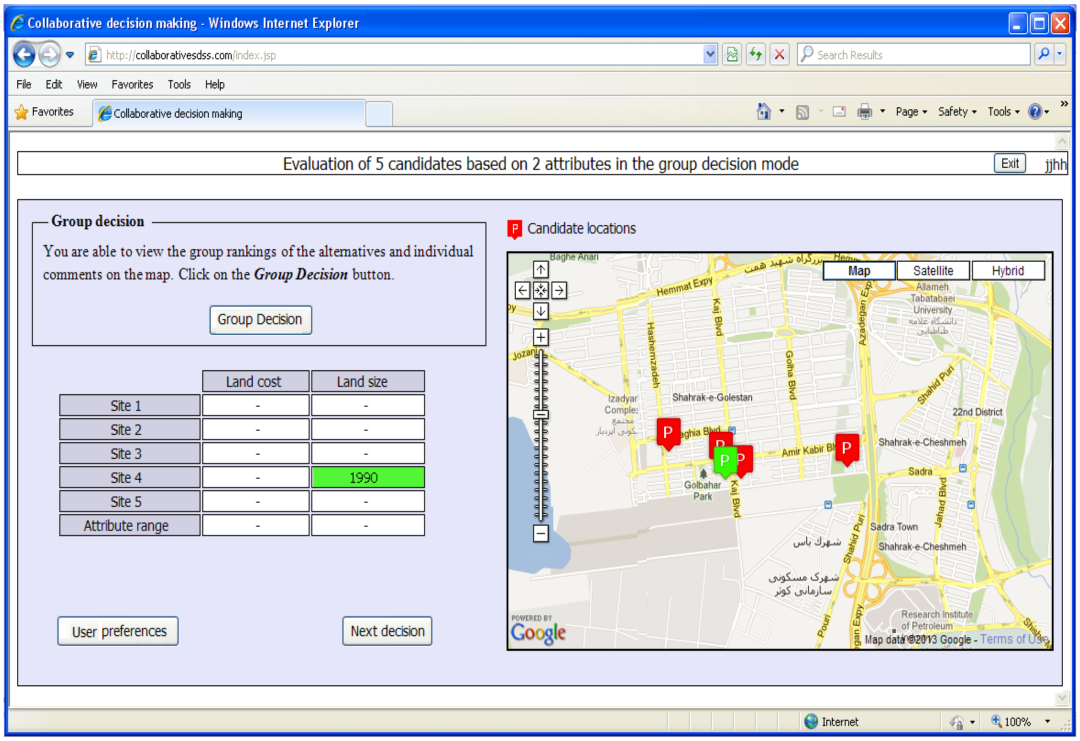


Figure 21. The GUI for the GIS-MCDA group mode in decision situation “5×2”.

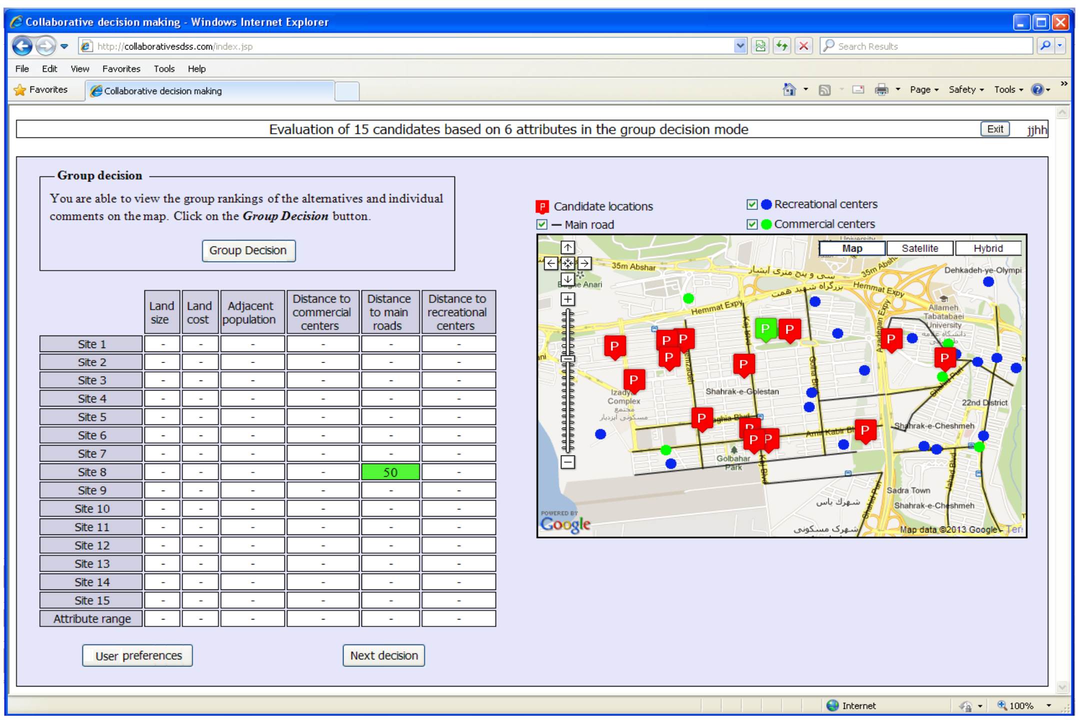


Figure 22. The GUI for the GIS-MCDA group mode in decision situation “15×6”.

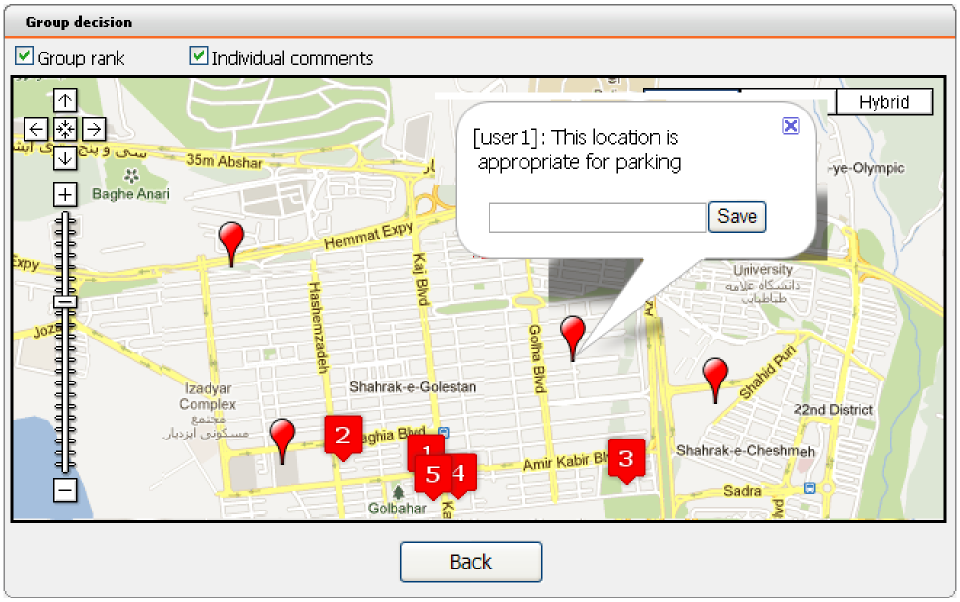


Figure 23. The group decision window for decision situation "5×2".

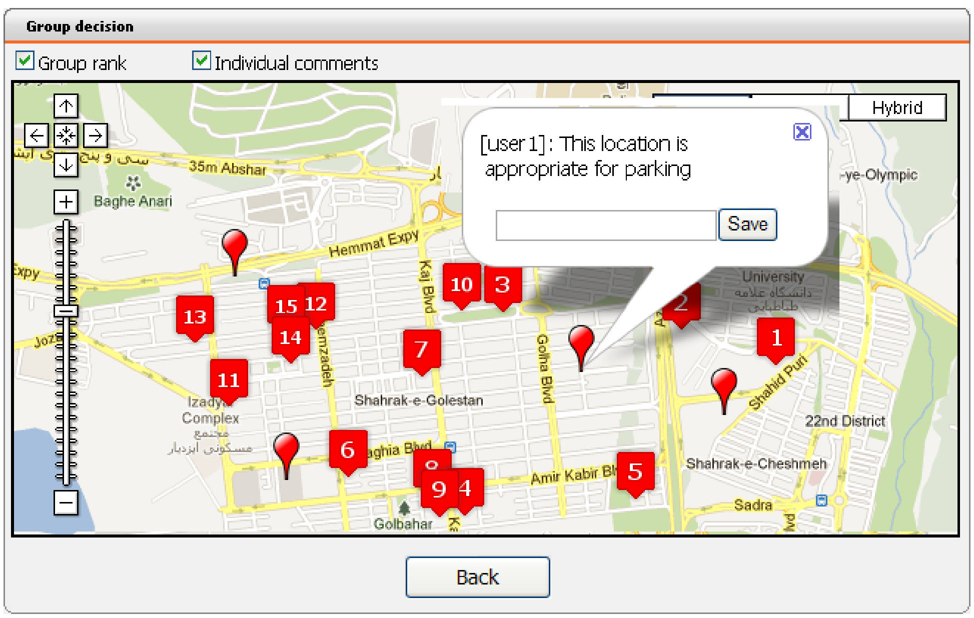


Figure 24. The group decision window for decision situation "15×6".

5.5 Web implementation and participants

The proposed collaborative MC-SDSS and relevant data were put on a server for use from January 1st, 2013 to May 30st, 2013 (see http://collaborativesdss.com). Students in the urban planning departments at Shahid Beheshti University and the University of Tehran were invited to participate in the collaborative parking site selection process. The website holding the system was advertised through announcements in the classes across the departments. The students were invited to identify their concerns, ideas, suggestions or preferences over the candidate sites and evaluation criteria for locating the new parking site(s). No special competence was sought, only an interest in the decision task to be undertaken. To join the decision-making process, a participant needed a computer and Internet service to access the website containing the relevant data and MC-SDSS. All of the students in the departments had direct twenty-four hours access to computers and the Internet network. A total of 55 volunteers participated throughout the parking site selection process, and out of the total 58 % were female and 42 % were male. Table 9 presents the number of the participants according to the levels of experience with GIS, web surfing and involvement in urban planning. Most of the participants had a low level of experience with GIS (52%), a high level of experience with the Internet (65%), and a medium level of experience with urban planning (48%).

Table 9. The number of participants according to their levels of experience with GIS, Internet and urban planning.

	Low	Medium	High	Total number of participants (%)
Experience with GIS	29 (52)	24(44)	2(4)	55(100)
Experience with Internet	0(0)	19(35)	36(65)	55(100)
Experience with urban planning	21(38)	26(48)	8(14)	55(100)

Note: The percentage of the number of participants is given in bracket.

A special emphasis was placed on the importance of reading instructions on the tutorial (instruction) page in the system. The instruction page provided the participants with a step-by-step walkthrough on how to use the Website for selecting the preferred location, and how to complete the experimental tasks (see Appendix B). This page informed the users that they would be participating in a study aimed at identifying the most suitable alternatives for locating the parking sites. Specifically, the participants were instructed that they: (i) would be performing two decision tasks (individual and group mode tasks) across four decision situations (complexity levels); (ii) would go through both tasks at the four decision conditions; (iii) would be presented with a number of alternatives, attributes, and a certain amount of information about each alternative during each of the decision situations; (iv) would specify their criteria preferences and ORness value on the basis of the information provided, and eventually the system would compute the individual solution for them according to their preferences; (vi) would be free to look at as much available information as they wanted to or felt was necessary to make a decision; and (vii) could spend as much time on the decision as they desired.

5.6 Collecting the human-computer interaction event log data: input data for the experiments

The data on the decision makers' activities during the experiments were recorded as the Web-based event logs using the logging module of the system. The event logs are an indirect record of what a user has done (Zhang, 2007). They provide an efficient and non-intrusive method for collecting data from the participants for the purpose of analyzing human-computer interactions. The main incentives for using the logs in the data collection process are low implementation cost, high speed, and high accuracy. In addition, the logging method does not require the use of personally administered questionnaires or interviews (Atterer, Wnuk, & Schmidt, 2006).

There are a number of log storage techniques/formats, such as text-based log files, flat text files, and databases (see Chuvakin, Schmidt, & Phillips, 2012). In this study, a database logging approach was employed to record the log information. Each time a user performed an interaction with the system, the system continuously wrote records to the log database describing the nature of the action (see Appendix D). The main advantage of using the database logging approach is that it allows for structuring the log information in a format that can be quickly read, searched, reviewed, analyzed, and queried. In contrast to the file-based approaches that take a lot of time and effort to read, filter, summarize, and analyze the log data, the database approaches allow for using standard SQL queries to combine all sorts of information from different entries and easily analyze the log records.

The log data for information acquisition behavior include the information the subject seeks (information cells) in the decision table, how much information is examined, how long the information is examined for, as well as the sequence in which they are looked at in the decision table. In addition to recording the data on the use of the decision table, the system records decision makers' activities during the use of the decision map. The records are date and time stamped, and when reviewed, provide a picture of the user interaction with the system. By querying the log data stored in the MySQL database, one can derive data for computing the information acquisition metrics defined in Chapter 4. Figure 25 shows an example of SQL query in the Navicat for MySQL[7] environment, which aims at retrieving the number of information cells examined by each decision maker. This query returns the number of information cells acquired specifically for each user in a particular decision situation (task complexity level) and a particular decision mode. The query results for two example decision makers are shown in Figure 26. For instance, the query results show that the number of information cells examined in the decision table by the decision maker with "UserID=1" in decision situation "5×2" (task complexity = 1) and within the GIS-MCDA individual mode is 14.

[7] http://www.navicat.com/download/navicat-for-mysql?gclid=CIX7qKW1v7gCFfFDMgodZV4AJg

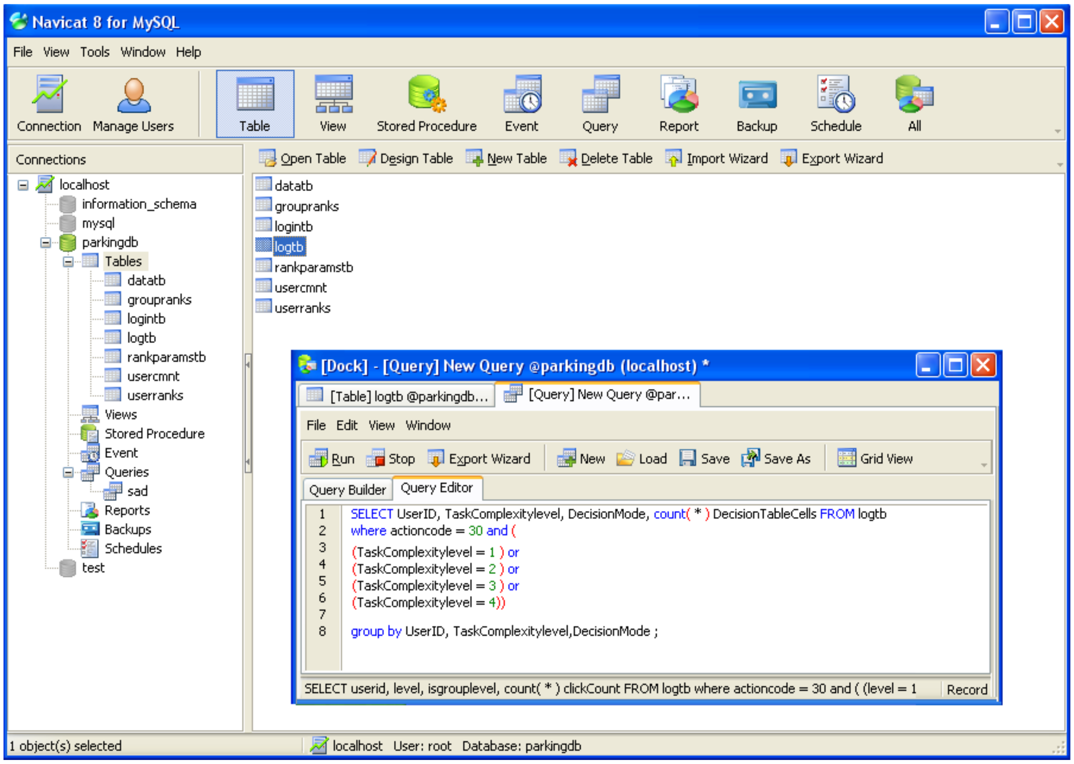
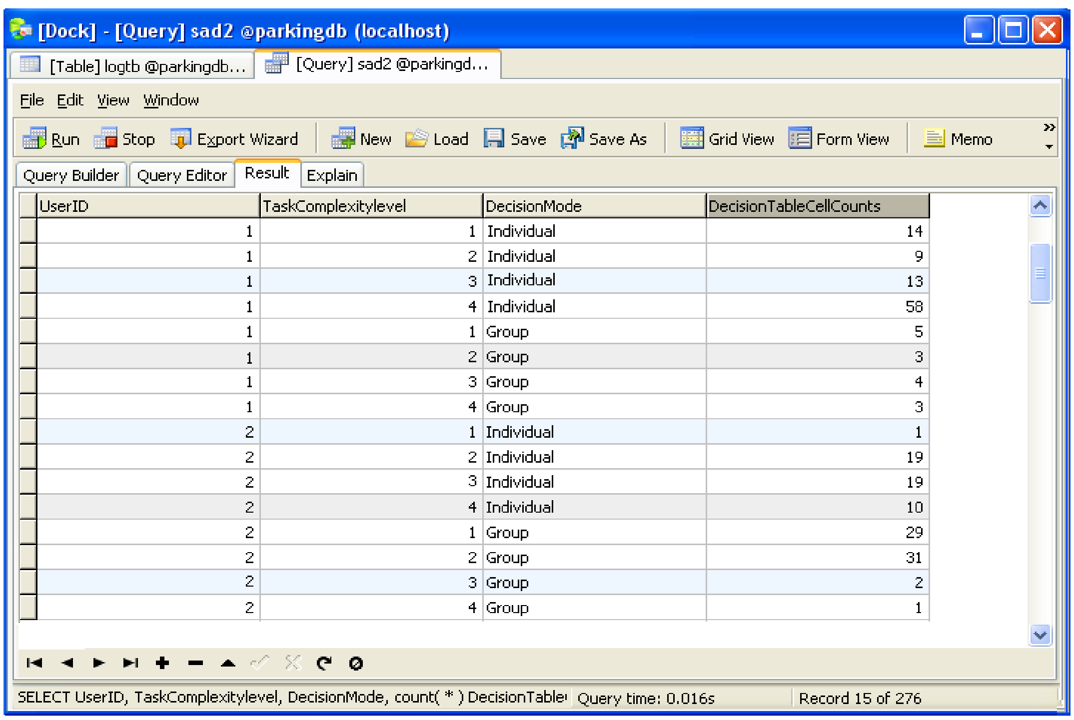


Figure 25. Querying the log data using the Navicat for MySQL.



UserID	TaskComplexitylevel	DecisionMode	DecisionTableCellCounts
1	1	Individual	14
1	2	Individual	9
1	3	Individual	13
1	4	Individual	58
1	1	Group	5
1	2	Group	3
1	3	Group	4
1	4	Group	3
2	1	Individual	1
2	2	Individual	19
2	3	Individual	19
2	4	Individual	10
2	1	Group	29
2	2	Group	31
2	3	Group	2
2	4	Group	1

Figure 26. Results for the query “what is the number of information cells acquired by each participant in a particular decision situation within a particular decision mode?”.

Chapter 6

6 Results and analysis

The research hypotheses developed for this study call for an examination of the differences in the information acquisition metrics when task complexity or information load increases (low vs. high), the information aid varies (the map vs. table), and the decision mode changes (individual vs. group). Additionally, the relationships between the metrics, and the effect of the decision mode and task complexity on these relationships will be examined. The hypotheses were tested by conducting Repeated Measures ANOVA (within-subjects ANOVA), Linear Mixed Model (LMM) analysis, and Pearson correlation tests using the Statistical Package for the Social Sciences (SPSS) software (SPSS IBM., 2012). Sixteen sets of hypotheses were examined (see Chapter 1). The hypotheses from H1 through H9 examine the effect of task complexity on the information acquisition metrics. These hypotheses were tested using the Repeated Measures ANOVA test (with the Greenhouse-Geisser correction as needed), with task complexity as the independent factor and each of the information acquisition metrics as the dependent variable. This would enable a comparison of the means for the dependent metrics at different levels of task complexity. The set of H10 hypotheses look at the effect of the decision mode on the information acquisition metrics. To test the differential effects of the decision mode on the metrics, the LMM test was carried out. The LMM procedure extends the general linear model so that the data are permitted to be correlated (SPSS IBM., 2011). The term "mixed model" refers to the use of both fixed and random effects in the same statistical analysis[8]. The presence of the random effects often introduces correlations between the subjects. The LMM test allows for integrating and analyzing the correlated repeated measurements by explicitly modeling a variety of correlation patterns (or random effects) (SPSS Inc., 2005).

[8] http://www.stat.cmu.edu/~hseltman/309/Book/chapter15.pdf

The set of H11 hypotheses examine the relationship between information acquisitions in the decision table and map. The hypotheses H12 look at the relationship between the information acquisition in the decision table and map. The H13 hypotheses investigate the inter-relationship among the information acquisition metrics in the decision table. The three sets of hypotheses, H11, H12, and H13, were tested by conducting the Pearson correlation test; however, some of the H11 hypotheses were also examined using the LMM test. The set of hypotheses H14 explore the effect of task complexity on the relationship between the information acquisition in the decision table and map. The H15 hypotheses look at the effect of task complexity on the relationship between the times spent on the decision table/map and the time spent viewing the group decision. The set of H16 hypotheses assess the influence of the decision mode on the relationship between the information acquisition in the decision table and on the map. The three hypotheses, H14, H15 and H16, were tested using the LMM test. All of the sixteen sets of hypotheses were examined at a significance level of $\alpha = 0.05$. In addition to the significance level of $\alpha = 0.05$, the Pearson correlation tests on the hypotheses were conducted at a level of $\alpha = 0.01$.

6.1 The effect of task complexity on the information acquisition metrics

Hypothesis 1

H1a: *In the GIS-MCDA individual mode, an increase in task complexity results in a significant decrease in the proportion of information search*. Participants were expected to search a larger proportion of available information in the lower levels of task complexity than the higher levels. Table 10 shows the descriptive statistics for the proportion of information search for each of the decision situations (the complexity levels). The results indicate that the mean proportion of information search declines as task complexity increases. For the task complexity of 5×2 information cells, 27% of the total available information is examined. This percentage decreases for the higher levels, where participants look at only 4% of the available information at the highest level of task complexity (a set of 20×8 information cells). These results imply that a smaller proportion of information is examined as the decision complexity increases.

Table 10. Descriptive statistics for the proportion of information search in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.271	0.312	0.000	1.000
2	10×4	0.150	0.205	0.000	1.000
3	15×6	0.078	0.109	0.000	0.433
4	20×8	0.043	0.070	0.000	0.331

Under the null hypothesis that there is no difference in the proportion of information search between the low-complexity and high-complexity decision situations, the ANOVA test gives a *p*-value of 0.000 ($F(2, 104) = 23.49$, $p = 0.000 < 0.05$). Thus, the null hypothesis should be rejected. This leads to the conclusion that the proportion of information search in the lower levels of task complexity is significantly greater than that in the higher levels; thus, the results provide evidence for the use of more non-compensatory strategies in high-complexity tasks. This conclusion is consistent with a number of empirical studies (see Payne, 1976; Ford et al., 1989; Chinburapa, 1991; Roe et al., 2001; Schrah et al., 2006; Katz et al., 2010; Schram & Sonnemans, 2011; Queen et al., 2012).

H1b: *In the GIS-MCDA group mode, an increase in task complexity results in a significant decrease in the proportion of information search*. Similar to the individual mode, participants were expected to search a larger proportion of available information in the low-complexity tasks than the high-complexity tasks. The proportion of information search in decision situations 1, 2, 3, and 4 are 17.3%, 4.6%, 2.1%, and 1.3%, respectively (see Table 11). The results suggest a negative relationship between task complexity and the proportion of information searched. The participants searched for a lesser amount of available information as the level of complexity increased. When faced with a lower number of alternatives and attributes, they searched for a larger proportion of information than when faced with a higher number of alternatives and attributes. This indicates that the proportion of information search is in the same direction as anticipated by the hypothesis.

Table 11. Descriptive statistics for the proportion of information search in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.173	0.213	0.000	1.000
2	10×4	0.046	0.082	0.000	0.400
3	15×6	0.021	0.034	0.000	0.133
4	20×8	0.013	0.022	0.000	0.118

The ANOVA test gives a p-value of 0.000 ($F(1, 71) = 25.68$, $p = 0.000 < 0.05$). Thus, the null hypothesis of no difference in the proportion of information search is rejected. There are statistically significant differences in the proportion of information searches among decision situations in the GIS-MCDA group mode. Consistent with the expectations, participants search a significantly higher proportion of available information in the lower levels of task complexity. This result provides a support for using a non-compensatory strategy in high-complexity tasks.

Hypotheses 2

H2a: *In the GIS-MCDA individual mode, an increase in task complexity results in a significant decrease in the proportion of attribute ranges searched*. Participants were expected to look at a higher number of attribute ranges in the low-complexity tasks than the high-complexity tasks. Table 12 shows the descriptive statistics for the proportion of attribute ranges searched in the four decision situations. The results show that decision makers examined a relatively low proportion of attribute ranges during the decision making process. This corroborates a number of early findings and suggestions, which state that decision makers remarkably ignore the attribute ranges when weighing the criteria in the decision making process (Beattie & Baron, 1991; Von Nitzsch & Weber, 1993; Fischer, 1995; Yeung & Soman, 2005; Monat, 2009; Riabacke, Danielson, & Ekenberg, 2012). For instance, in an empirical study,Von Nitzsch and Weber (1993) found that decision makers do not properly adjust their criteria judgments if the range values vary.

The mean proportion values of 55.5%, 26.8%, 24.5%, and 14.5% for decision situations 1, 2, 3, and 4, respectively, indicate a negative relationship between task complexity and the proportion of attribute ranges. Given the null hypothesis of no difference in the proportion of attribute ranges between the low- and high-complexity decision tasks, the ANOVA test gives a p-value of 0.000 ($F(3, 162) = 19.755$, $p = 0.000 < 0.05$). This indicates a statistically significant difference in the proportion of attribute ranges examined among the four experimental conditions. In other words, participants searched a significantly higher number of attribute ranges in the lower levels of task complexity.

When the task complexity increases, the addition of alternatives and attributes to the initial set of alternatives is more likely to expand the variations of ranges across the attributes (Broniarczyk, 2006). For example, the attribute values associated with the added alternatives may not be within the range of the existing attributes or the added attributes may have larger ranges across the existing alternatives, thereby increasing the dissimilarity of attribute ranges. Dissimilarity in attribute ranges in turn leads to an increase in cognitive strain in the examination of information as there are many distinct attribute ranges that should be considered. Several studies show that the greater the attribute ranges, and thus the less similar the alternatives, the lower is the proportion of search (e.g., Bockenholt, Albert, Aschenbrenner, & Schmalhofer, 1991; Pfeiffer, 2012). With an increased task complexity, the proportion of attribute ranges examined by decision makers decreases as a kind of unintentional cognitive short cut. This means that decision makers avoid a full compensation or trade-off between attributes by considering an only subset of available attribute ranges, and therefore it is an indication of a non-compensatory strategy.

Table 12. Descriptive statistics for the proportion of attribute ranges searched in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.555	0.426	0.000	1.000
2	10×4	0.268	0.336	0.000	1.000
3	15×6	0.245	0.286	0.000	1.000
4	20×8	0.145	0.230	0.000	1.000

H2b: *Under the use of the GIS-MCDA group mode, an increase in task complexity results in a significant decrease in the proportion of attribute ranges searched*. Similar to the GIS-MCDA individual mode, the participants were expected to examine a higher number of attribute ranges in the low-complexity tasks than the high-complexity tasks. Table 13 shows the descriptive statistics for the proportion of attribute ranges searched in the GIS-MCDA group mode. The proportions of 21.8%, 8.6%, 8.4%, and 7.9% in decision situations 1, 2, 3, and 4, respectively, indicate that an increase in task complexity leads to a decreased proportion of attribute ranges.

Table 13. Descriptive statistics for the proportion of attribute ranges searched in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.218	0.369	0.000	1.000
2	10×4	0.086	0.221	0.000	1.000
3	15×6	0.084	0.207	0.000	1.000
4	20×8	0.079	0.204	0.000	0.875

The ANOVA test results for task complexity effects on the proportion of attribute ranges searched provides evidence that the null hypothesis of no difference in the proportion of attribute ranges searched should be rejected ($F(2, 118) = 5.21$, $p = 0.005 < 0.05$). Therefore, there is a statistically significant difference in the proportion of attribute ranges searched among the decision situations, as was the case in the individual mode. This provides evidence that a non-compensatory strategy is used in the high-complexity tasks.

Hypotheses 3

H3a: *In the GIS-MCDA individual mode, the average amount of time significantly decreases with an increase in task complexity.* The participants were expected to spend more time on each piece of information acquired in the low-complexity tasks than the high-complexity tasks. Table 14 summarizes the descriptive statistics for the average time spent in the four decision situations. Contrary to the expectations, the mean decision times of 4.54, 5.99, 3.79, and 6.65 seconds in decision situations 1, 2, 3, and 4, respectively, are not in a descending order. The results of the ANOVA test indicate that the null hypothesis of no difference in the average amount of time between the low and high complexity situations should be accepted (F (2, 84) = 1.45, p = 0.239). In other words, task complexity has no significant effect on the average time. The findings from this study are inconsistent with the results of research by Ford et al. (1989) and Klemz and Gruca (2001). For example, Klemz and Gruca (2001) changed the level of task complexity by manipulating the number of alternatives from three to seven, and found that the mean search time in the low complexity condition was 4.15 and 2.97 in the high complexity condition. This difference was also significant at the p = 0.01 level (F (1,109) = 24.15). The discrepancy between the findings of present and previous studies may be explained by the differences in the type of decision (spatial vs. non-spatial), decision making platforms (moderated decision making vs. Web-based non-moderated decision making), methods (MCDA vs. simple multicriteria choice), and tools used (MC-SDSSs vs. non-GIS based DSS systems) in the studies. The multicriteria methods used in the previous studies mostly involved the ability of decision makers to simply rank non-spatial alternatives based on multiple criteria, whereas the present study employed a MCDA technique (OWA-based approach) for the evaluation of geographic alternatives based on the individual preferences. In other words, the inconsistency between the findings may be due to the different methods used for the multicriteria evaluations (this applies to all of the hypotheses in the study).

Table 14. Descriptive statistics for the average time spent acquiring per item of information in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	4.540	5.240	0.000	29.400
2	10×4	5.990	11.820	0.600	70.300
3	15×6	3.790	3.030	0.910	15.400
4	20×8	6.650	7.070	0.000	38.000

H3b: *In the GIS-MCDA group mode, an increase in task complexity results in a significant decrease in the average time spent acquiring information*. Similar to the individual mode, participants were expected to spend more time on each piece of information acquired in the low-complexity tasks than the high-complexity tasks. Descriptive statistics for the average decision time in the GIS-MCDA group mode are shown in Table 15. The mean times in decision situations 1, 2, 3, and 4 are 2.95, 2.56, 2.99, and 3.47 seconds, respectively. Clearly, these times are not in the hypothesized direction. Based on the ANOVA results, one cannot reject the null hypothesis of no difference in the average decision time ($F(1, 17) = 3.09$, $p = 0.086$). In other words, the main effect of task complexity on the average decision time is insignificant.

Table 15. Descriptive statistics for the average time spent acquring per item of information in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	2.950	3.550	0.600	16.000
2	10×4	2.560	2.130	0.667	10.500
3	15×6	2.990	1.920	0.615	7.000
4	20×8	3.470	3.740	0.000	18.110

Hypotheses 4

H4a: *In the GIS-MCDA individual mode, an increase in task complexity results in a significant increase in the variability of information search per attribute*. Participants were expected to have a lower variability of information searched in the lower level of task complexity as compared to the higher levels. Table 16 shows the descriptive statistics for the variability in the four decision situations. The variability in decision situations 1, 2, 3, and 4 are 0.82, 1.34, 1.66, and 1.73, respectively; thus indicating a positive relationship between task complexity and variability. Therefore, the direction of these values is consistent with that specified in the hypothesis.

Under the null hypothesis of no difference in the variability of information search per attribute between low- and high-complexity tasks, the ANOVA test gives a *p*-value of 0.002 ($F(3, 84) = 5.50$, $p = 0.002 < 0.05$). This means that task complexity has a significant effect on the variability of information searched per attribute. Clearly, there is sufficient evidence to conclude that participants have a significantly higher amount of variability in the higher levels of task complexity than the lower levels. This suggests that decision makers employ a non-compensatory decision strategy in the high-complexity tasks. The result is consistent with Chinburapa's (1991) finding, where decision makers had a lower variability per attribute when faced with three alternatives than when faced with six alternatives.

Table 16. Descriptive statistics for the variability of information search per attribute in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.820	1.030	0.000	3.530
2	10×4	1.340	1.410	0.000	5.770
3	15×6	1.660	1.930	0.408	7.740
4	20×8	1.730	2.420	0.000	9.250

H4b: *Given the use of GIS-MCDA in the group mode, an increase in task complexity results in a significant increase in the variability of information search per attribute.* Similar to the GIS-MCDA individual mode, variability in the high-complexity tasks were expected to be higher than the corresponding value in the low-complexity tasks. Table 17 shows the descriptive statistics for the variability of the information search per attribute in the GIS-MCDA group mode. The mean variability values in decision situations 1, 2, 3, and 4 are 0.77, 1.21, 1.18, and 0.94, respectively. Contrary to the individual mode, the variability values are not in the same direction as predicted by the hypothesis. Under the null hypothesis of no differences in the mean variabilities between the low- and high-complexity tasks, the ANOVA test gives a *p*-value of 0.445 ($F(3, 27) = 0.91$, $p = 0.44$), indicating that the null hypothesis should be accepted. This means that the main effect of task complexity on the variability of search per attribute is statistically insignificant.

Table 17. Descriptive statistics for the variability of information search per attribute in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.770	0.910	0.000	3.530
2	10×4	1.210	1.240	0.500	5.000
3	15×6	1.180	1.080	0.408	4.490
4	20×8	0.940	1.200	0.354	6.710

Hypotheses 5

H5a: *In the GIS-MCDA individual mode, the variability of information search per alternative increases with an increase in task complexity*. Participants were expected to have a higher variability in the higher levels of complexity as compared to the lower levels. Table 18 shows the descriptive statistics for the variability in the four decision situations. The variability in decision situations 1, 2, 3, and 4 are 0.474, 0.575, 0.567, and 0.560, respectively. This indicates that the amount of variability is not in the hypothesized direction. Given the null hypothesis that the means of the variability are equal among the low and high-complex decision situations, the *p*-value value is .468, and therefore the null hypothesis cannot be rejected (F (2, 52) = .75, $p = 0.468$). As a result, the main effect of task complexity on the variability of search per alternative is not statistically significant. This suggests that, with an increase in task complexity, participants do not necessarily search a less constant and equal amount of information for each of the available alternatives. Thus, hypothesis H5a is not supported by the evidence. This result is confirmed by Schrah et al. (2006) finding that the variability of information search per alternative differs insignificantly as a function of task complexity. However, it is inconsistent with some empirical studies. For example, Payne, 1976; Ford et al., 1989) suggested that an increase in the information load would result in a significant increase in the variability of search per alternative. As was discussed earlier, the discrepancy between the findings of this study and those of the others is most likely due to the difference in the MCDA methods (see H3a).

Table 18. Descriptive statistics for the variability of information search per alternative in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.474	0.306	0.000	1.090
2	10×4	0.575	0.318	0.000	1.430
3	15×6	0.567	0.359	0.000	1.990
4	20×8	0.560	0.424	0.000	9.250

H5b: *Under the use of GIS-MCDA group mode, an increase in task complexity results in an increase in variability of information search per alternative.* Similar to the individual mode, participants were expected to have a lower variability of information search in the lower levels of task complexity. Descriptive statistics for the variability in the four decision situations are shown in Table 19. The mean variability in decision situations 1, 2, 3, and 4 are 0.585, 0.572, 0.469, and 0.484, respectively. Similar to the individual mode, the mean differences in the variability are not in the expected direction. The ANOVA test fails to reject the null hypothesis of no difference (F (3, 27) = 0.040, p =0.986), indicating that the effect of task complexity on the variability of information search per alternative is statistically insignificant.

Table 19. Descriptive statistics for the variability of information search per alternative in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.585	0.264	0.000	1.000
2	10×4	0.572	0.276	0.000	1.350
3	15×6	0.469	0.162	0.258	0.862
4	20×8	0.484	0.384	0.224	1.790

Hypotheses 6

H6a: *In the GIS-MCDA individual mode, participants use a more attribute-wise strategy than an alternative-wise in the information search process*. As discussed in Chapter 4, the two main approaches suggested in the literature were used as the measures of search direction (the sequence of information acquisition): *SI* and *SM*. These two measures indicate the extent of alterative-wise (where an alternative is selected and attributes are searched for that alternative) or attribute-wise (in which case an attribute is selected and alternatives are searched for that attribute) processing in the information acquisition process. The negative values of the *SI* indicate an attribute-wise processing, while the positive values indicate an alternative-wise pattern for the information search. The treatment means for both the *SI* and *SM* are shown in Tables 20 and 21, respectively. Both the *SI* and *SM* values are negative in all of the four decision situations. This means that participants used more attribute-wise than alternative-wise strategies, thus providing the evidence that supports the hypothesis.

Table 20. Descriptive statistics for the *SI* index in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	-0.284	0.551	-1.000	1.000
2	10×4	-0.245	0.631	-1.000	1.000
3	15×6	-0.255	0.666	-1.000	1.000
4	20×8	-0.086	0.645	-1.000	1.000

Table 21. Descriptive statistics for the *SM* index in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	-0.239	1.420	-3.530	2.610
2	10×4	-0.779	2.720	-10.240	4.490
3	15×6	-1.350	3.760	-11.100	5.360
4	20×8	-1.420	5.440	-16.140	10.920

H6b: *Under the use of the GIS-MCDA group mode, participants use a more attribute-wise strategy than alternative-wise in the information search process*. The *SI* values for all of the four decision situations are negative (see Table 20). This means that participants used more attribute-wise than alternative-wise strategies in all of the four decision situations; thus providing the evidence to support H6b. As for the *SM* measure, the mean values are negative for all of the decision situations, except for decision situation 1 (see Table 21). This implies that participants used an alternative-wise strategy in decision situation 1, and an attribute-wise strategy in the other three conditions. Consequently, the values of *SM* provide insignificant evidence for supporting the hypothesis.

H6c: *Increased task complexity in the GIS-MCDA individual mode results in a direction of search that is more attribute-wise than alternative-wise.* According to this hypothesis, participants switch from an alternative-wise to attribute-wise direction as task complexity increases. A higher value for *SI* and *SM* indicates a higher level of alternative-based processing. The mean *SI* values in decision situations 1, 2, 3, and 4 are -0.284, -0.245, -0.255, and -0.086, respectively (see Table 20). Clearly, the levels of these mean values are not in the direction suggested by the hypothesis.

As the number of alternatives is higher than the number of attributes in all of the decision situations, the *SI* measure is biased in the direction of an attribute-wise search strategy, and therefore, the *SM* measure might better represent the direction of search (see Chapter 4). The results suggest that the average value of *SM* is higher when task complexity is lower. As indicated in Table 21, the respective *SM* mean values of -0.239, -0.779, -1.357, and -1.423 in decision situations 1, 2, 3, and 4 are in the direction predicted by the hypothesis. This implies that the participants used a type of attribute-wise search strategy in the higher levels of task complexity, while they exhibited a more alternative-wise search pattern in the lower levels. However, contrary to the expectations, although the *SM* means are in the hypothesized direction, the null hypothesis of no difference in the direction of search cannot be rejected (F (2, 54) = 2.290, p = 0.111). In other words, the effect of task complexity on the *SM* is not statistically significant. The finding by Schrah et al. (2006) confirms the results of this study that the search pattern (direction of search) varies insignificantly as a function of task complexity. However, this contradicts a number of studies (e.g., Payne, 1976; Roe et al., 2001; Katz et al., 2010; Queen et al., 2012), which found that increased task complexity has a significant effect on the direction of search. Differences between the findings of this study and previous work can be accounted for by the difference in the MCDA methods used (see H3a).

H6d: *Increased task complexity in the GIS-MCDA group mode results in a direction of search that is more attribute-wise than alternative-wise*. Likewise in the individual mode, it was expected that participants in the lower complexity levels would use a relatively more alternative-wise strategy than an attribute-wise processing strategy. Clearly, neither the mean *SI* values nor the mean *SM* values in decision situations 1, 2, 3, and 4 are in the predicted direction (see Tables 22 and 23). In addition, the ANOVA results indicate that there were statistically insignificant differences in the *SM* measures between the decision situations (F (2, 21) =0.140, p = 0.898), as was the case in the individual mode. Consequently, the evidence cannot support the hypothesis.

Table 22. Descriptive statistics for the *SI* in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	-0.246	0.552	-1.000	1.000
2	10×4	-0.195	0.603	-1.000	1.000
3	15×6	-0.270	0.626	-1.000	1.000
4	20×8	-0.160	0.632	-1.000	1.000

Table 23. Descriptive statistics for the *SM* in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.023	1.130	-3.090	2.030
2	10×4	-0.180	2.060	-5.750	4.360
3	15×6	-0.700	2.270	-5.640	3.460
4	20×8	-0.340	3.010	-10.440	5.890

Hypotheses 7

H7a: *In the GIS-MCDA individual mode, the total time spent acquiring the information in the decision table significantly increases with an increase in task complexity*. According to this hypothesis, increased task complexity results in an increase in the total time spent in the decision table. Table 24 shows the descriptive statistics for the total time spent in the four decision situations. The respective mean times of 20.92, 32.41, 44.52, and 34.18 seconds in decision situations 1, 2, 3, and 4, respectively, indicate that the amount of time spent across the decision situations are not in the hypothesized direction.

Table 24. Descriptive statistics for the total time spent on the table under the use of the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	20.920	33.370	0.000	168.000
2	10×4	32.410	46.840	0.000	211.000
3	15×6	44.520	124.720	0.000	911.000
4	20×8	34.180	40.920	0.000	189.000

Given the null hypothesis of no difference in total time among the decision situations, the ANOVA test gives a *p*-value of 0.368 (F (3, 162) = 1.06, p = 0.368). This provides evidence that the null hypothesis of no difference should be accepted. Therefore, one can conclude that task complexity in the individual mode has an insignificant effect on the total time spent acquiring the information in the decision table. These results are inconsistent with the previous findings by Chinburapa (1991) and Queen et al. (2012). The possible reasons for the discrepancy between these findings might be those described for H3a.

H7b: *In the GIS-MCDA group mode, the total time spent acquiring the information in the decision table significantly increases with an increase in task complexity.* Similar to the individual mode, participants were expected to spend more time on the information pieces in the high-complexity tasks than the low-complexity tasks. Descriptive statistics for the total time in the group mode are shown in Table 25. Looking at the table, we note that the respective decision times of 6.27, 5.94, 6.16, and 10.27 seconds in decision situations 1, 2, 3, and 4 are not in the hypothesized direction. The ANOVA results suggest that there is a statistically insignificant difference in the total times among the decision situations, similar to the individual mode (F (3, 162) = 1.250, p = 0.294). Therefore, the hypothesis is rejected.

Table 25. Descriptive statistics for the total time spent on the table under the use of the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	6.270	9.400	0.000	48.000
2	10×4	5.940	10.470	0.000	47.000
3	15×6	6.160	8.730	0.000	41.000
4	20×8	10.270	23.270	0.000	163.000

Hypotheses 8

H8a: *Under the use of the GIS-MCDA individual mode, participants spend more time on the map in the high-complexity tasks than the low-complexity tasks*. Table 26 summarizes the descriptive statistics for time spent on the map in the four decision situations. It is evident that the respective mean times of 1.32, 0.74, 2.27, and 2.32 seconds in decision situations 1, 2, 3, and 4 are not in the hypothesized direction. Under the null hypothesis of no difference in the mean times, this difference is associated with a p-value of 0.612 (F (2, 133) = 0.55, p = 0.612). Consequently, the null hypothesis of no difference is accepted and therefore one can conclude that the time spent on the map in the GIS-MCDA individual mode is not influenced by task complexity. These results are inconsistent with previous findings by Jankowski and Nyerges (2001a). They reported that the maps were used more in the simple task than in the complex situation. Although both Jankowski and Nyerges (2001a) study and this research investigated the effect of task complexity on information acquisition times within a collaborative GIS-MCDA context, the discrepancy between the findings may be due to the use of different GIS-MCDA methods, decision problems, and/or decision making platforms (Web-based vs. Desktop-based) in the empirical studies.

Table 26. Descriptive statistics for the total time spent on the map in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	1.320	6.810	0.000	42.000
2	10×4	0.745	4.270	0.000	31.000
3	15×6	2.270	10.350	0.000	60.000
4	20×8	2.320	7.830	0.000	45.000

H8b: *Given the use of the GIS-MCDA group mode, participants spend more time on the map in the high-complexity tasks than the low-complexity tasks.* The mean times in decision situations 1, 2, 3, and 4 are 0.52, 0.80, 0.61, and 0.09 seconds, respectively (see Table 27). Similar to the individual mode, the mean times are not in the expected direction. In addition, the ANOVA results indicate that there were statistically insignificant differences in the mean times (F (2, 123) = 0.64, p = 0.549). Therefore, the hypothesis cannot be accepted.

Table 27. Descriptive statistics for the total time spent on the map in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.527	2.480	0.000	14.000
2	10×4	0.800	3.210	0.000	19.000
3	15×6	0.618	3.740	0.000	27.000
4	20×8	0.090	0.674	0.000	5.000

H8c: *In the GIS-MCDA individual mode, participants have a higher number of moves on the map in the high-complexity tasks than the low-complexity tasks*. Table 28 shows the descriptive statistics for the mean number of map moves in the four decision situations. The mean map moves in decision situations 1, 2, 3, and 4 are 0.30, 0.07, 0.18, and 0.61, respectively. Thus, these values are not in the hypothesized direction. The ANOVA results for this hypothesis indicate that there is an insignificant difference in the number of map moves among the four experimental conditions (F (1, 99) = 1.48, p = 0.233).

Table 28. Descriptive statistics for the number of map moves in the GIS-MCDA individual mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.309	1.650	0.000	13.000
2	10×4	0.072	0.325	0.000	2.000
3	15×6	0.181	0.795	0.000	5.000
4	20×8	0.618	2.230	0.000	12.000

H8d: *In the GIS-MCDA group mode, an increase in task complexity results in an increase in the number of the map moves.* Similar to the individual mode, participants were expected to have a higher number of moves in the higher levels of task complexity than the lower levels. The difference in the number of map moves between the decision situations was expected to be significant. Table 29 shows the descriptive statistics for the map moves in the four decision situations. The results indicate that the mean values for the map moves are not in the anticipated direction. The effects of task complexity on the number of map moves was found to be statistically insignificant (F (1, 66) = 1.60, p = 0.211), as was the case in the individual mode. Therefore, the hypothesis is not supported by the evidence.

Table 29. Descriptive statistics for the number of map moves in the GIS-MCDA group mode.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	0.363	1.740	0.000	11.000
2	10×4	0.145	0.558	0.000	3.000
3	15×6	0.072	0.325	0.000	2.000
4	20×8	0.018	0.134	0.000	3.000

Hypotheses 9

H9: *Increased task complexity results in a significant increase in the amount of time spent viewing the group decision*. Participants were expected to spend more time on examining the group decision in the higher levels of task complexity as compared to the lower ones. Table 30 summarizes the descriptive statistics for the time spent viewing the group decision in the four decision situations. The respective mean times in decision situations 1, 2, 3, and 4 are 10.92, 17.09, 27.01, and 16.87 seconds, respectively. Clearly, the differences in the mean times are not in the same direction as suggested by the hypothesis. Under the null hypothesis that there is no difference in the total time spent, the ANOVA test gives a significant level of 0.283 (F (1, 75) = 1.24, p = 0.283). This means that the null hypothesis of no difference should be accepted, or alternatively that the task complexity has an insignificant impact on the time spent examining the group decision. These results contradict the early findings reported by Jankowski and Nyerges (2001a), Schrah et al. (2006), and Gino and Moore (2007). Jankowski and Nyerges (2001a) found that, in the collaborative GIS-MCDA context, participants examine the group decision (consensus aids) more in the complex task than the simple task. Schrah et al. (2006) suggest that decision makers discount the choice advice or recommendations less when tasks are complex. The inconsistency between the findings is probably due to a difference in the use of GIS-MCDA methods (OWA-base method vs. weighted summation method), platforms (Desktop-based vs. Web-based), decision problems, decision making methods, etc. (see H3a).

Table 30. Descriptive statistics for the time spent viewing the group decision.

Level of task complexity	(Alternatives × Attributes)	Mean	Std. Deviation	Minimum	Maximum
1	5×2	10.920	15.780	0.000	80.000
2	10×4	17.090	25.640	0.000	140.000
3	15×6	27.010	77.780	0.000	500.000
4	20×8	16.870	25.480	0.000	140.000

6.2 The effect of decision mode on the information acquisition metrics

H10a: *There is a significant difference between the proportions of information search in the GIS-MCDA individual and group modes.* The null hypothesis is that the decision mode has no influence on the proportion of information search. The hypothesis was tested by comparing the mean proportion of information searched in the two decision modes. The comparison illustrates that this metric is higher in the individual mode than that in the group mode (see Figure 27). For the effect of the decision mode, the LMM test results give a *p*-value of 0.010 (F =7.24, p =0.010 < 0.05), thereby rejecting the null hypothesis and suggesting there is a statistically significant difference in the proportion of information searched between the two decision modes. In other words, there is sufficient evidence from the data to conclude that decision makers search a significantly different proportion of the available information in the GIS-MCDA individual mode as compared to the group mode. This is consistent with the findings reported by Schrah et al. (2006) that the information acquisition strategies differ between the decision situations where recommendations are provided (advice acquisition) and those where they are not. They found that recommendations concerning the choice of one or more specific alternatives affect the information acquisition strategies (e.g., the proportions of information search) used by the decision makers (see also Bonaccio & Dalal, 2006). Consequently, it is likely that the representation of the group/consensus ranking of alternatives as the choice recommendations influence the way that participants acquire and integrate information in their individual decisions.

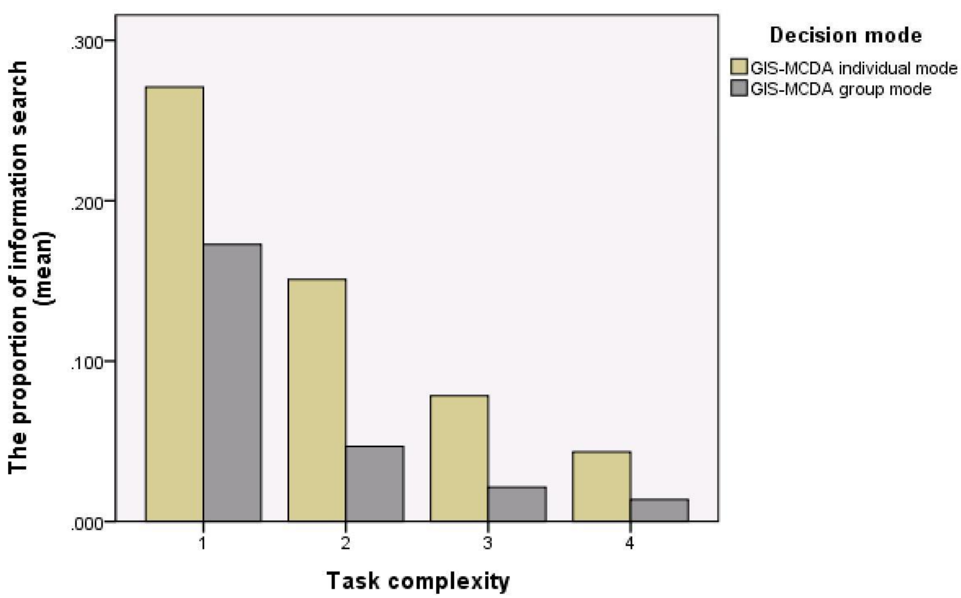


Figure 27. A comparison between the proportions of information search in the two decisions modes.

H10b: *The difference in the proportion of attribute ranges searched between the GIS-MCDA individual and group modes is significant*. The null hypothesis states that the decision mode has no impact on the proportion of attribute ranges searched. By comparing the proportion of attribute ranges searched in the two decision modes, it is evident that this variable in the individual decision mode is higher than that in the group mode (see Figure 28). The LMM test results suggest that the null hypothesis of no difference between the two decision modes in terms of the proportion of attribute ranges searched should be rejected (F = 16.92, p = 0.001 < 0.05). Therefore, one can conclude that there is a significant difference in the proportion of attribute ranges examined between the two decision modes.

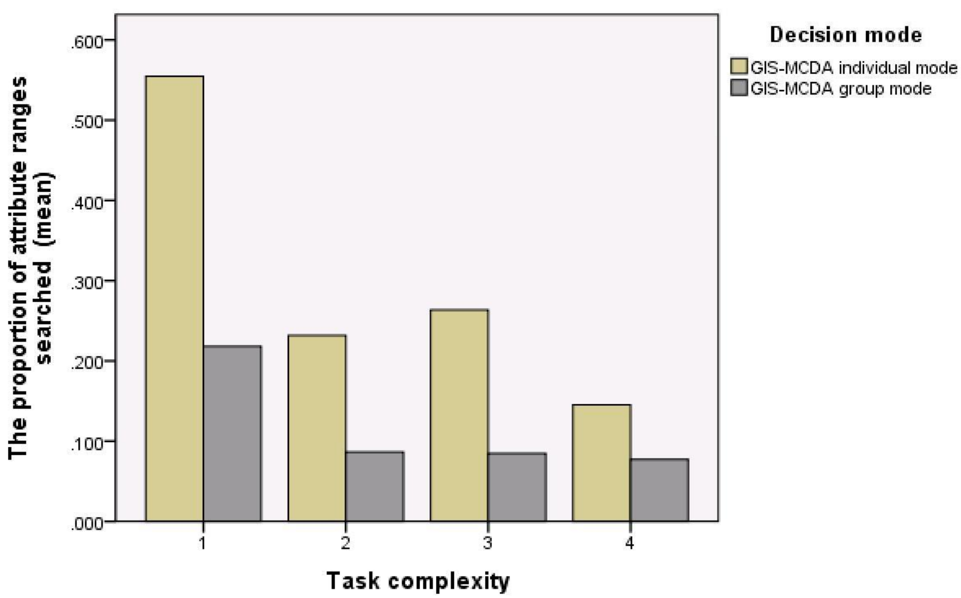


Figure 28. A comparison between the proportions of attribute ranges searched in the two decisions modes.

H10c: *The amount of average time spent on each piece of information acquired is significantly different between the two decision modes.* The null hypothesis is that the amount of average time spent on each piece of information is not affected by the decision mode. By comparing the average decision time between the two decision modes in the four experimental conditions (see Figure 29), one can indicate that the time spent acquiring the information pieces in the individual mode is more than that in the group mode. Under the null hypothesis that there is no difference in the average decision time between the two decision modes, the LMM test gives a *p*-value of 0.033 (F = 5.04, p =0.033 < 0.05). This suggests that there is a significant difference in the average decision time between the two decision modes.

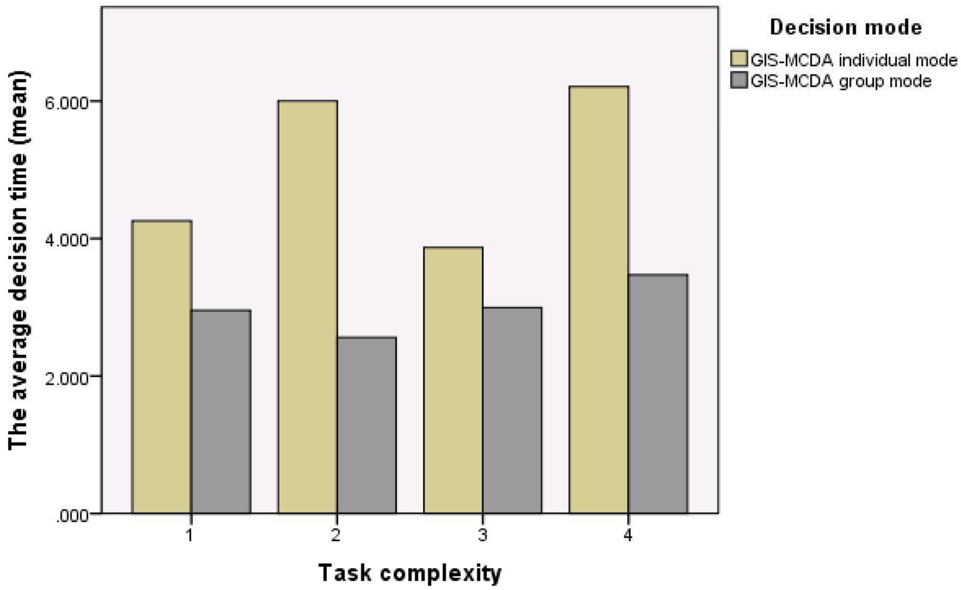


Figure 29. A comparison between the average decision times in the two decision modes.

H10d: *There is a significant difference in the variability of information search per attribute between the GIS-MCDA individual and group decision modes*. The null hypothesis states that the two decision modes are not significantly different in terms of the variability of information searched per attribute. Comparing the mean variability values of the information searched between the two modes indicates that the variability is higher in the individual mode as compared to the group mode (see Figure 30). The results indicate that there is a statistically significant difference in the variability of information searched between the two modes of GIS-MCDA. For the decision mode effect, the LMM test gives a *p*-value of 0.047 (F =4.63, p = 0.047 < 0.05), thereby suggesting that we reject the null hypothesis, or alternatively that the decision mode has an insignificant impact on the variability of information searched per attribute. These findings are consistent with the suggestion by Schrah et al. (2006), that recommendations regarding which alternative to choose have an influence on the variability of information search per attribute. Consequently, the group recommendations regarding the rankings of decision alternatives significantly affect the variability of information search per attribute.

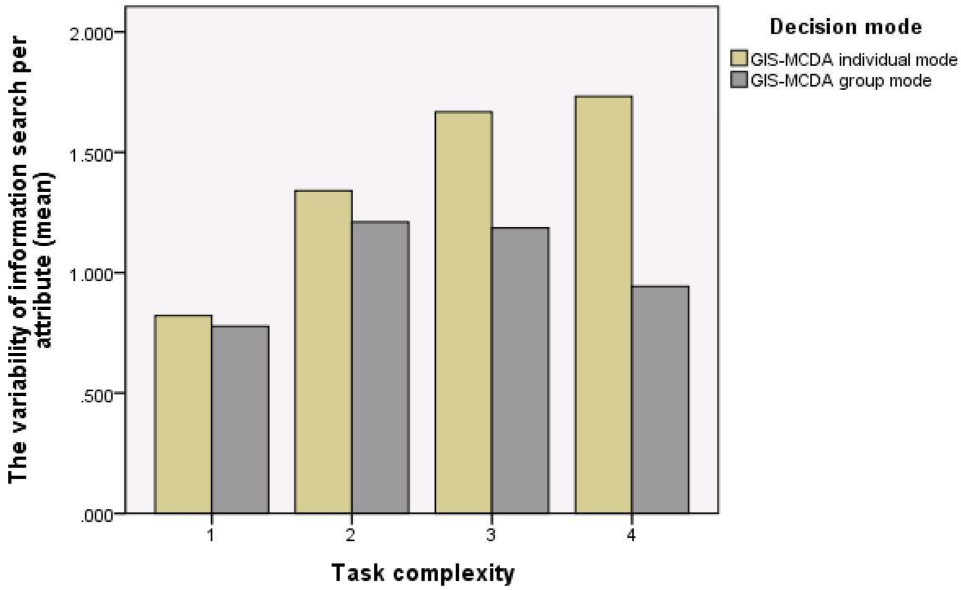


Figure 30. Comparing the variability of information search per attribute in the two decisions modes.

H10e: *There is a significant difference in the variability of information search per alternative between the GIS-MCDA individual and group decision modes*. The null hypothesis is that the decision mode has no influence on the variability of information search per alternative. Figure 31 shows a comparison of information searched per alternative between the two decision modes in each of the four decision situations. A comparison of the mean variability values in the two decision modes indicates that the variability is pretty much the same in the two decision modes. This is confirmed by the LMM results, indicating that the observed difference in the variability is not statistically significant (F = 1.47, p = 0.233). Thus, this hypothesis is not supported by the evidence (see also Schrah et al., 2006).

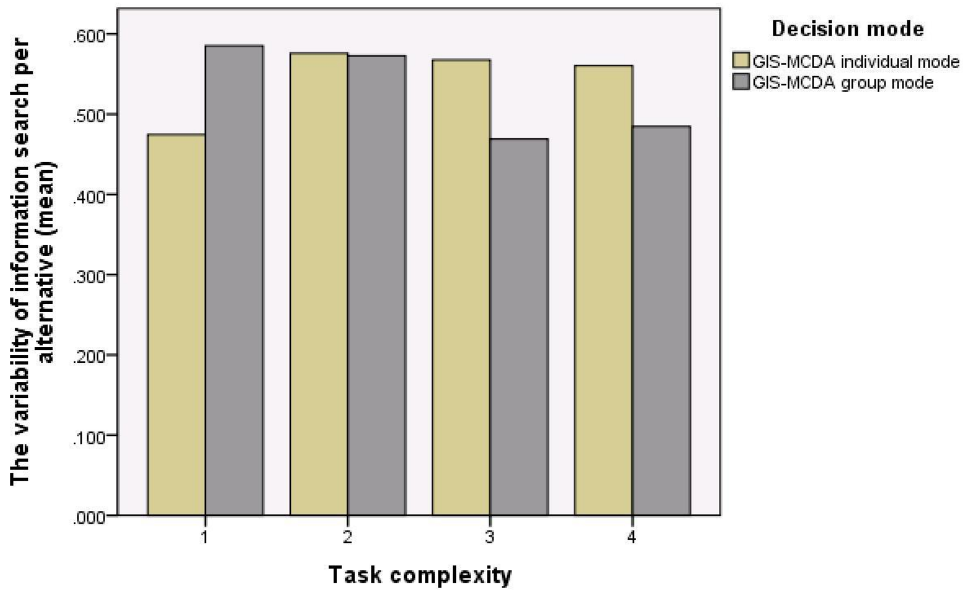


Figure 31. A comparison between the variability of information search per alternative in the two decision modes.

H10f: *The direction of information search is significantly different between the GIS-MCDA individual and group decision modes*. The null hypothesis states that there is no difference between the directions of information search in the two decision modes. Participants were expected to adopt different information search directions when the decision mode was changed. Comparing the *SI* and *SM* mean values in the two modes suggests that the participants used different search patterns in the two decision modes (see Figures 32 and 33). The LMM results for differences in the direction of information searched between the two decision modes gives a *p*-value of 0.570 (F = 0.32, p = 0.570) and 0.421 (F = 0.67, p = 0.421) for *SI* and *SM*, respectively. This implies that the null hypothesis of no difference cannot be rejected (or the decision mode has an insignificant impact on the directions of information search). It provides evidence that the direction of information search in the individual decision mode is insignificantly different from that in the group decision mode. The result contradicts Schrah et al. (2006) findings. In their research, the effect of advice acquisition (choice recommendation) on search pattern was found significant at the low and medium complexity levels, and insignificant at the high level of task complexity. The possible reasons for the discrepancy between the findings of this study and Schrah et al. (2006) findings might be those discussed with reference to H3a .

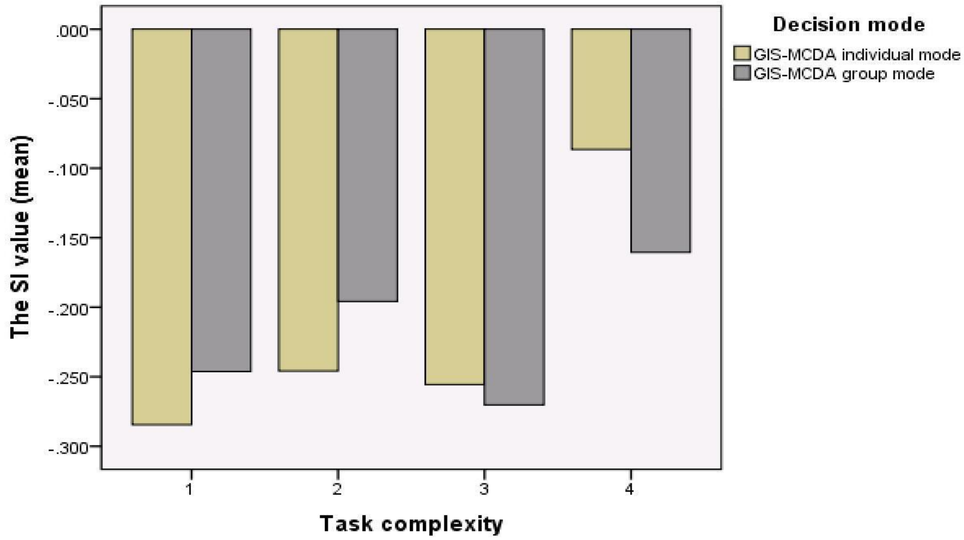


Figure 32. A comparison between the directions of information search (*SI* index) in the two decision modes.

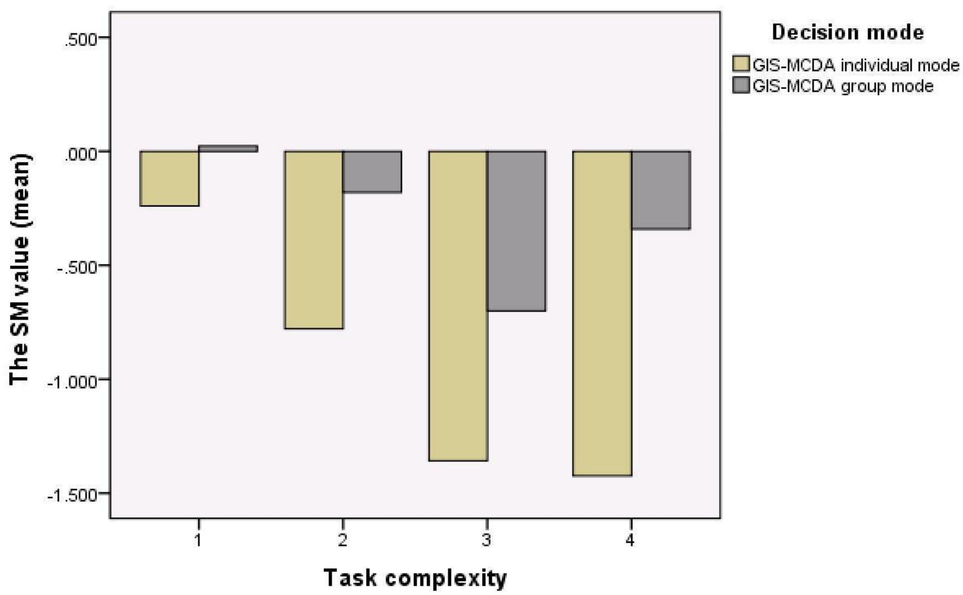


Figure 33. A comparison between the directions of information search (*SM* index) in the two decision modes.

H10g: *There is a significant difference in the total time spent acquiring information in the decision table between the GIS-MCDA individual and group decision modes*. The null hypothesis states that the decision mode has no influence on the total time spent acquiring information in the decision table. It was expected that the difference in the total time between the two decision modes would be significant. A comparison of the mean times in the two modes confirms that the participants spent different amounts of time in the two decision modes (see Figure 34). Given the null hypothesis of no difference in the total time between the two decision modes, the LMM test gives a p-value of 0.000 (F = 34.86, p = 0.000). This suggests that the null hypothesis of no difference in the total time should be rejected, meaning that the total time spent in the individual decision mode is significantly different from that in the group mode.

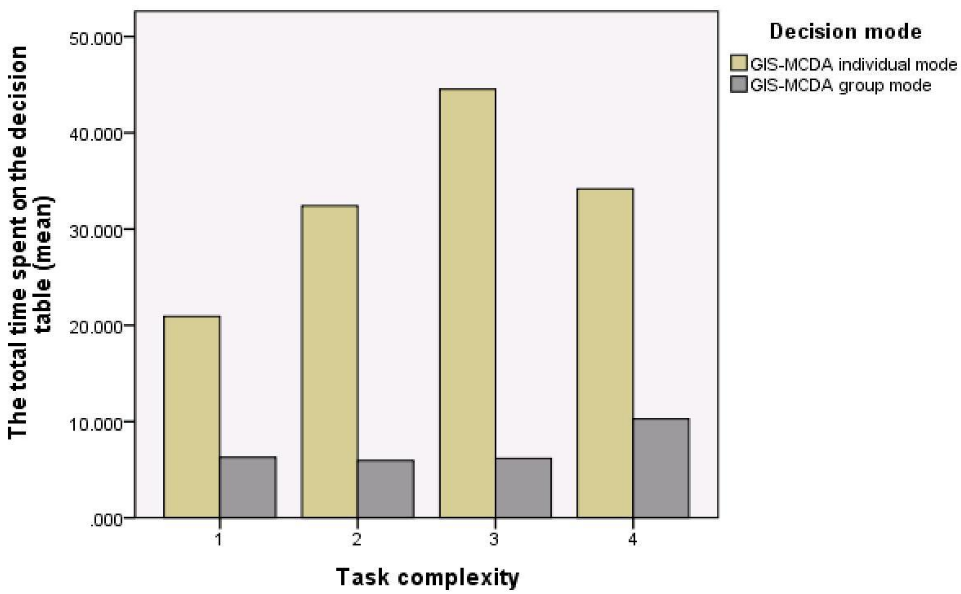


Figure 34. A comparison between the total times spent acquiring the information in the two decision modes.

H10h: *The total time spent on the map is significanttly different between the GIS-MCDA individual and group decision modes*. The null hypothesis is that the total time spent on the map is not influenced by the decision mode. By comparing the mean times for the two modes in the four experimental conditions, it becomes clear that the total time spent on the map in the individual mode differs from that in the group mode (see Figure 35). However, under the null hypothesis that there is no difference in the decision times between the two decision modes, the LMM test gives a p-value of 0.168 (F = 1.95, p = 0.168). This suggests that there is an insignificant difference in the decision time spent on the map between the decision modes. The lack of significant difference may be, in part, due to the fact that the decision makers focus more on the decision table than the map. In other words, the use of a map in the two decision modes is insignificant, and therefore the difference is intangible.

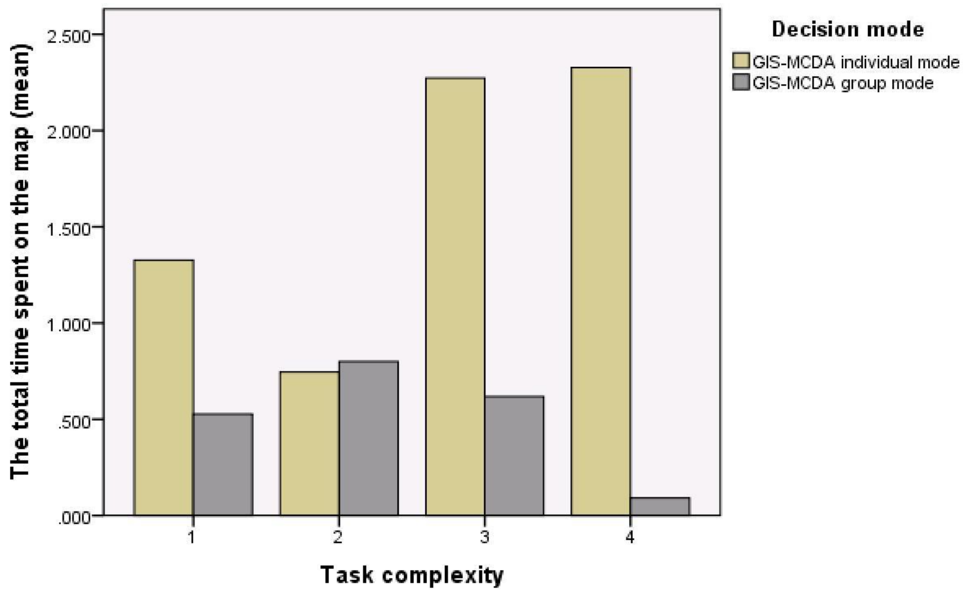


Figure 35. A comparison between the total times spent on the map in the two decision modes.

H10i: *There is a significant difference in the number of map moves between the two decision modes*. The null hypothesis states that the decision mode has no significant effect on the number of map moves. A comparison between the number of map moves in the two decision modes is shown in Figure 36. For the decision mode effect, the LMM test gives a p-value of 0.722 (F = 0.12, p = 0.722), thereby suggesting that the null hypothesis of no difference in the total map moves should be accepted. Thus, the hypothesis has not been supported by the evidence.

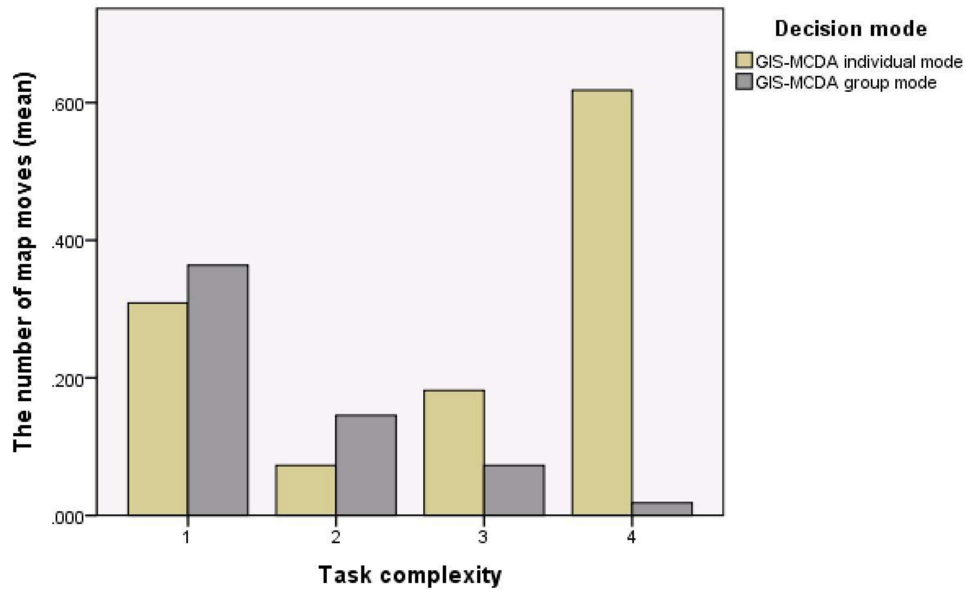


Figure 36. A comparison between the number of map moves in the two decision modes.

6.3 The effect of aid on the information acquisition metrics

Hypotheses 11

H11a: *In the use of the GIS-MCDA individual mode, the number of moves in the decision table is significantly higher than that on the map*. Participants were expected to have a higher number of moves in the decision table than on the map. Figure 37 shows a comparison between the numbers of moves in the table and map for each of the four decision situations. As indicated in the figure, the number of table moves is higher than the number of map moves. Under the null hypothesis that there is no difference in the number of moves between the decision table and map, the LMM test gives a p-value of 0.000 (F = 39.05, p = 0.000< 0.05). This provides the evidence to reject the null hypothesis and conclude that the number of table moves is significantly higher than the number of map moves. The possible reasons for using the decision table more than the map could be: (i) the importance of information that decision table represents, and (ii) the way that it represents the information. Although both the map and table representations complement each other, they contain different information (criteria outcome vs. geographic decision space) in fundamentally different ways. The map represents the spatial information relevant with the geographic decision space using a graphical structure, while the table emphasizes symbolic information, and uses a precise yet compact way for representing criteria outcome space. Speier (2006) argues that data visualized using such techniques as graphs, scatterplot displays, tables, and maps allows the decision-maker to shift some of the cognitive processing burden to perceptual operations that typically occur automatically and result in significantly lower mental workload (see also Dennis & Carte, 1998; Kim, Hahn, & Hahn, 2000). Therefore, it is reasonable to expect that the types of decision aids offered in the GIS-MCDA environment have a significant influence on the number of times that they are used and the way they are brought into use.

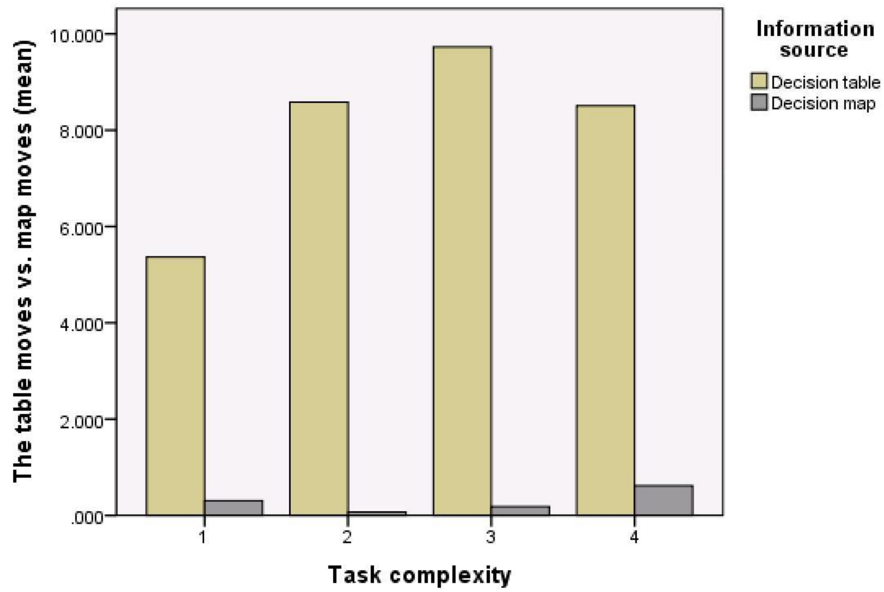


Figure 37. A comparison between the number of table and map moves in the individual decision mode.

H11b: *Under the use of the GIS-MCDA group mode, the number of moves in the decision table is significantly higher than that on the map*. Similar to the individual mode, participants were expected to have a higher number of moves in the decision table than the map. A comparison of the moves between the table and map for each of the decision situations is presented in Figure 38. The results suggest that the number of moves in the decision table is higher than that on the map, as was observed in the individual mode. Given the null hypothesis of no difference in the number of moves between the decision table and map, the LMM test gives a significance level of 0.000 (F = 52.69, p = 0.000< 0.05); therefore, we reject the null hypothesis and suggest that the number of table moves is significantly higher than map moves.

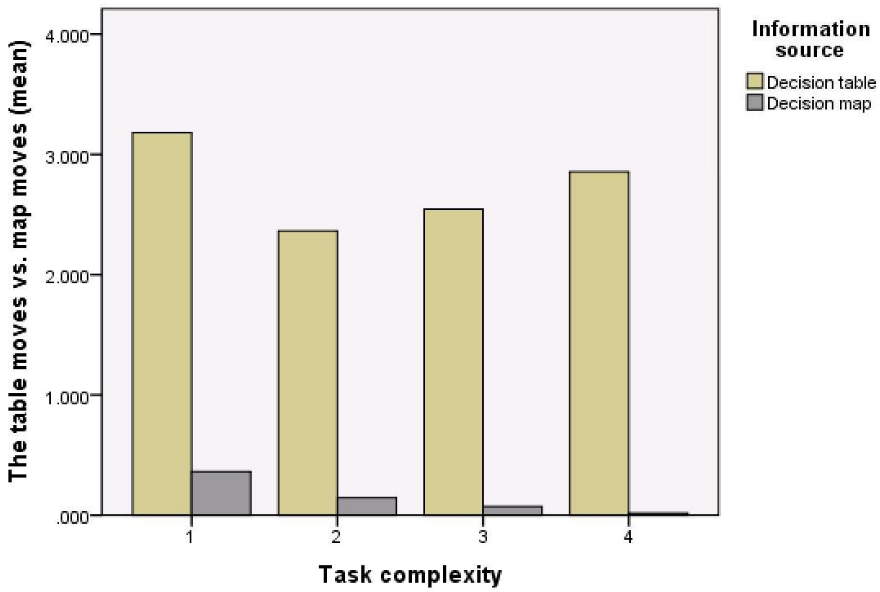


Figure 38. A comparison between the number of table and map moves in the GIS-MCDA group mode.

H11c: *In the GIS-MCDA individual mode, the amount of time spent on the decision table is significantly more than that on the map*. Participants were expected to spend more time acquiring the information in the table than the map. Figure 39 shows a comparison of the time spent between the decision table and map in each of the four decision situations. As can be seen from the figure, the time spent examining the information pieces in the decision table is higher than that on the map. The LMM test results indicate that one should reject the null hypothesis that there is no difference in the amount of time spent between the decision table and map. In other words, there is a statistically significant difference in the time spent between the table and map ($F = 62.29$, $p = 0.000 < 0.05$). This means that participants spent a significantly higher amount of time on information acquired in the decision table than the map.

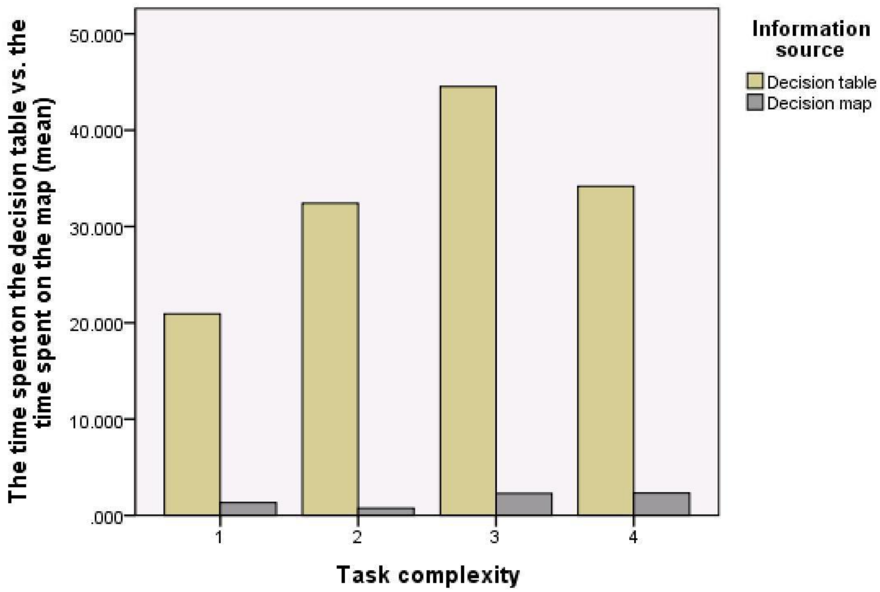


Figure 39. A comparison between the time spent on the decision table and map in the GIS-MCDA individual mode.

H11d: *In the GIS-MCDA group mode, the amount of time spent on the decision table is significantly more than that on the map*. Comparing the time spent between the table and map confirms that participants spent more time on the table than the map, as was observed in the individual mode (see Figure 40). As the LMM test results suggest (F = 56.13, $p = 0.000 < 0.05$), the null hypothesis of no difference in the time spent between the decision table and map should be rejected. This means that, similar to the individual mode, the participants spent significantly more time examining the decision table than the map. This is consistent with the findings of the previous study by Jankowski and Nyerges (2001b). They found that, in the group GIS-MCDA setting, participants tend to spend a longer time on the decision table than the map. Similar arguments to the ones made for the hypothesis H11a can be applied here to explain why participants tend to spend more time on the use of the decision table, rather than the map.

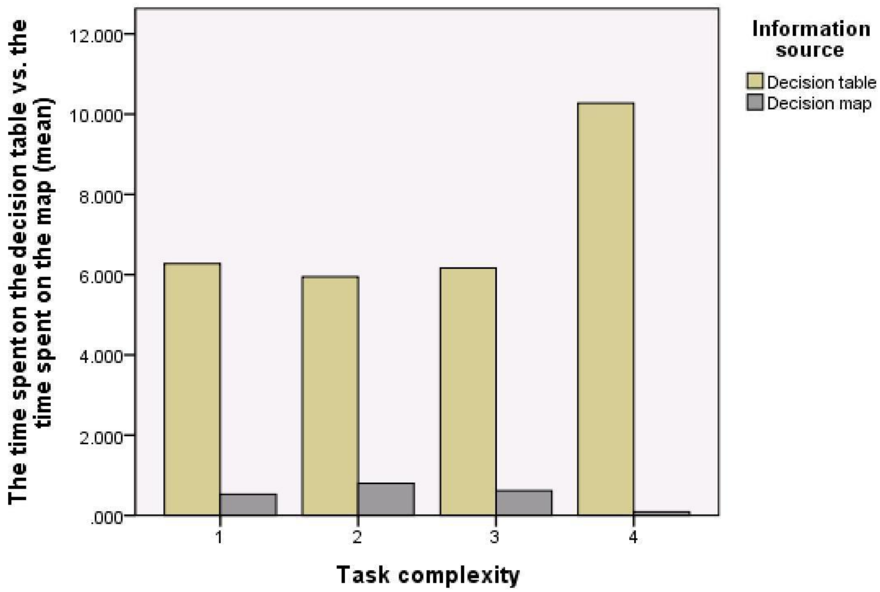


Figure 40. Comparing the time spent on the decision table and map in the GIS-MCDA group mode.

H11e: *In both the GIS-MCDA individual and group modes, there is a significant correlation between the time spent on the decision table and the time spent on the map across the decision situations*. Within the individual decision mode, the Pearson correlation coefficients show that these two metrics are positively correlated in each of the decision situations (see Table 31). However, the metrics are either weakly or insignificantly correlated with each other in all of the decision situations, except for decision situation 2, in which the correlation is significant. As regards the group mode, the direction of correlation varies across the decision situations. The two metrics are positively correlated in the former decision situations and negatively in the latter decision situations. Except for decision situation 1, there is an insignificant relationship between the two metrics. Consequently, there is not enough evidence to support the hypothesis.

H11f: *Given the use of both the GIS-MCDA individual and group modes, there is a significant correlation between the number of table moves and the number of map moves*. Examining the correlation coefficients in the GIS-MCDA individual mode indicates that the correlations are not in the same direction across the decision situations (see Table 31). Specifically, the number of table and map moves are either weakly or insignificantly correlated with each other in all of the decision situations, except for decision situation 2, in which the correlation is moderate and significant. These findings are consistent with other studies on information acquisition behavior in the GIS-MCDA context (Jankowski & Nyerges, 2001a; Meng, 2010). For example, Jankowski and Nyerges (2001a) found a very weak relationship between the table and map moves. They suggested that the map and table moves are not likely to occur in a systematic manner across decision tasks. When it comes to the correlations in the group mode, the two metrics are significantly and moderately correlated with each other in the former decision situations and either weakly or insignificantly correlated in the latter conditions. Accordingly, the evidence cannot support the hypothesis.

Table 31. The correlation between the time spent on the table and map, as well as the table and map moves.

	GIS-MCDA individual mode				GIS-MCDA group mode			
Decision situation	1	2	3	4	1	2	3	4
TT and *MT*	0.165	0.294*	0.053	0.096	0.285*	0.209	-0.079	-0.008
TM and *MM*	-0.046	0.329*	-0.056	0.100	0.769**	0.414**	-0.067	0.005

Note: ** significant at $p < 0.01$, *significant at $p < 0.05$, *TM* = the number of table moves, *TT* =the time spent on the decision table, *MM* = the number of map moves, *MT* = the time spent on the map.

6.4 The relationship between time spent examining the decision table/map and the time spent viewing the group decision

Hypothesis 12

H12a: *There is a significant relationship between the time spent on the map and the time spent viewing the group decision in the GIS-MCDA group mode*. As shown in Table 32, the correlation coefficients are weak and insignificant in all of the four decision situations. The results suggest there is an insignificant relationship between the time spent on the map and the time spent viewing the group decision. The lack of a relationship implies that those who spend a great or low amount of time acquiring information on the map do not necessarily spend this same amount of time examining the consensus ordering of alternatives and group discussions on the group decision map. These results are somehow consistent with the findings reported by Jankowski and Stasik (2006) and Meng (2010). For example, Meng (2010) found that there is a relatively low and insignificant correlation between the use of mapping functions and group deliberation/argumentation functions in a collaborative GIS-MCDA process. The use of the decision table and the group decision map in this study reflect the use of MCDA functions and deliberation/argumentation functions, respectively.

H12b: *In the GIS-MCDA group mode, there is a significant relationship between the time spent on the decision table and the time spent viewing the group decision*. The correlation coefficients show that these two metrics are positively correlated in all of the decision situations (see Table 32). However, the positive correlations are fairly low, and insignificant in decision situations 2 and 4. The correlation overall shows that those decision makers spending more time on the examination of information in the decision table are likely to spend more time on viewing the group decision, and vice versa. To some extent, the correlation results corroborate the finding reported by Meng (2010). He found that there is a statistically significant, moderate and positive relationship between the number of MCDA functions used and the number of group deliberation functions in the context of a collaborative GIS-MCDA.

Table 32. The correlation coefficients between the time spent on the decision table/ map and time spent viewing the group decision.

	Decision situation			
	1	2	3	4
MT and *GT*	-0.117	0.118	0.056	0.017
TT and *GT*	0.278^{*}	0.026	0.355^{**}	0.202

Note: ** significant at $p < 0.01$, * significant at $p < 0.05$, *MT* = the time spent on the map; *GT* = the time spent viewing the group decision; *TT* = the time spent on the decision table.

6.5 The relationship between information acquisition metrics

Hypothesis 13

H13: *There is a significant relationship between the information acquisition metrics across the decision situations.* This hypothesis was tested using the Pearson correlation coefficient for a pair of metrics. As shown in Table 33, there is an insignificant and fairly weak relationship between the proportion of information search and the proportion of attribute ranges examined. In addition, the direction and value of the correlation differ across the decision situations in both the individual and group modes. It can be concluded that there is an insignificant relationship between these two metrics. This implies that the examination of available information cells (alternative-attribute values) is not proportional to the examination of attribute ranges, and vice versa.

Table 33. The correlation coefficients among the information acquisition metrics in the decision table.

	Decision situation							
	GIS-MCDA individual mode				GIS-MCDA group mode			
	1	2	3	4	1	2	3	4
P and *R*	-0.053	0.239	0.070	-0.051	-0.071	-0.255	-0.365	-0.301
P and *SI*	-0.464**	-0.339*	-0.385**	-0.515**	-0.399*	-0.330	-0.394	-0.190
P and *SM*	-0.475**	-0.654**	-0.818**	-0.744**	-0.330	-0.570**	-0.550**	-0.311
P and *AT*	-0.077	-0.189	0.083	-0.271	-0.241	0.011	-0.383*	-0.047
P and *VAL*	-0.535**	-0.044	0.505**	0.350*	-0.300	0.330	0.624**	0.451*
P and *VAT*	-0.064	0.505**	0.813**	0.874**	0.172	0.879**	0.834**	0.786**
R and *SI*	0.028	0.067	-0.038	-0.138	-0.187	-0.119	-0.203	-0.135
R and *SM*	-0.030	-0.238	-0.192	-0.204	-0.243	-0.277	-0.075	-0.123
R and *AT*	-0.028	0.093	0.354*	0.022	-0.096	-0.104	-0.050	-0.016
R and *VAL*	-0.066	-0.150	-0.015	-0.044	-0.218	-0.296	-0.285	-0.218
R and *VAT*	-0.101	0.076	0.097	0.158	0.079	0.169	-0.080	-0.035
AT and *SI*	0.126	0.204	0.175	0.101	0.196	0.215	-0.060	0.357
AT and *SM*	0.218	0.165	-0.118	0.151	0.187	0.182	-0.009	0.471

AT and *VAL*	0.105	-0.139	0.116	-0.206	0.270	0.132	-0.256	0.594*
AT and *VAT*	0.020	-0.181	0.010	-0.232	-0.041	-0.078	-0.151	-0.199
VAT and *SI*	-0.463**	-0.492**	-0.435**	-0.635**	-0.617**	-0.498*	-0.548**	-0.441*
VAT and *SM*	-0.391*	-0.619**	-0.852**	-0.890**	-0.834**	-0.782**	-0.831**	-0.764**
VAL and *SI*	0.623**	0.219	0.073	0.209	0.400*	0.275	0.171	0.380
VAL and *SM*	0.710**	0.470**	0.078	0.243	0.687**	0.411*	0.138	0.591**
VAL and *VAT*	-0.297	-0.123	0.022	-0.016	-0.560**	-0.069	0.269	-0.114

Note: ** significant at $p < 0.01$, * significant at $p < 0.05$, P = the proportion of information search, R = the proportion of attribute ranges examined, AT = the average decision time, VAT = the variability of information search per attribute, VAL = the variability of information search per alternative, SI = the search index, SM = the strategy measure (for definitions of the metrics see Chapter 4).

In the individual mode, the proportion of information search is either moderately and negatively correlated or significantly correlated with the direction metrics (i.e., the *SI* and *SM*) in all of the decision situations (see Table 33). This means that the greater the number of information (cells) examined by the decision maker, the lower the values of *SI* and *SM*, and therefore the more attribute-wise strategy is used. These results are inconsistent with the findings of the previous studies by Abdul-Muhmin (1994) and Stafford (2007), which show a positive correlation between the proportion of information searched and the direction of search. According to those studies, the greater the amount of information that is searched, the more likely an alternative-wise strategy is used. The discrepancy between the findings of this research and findings of the previously described studies may be explained by the differences in the methodological approaches or decision making techniques. The previous studies involved ranking the alternatives based on a set of attributes in a moderated experimental sessions, while the present study employed a Web-based GIS-MCDA technique in the decision making process (see H3a). Similar to the individual mode, the coefficients show a moderate and negative correlation between the two metrics in the group mode. However, the proportion of information search is insignificantly correlated with the direction metrics in all of the decision situations.

In the individual mode, the proportion of the information search and the average decision time are weakly and insignificantly correlated in all of the decision situations. In addition, the direction and value of the correlation differ across the decision situations. When it comes to the group mode, Table 33 shows a weak and insignificant correlation between the two metrics, except for decision situation 3, in which the correlation is significant. Also, the direction and value of the correlation varies across the decision situations, as was the case in the individual mode.

It is evident that, in the individual mode, the proportion of information search and the variability of information search per alternative are not strongly and significantly correlated in all of the four decision situations. In addition, the coefficients indicate that the significance level, direction, and value of the correlation vary across the decision situations. For the group mode, the coefficients show a low and insignificant value of the correlation coefficient for decision situations 1 and 2 and a significant and moderate correlation for decision situations 3 and 4. In addition, the significance level, direction, and values of the coefficient are different in the decision situations, as is observed in the individual mode.

In the individual mode, except for an insignificant correlation in the first decision situation, the proportion of the information search is strongly and significantly correlated with the variability of information search per attribute. The significance level and direction of the correlation in the first decision situation are different from those in the remaining decision situations. In the group mode, the two metrics are positively correlated. Similar to the individual mode, the two metrics are strongly and significantly correlated, except for the insignificant correlation in decision situation 1. Moreover, the significance level and value of the correlation in the first decision situation differ from those in other conditions, as is the case in the individual mode.

In both of the decision modes, the correlation between the proportion of attribute ranges on the one hand, and the direction of search (i.e., *SI* and *SM*), the average decision time, the variability of information search per alternative, and the variability of information search per attribute on the other hand is generally insignificant and relatively low (see Table 34). Similarly, in both of the decision modes, the correlation coefficients overall indicate an insignificant and weak relationship between the average decision time on the one hand, and the direction of search (i.e., *SI* and *SM*), the variability of information search per alternative, and the variability of information search per attribute on the other hand. The significance level, direction, and value of the correlation vary across the decision situations.

In both the individual and group decision modes, the variability of information search per attribute is either strongly (overall) and negatively correlated or significantly correlated with the direction of search (i.e., *SI* and *SM*). This means that the variability of information search per attribute increases as the participants use a more attribute-wise strategy during the information search. The correlation between the direction of search (*SI* and *SM*) and the variability of information search per alternative is positive and relatively low in both of the decision modes. Considering *SI* as the direction metric, the correlation is significant in the first decision situation in both the individual and group modes. With regard to *SM*, the correlation is significant in decision situations 1 and 2 in the individual decision mode, and 1, 2 and 4 in the group mode. The correlation coefficients show that, in the individual decision mode, the variability of information search per alternative is overall weakly and insignificantly related with the variability of information search per attribute. When it comes to the group decision mode, the correlation is significant only in the first decision situation. In addition, the direction and value of the correlation vary across the decision situations in both the individual and group modes.

6.6 The effect of task complexity on the relationship between the information acquisition in the decision table and map

Hypotheses 14

H14a: *In the GIS-MCDA individual mode, task complexity has an insignificant impact on the relationship between the time spent on the decision table and map*. The dependent variable was the time spent on the map, the covariate was the time spent on the decision table, and the factor was task complexity. Consistent with the expectations, the LMM results suggest that an increase in task complexity has an insignificant effect on the relationship between the table and map time (F = 0.82, p = 0.485). In other words, task complexity has no impact on the interaction between the geographic (decision) and criteria outcome spaces (the interaction between the map and table uses). There is, therefore, evidence from the data in support of the hypothesis.

H14b: *In the GIS-MCDA group mode, task complexity has an insignificant impact on the relationship between the time spent on the decision map and table*. Similarly with the individual mode, the LMM test results show that an increase in task complexity has an insignificant effect on the relationship between the two times (F = 1.51, p = 0.221). Thus, the hypothesis that the strength of the relationship between the two measures (the times spent on the decision map and table) is not moderated by the task complexity is confirmed. This is an indication that the interaction between the exploration of the geographic and criteria outcome spaces in the GIS-MCDA group mode is not affected by the complexity of decision task.

H14c: *In the GIS-MCDA individual mode, task complexity has an insignificant influence on the relationship between the number of map and table moves*. In the LMM test, the number of map moves was considered as the dependent variable and the table moves as the covariate. For task complexity effect, the LMM test gives a significant value of 0.156 (F = 1.814, p = 0.156), which means that task complexity has an insignificant effect on the relation between the map and table moves in the individual mode. This confirms the results of H14a; that is, task complexity has no effect on the interaction between the geographic and criteria outcome space. Consequently, the strength of the relationship between the table and map uses does not vary under different level of task complexity.

H14d: *In the GIS-MCDA group mode, task complexity has an insignificant influence on the relationship between the number of map and table moves*. Similarly with the individual mode, the LMM test results for this hypothesis indicate that task complexity has an insignificant effect on this relationship (F = 1.45, p = 0.236). This implies that task complexity has no effect on the interaction between the geographic and criteria outcome spaces. The result corroborates the findings reported by Jankowski and Nyerges (2001a). They found that, in the GIS-MCDA group mode, task complexity has an insignificant effect on the interaction between the number of map and table moves.

6.7 The effect of task complexity on the relationship between the time spent on the decision table/map and the group decision

Hypotheses 15

H15a: *In the GIS-MCDA group mode, increased task complexity has an insignificant influence on the relationship between the time spent viewing the group decision and the time spent on the decision table*. In the LMM test, the dependent variable was the time spent viewing the group decision, the covariate was the time spent on the decision table, and the factor was task complexity. For task complexity effect, the LMM test gives a significance value of 0.175 ($F = 1.71$, $p = 0.175$), indicating that the task complexity has an insignificant effect on the relationship. What this suggests is that the relationship between the times spent to explore the criteria outcome space in the decision table and to review the other participants' comments and group rankings of the alternatives on the group decision map is not affected by the task complexity.

H15b: *In the GIS-MCDA group mode, increased task complexity has an insignificant influence on the relationship between the time spent viewing the group decision and the time spent on the map*. The dependent variable was time spent viewing the group decision, the covariate was the time spent on the map, and the factor was task complexity. The LMM test gives a significance value of 0.975 ($F = 0.001$, $p = 0.975$) for task complexity effect, which means that task complexity has an insignificant effect on this relationship. Consequently, the relationship between the times spent for the acquisition of information on the map (the geographic decision space) and the examination of the group rankings of the alternatives and geo-referenced discussions on the group decision map is not influenced by the task complexity.

6.8 The effect of decision mode on the relationship between decision table and map

Hypotheses 16

H16a: *The decision mode has an insignificant effect on the relationship between the time spent searching for information using the decision table and map*. The dependent variable was the time spent searching the map while the covariate is the time spent looking for information in the decision table, and the factor is the decision mode (that is, individual versus group decision making). For the effect of the decision mode on this relationship, the LMM test results give a significance value of 0.666 (F = 0.18, p = 0.666). This implies that the interaction between the exploration of the geographic decision space and the criteria outcome space is not significantly different between the two decision modes. As was observed in the hypothesis 11, in both of the decision modes, the amount of time spent on the decision table is higher than that on the map. This in part confirms that the relationship between the table and map uses in the GIS-MCDA individual decision making mode differ insignificantly from that in the group mode.

H16b: *The decision mode has an insignificant impact on the relationship between the number of map and table moves*. In the LMM test, the factor was the decision mode and the covariate was the number of table moves whereas the dependent variable was the number of map moves. For the effect of the decision mode on this relationship, the LMM test gives a significance value of 0.887 (F = 0.02, p = 0.887). Clearly, there is enough evidence from the data in support of the hypothesis. Consequently, the relationship between the number of map and table moves is not significantly different between the two decision modes. This confirms that the interaction between the exploration of the geographic decision space and the criteria outcome space is not affected by the decision mode, as was the case for the hypothesis H16a.

Chapter 7

7 Conclusions

This chapter begins with an overview of the main findings and research contributions made by this thesis. It highlights the significant theoretical, technical, and empirical contributions of the thesis, as well as the potential implications of the overall findings. Next, a number of practical and theoretical limitations of the present study that need to be addressed are discussed. Finally, the chapter gives some prospective points, directions, and suggestions for future research.

7.1 Research contributions

The main purpose of the study was to examine human-computer interaction patterns within a Web 2.0- based collaborative MC-SDSS. Specifically, the study investigated: (i) how participants acquire decision-related information in making their individual decisions, and (ii) how the decision situations involving different levels of task complexity, types of information aids and decision modes affect the information acquisition strategies used by the decision makers. Through achieving these objectives, this research has made several theoretical, technical and empirical contributions to the research on Web 2.0-based collaborative MC-SDSSs.

7.1.1 Theoretical contribution

The major theoretical contributions of the research are the development of: (i) a collaborative GIS-MCDA framework and (ii) a conceptual model for studying information acquisition behavior in the collaborative GIS-MCDA context. The collaborative GIS-MCDA framework involves four main steps, including the acquisition of decision information, the specification of criteria preferences, and the computation of individual and group/consensus solutions using decision rules. During the information acquisition step, decision makers search for information on the alternatives, attributes, and attribute values in a decision table (criteria outcome space) or map (geographic decision space). This enables them to recognize the decision situation, and optimally specify their judgments and preferences with respect to the evaluation criteria. The approach employs a rank-order approach for specification of the criteria preferences; that is, every criterion under consideration is ranked in the order of the decision maker's preference. The rank-order method is simple, reliable, and requires less time to specify the criteria/attribute preferences (Bakhsh, 2008). The collaborative GIS-MCDA framework uses a decision rule that involves two stage procedures: (i) the MCDA decision rule for modeling the individual decision making (individual ordering of alternatives) based on the individual preferences and (ii) the collective decision rule for combining individual preferences to produce group preference (group ordering of alternatives). The first stage is operationalized by an OWA-based GIS-MCDA approach to create individual decision maker's solutions. The OWA-based method allows participants to define a decision strategy on a continuum between pessimistic and optimistic strategies. By changing a parameter (ORness value), a participant can control the level of decision risk and provide a low- or high- risk solution for the decision problem. The second stage employs the Borda voting method for aggregating the individual solutions to a consensus solution. The simplicity and comprehensibility are central advantages of the voting approaches for collaborative decision making (Malczewski, 2006b).

The second theoretical contribution was the development of a conceptual framework for investigating the information search behavior in the collaborative GIS-MCDA context. The framework provides a formal approach for the study of cognitive processes in the use of Web 2.0-based collaborative MC-SDSS, based on concepts drawn from behavioral decision theory and information processing psychology. Based on the research hypotheses (see Chapter 1) and the literature review (see Chapter 2), this study presented a set of information acquisition metrics to be used as a means of describing information acquisition behavior and decision strategies. The metrics for the information search fell within three broad categories: decision table, map, and group decision metrics. The metrics used in the decision table (criterion outcome space) were operationalized in terms of: (i) the proportion of information search, (ii) the variability of information search per attribute, (iii) the variability of information search per alternative, (iv) the direction of search (sequence of information search), (v) total time spent acquiring the information, (vi) and average time spent acquiring each piece of information. The map metrics represent the information search variables concerned with exploring the map or geographic decision space. These include (i) the total time spent on the map exploration and (ii) the number of moves on the map (Jankowski & Nyerges, 2001b). The third metric was concerned with acquiring information from the other decision makers in the collaborative decision making process. This metric was operationalized in terms of the time spent exploring the group decision, deliberations, and discussions.

7.1.2 Technical contribution

From a technical point of view, this research has presented the design and development of a Web 2.0-based collaborative MC-SDSS for a spatial decision making process based on the proposed GIS-MCDA approach. The collaborative MC-SDSS provides an open, asynchronous, distributed, and active decision making process. People can have access to relevant geographical data and GIS-MCDA tools anywhere (any location that has the Internet access), anytime (24 hours a day, 7 days a week), and through any PC or handheld device (e.g., PDA, smart phones) and network (wired or wireless technologies), thus enhancing the level of community participation in spatial planning. It has been argued that the concept of “24/7” access (i.e., 24 hours a day, 7 days a week) opens up opportunities for more people to participate in the decision process (Kingston, 2002; Tang & Waters, 2005).

The system consists of two key elements for supporting the spatial decision making: analytic and deliberative. The analytic (or mathematical) dimension of the system deals with a mechanism that allows individual decision-makers to input their value judgments about the decision problem, develop individual solutions, and eventually arrive at a group decision in such a way that represents best the preferences of all participants. The deliberative aspect of the system focuses on building consensus among participants through organizing debates and facilitating negotiation and communication. It involves participants' comments and discussions regarding different aspects of the decision problem. The deliberative element of the system enhances communication, the exchange of values, and the sharing of information among decision-makers and stakeholders regarding the geospatial issue in question (Boroushaki & Malczewski, 2010b).

The proposed analytic-deliberative MC-SDSS has been developed based on Web 2.0 techniques, including Google Web Toolkit (GWT) and Google Maps APIs. Web 2.0 techniques have made significant contributions to the interactivity, user-centeredness, deliberation, collective intelligence, content generation (both by users and for users) of the collaborative GIS-based MCDA frameworks. GWT, an AJAX (Asynchronous JavaScript and XML) development tool, is one of the best existing frameworks to build Web 2.0 applications. The Ajax-powered MC-SDSS allows for seamless interaction between the users and the system; it provides a more interactive platform for collaborative decision making (Rinner et al., 2008; Bugs et al., 2010).

The Google Maps services provide open source or free-to-use software and geospatial data that allow novices and experts to use them in a user-friendly and familiar environment (Hall & Leahy, 2006; Miller, 2006; Udell, 2008; Boroushaki & Malczewski, 2010b). Goodchild (2007) calls the Google Maps phenomenon the "democratization of GIS," since it has opened some of the more straightforward capabilities of GIS to the general public. This demonstrates the realization of what researchers have theorized about in reference to the concept of PGIS, and therefore allows Google Maps to build the foundation for any collaborative WebGIS development (Boroushaki, 2010; Leahy, 2011).

7.1.3 Empirical contribution

The empirical contribution of this dissertation lies in the use of a case study (parking site selection) to examine the effect of task complexity, information/decision aids, and decision modes on information acquisition metrics and their relations. The study investigated the differences in information acquisition (metrics) and their relationships when task complexity or information load increased (low complexity vs. high complexity), the structures of information sources varied (the map vs. table), and the decision mode changed (individual vs. group decision making).

As was discussed in Chapters 1 and 2, the basic assumption underlying an examination of task complexity effects was that information search strategies shift from compensatory to non-compensatory as the amount of information used or task complexity increases. The following hypotheses represented six fundamental ways this shift in strategies manifest itself: (1) a smaller proportion of available information is examined; (2) a smaller proportion of attribute ranges is examined; (3) there is a decrease in the average time spent acquiring each piece of information (information cells); (4) there is increased variation in the amount of information examined per alternative; (5) and per attribute; and (6) search becomes organized by attributes rather than by alternatives. In addition to these hypotheses, it was expected that an increase in task complexity would result in an increase in: (1) the total time spent acquiring the information in the decision table; (2) the total time spent on the map exploration; (3) the number of moves on the map; and (4) the time spent exploring the group decision.

Table 34 summarizes findings from the empirical study for the task complexity and decision mode effects. With regards to the task complexity effects, support was found for hypotheses concerning the following information acquisition metrics: (1) the proportion of information search; (2) the proportion of attribute ranges examined; (3) the variability of information search per attribute; and (4) the direction of search. The effects on the proportion of information searched and attribute ranges examined were either significant or in the hypothesized direction in both of the decision modes. For the variability of information search per attribute, the effect was in the hypothesized direction, and significant only within the GIS-MCDA individual mode. The effect of task complexity on the direction of search (*SM* index) was in the expected direction only within the GIS-MCDA individual mode and lacked statistical significance in both of the decision modes. The impact of the task complexity on the other metrics in both of the decision modes were neither significant nor in the direction suggested by the relevant hypotheses. Despite the lack of significant differences for some of the hypotheses, it is reasonable to conclude that overall, an increase in task complexity results in the use of non-compensatory decision strategies.

The hypotheses concerning the decision mode effects stated that there is a significant difference in the information acquisition metrics between the GIS-MCDA individual and group modes. Looking at the table, it is evident that the two decision modes are significantly different in terms of: (1) the proportion of information search, (2) proportion of attribute ranges examined, (3) variability of information search per attribute, (4) the total time spent acquiring the information in the decision table, and (5) the average time spent acquiring each piece of information. However, no support has been found for the effects of decision mode on the variability of search per alternative, direction of search, the total time spent on the map exploration, and the number of moves on the map. Although, not all of the metrics were found to be significantly different between the two decision modes, the findings overall show that the information acquisition and integration behaviors of decision participants in the GIS-MCDA individual mode differ from those in the GIS-MCDA group mode.

Table 34. The effect of task complexity and decision mode on the information acquisition metrics.

		The effect of task complexity		The effect of decision mode [b]
Information aid	Information acquisition metric	Individual mode [a]	Group mode [a]	
Decision table	Proportion of information search	Yes/Yes	Yes/Yes	Yes
	Proportion of attribute ranges examined	Yes/Yes	Yes/Yes	Yes
	Variability of information search per attribute	Yes/Yes	No/No	Yes
	Variability of information search per alternative	No/No	No/No	No
	Direction of search (SI)	No/No	No/No	No
	Direction of search (SM)	Yes/No	No/No	No
	Total time spent acquiring the information	No/No	No/No	Yes
	Average time spent acquiring the each piece of information	No/No	No/No	Yes
Map	The total time spent on the map exploration	No/No	No/No	No
	The number of moves on the map	No/No	No/No	No
Group decision map	The time spent exploring the group decision	N/A	No/No	N/A

Note: [a] the effect is in the hypothesized direction/ the effect is significant, [b] the effect is significant.

With regards to the effect of information aids (map and decision table aids) on the information acquisition behavior (or the dynamics of using GIS decision aids) during the collaborative decision making, the hypotheses proposed that, in both the GIS-MCDA individual and group modes, the decision table is used more than the map. It was expected that the number of moves in and time spent on the decision table would be significantly higher than that in the decision map. As shown in Table 35, the findings emerging from this study clearly demonstrate that, in both of the decision modes, the participants had a higher number of moves and spent more time on the decision table than the map. These effects were either significant or in the direction predicted by the relevant hypothesis.

Table 35. The effect of information aid on the information acquisition metrics.

	The effect of information aid	
	Individual mode [a]	Group mode [b]
Total time spent on the table vs. the map	Yes/Yes	Yes/Yes
The number of moves in the table vs. on the map	Yes/Yes	Yes/Yes

Note: [a,b] the effect of information aid is in the hypothesized direction/ the effect is significant.

Table 36 summarizes the significance of correlation among the information acquisition metrics in the decision table. In the GIS-MCDA individual mode, the proportion of information search is significantly correlated with the direction metrics (i.e., *SI* and *SM*) in all of the four decision situations. In both the individual and group decision modes, there is a significant correlation between the variability of information search per attribute and the direction of search (*SI* and *SM*). This means that the variability of information search per attribute increases as the decision makers use a more attribute-wise strategy during the information search. The other correlations, in both the individual and group decision modes, are not significant in all of the four decision situations.

Table 36. The significance of correlation among the information acquisition metrics in the decision table

	GIS-MCDA individual mode	GIS-MCDA group mode
P and *R*	No	No
P and *SI*	Yes	No
P and *SM*	Yes	No
P and *AT*	No	No
P and *VAL*	No	No
P and *VAT*	No	No
R and *SI*	No	No
R and *SM*	No	No
R and *AT*	No	No
R and *VAL*	No	No
R and *VAT*	No	No
AT and *SI*	No	No
AT and *SM*	No	No
AT and *VAL*	No	No
AT and *VAT*	No	No
VAT and *SI*	Yes	Yes
VAT and *SM*	Yes	Yes
VAL and *SI*	No	No

VAL and *SM*	No	No
VAL and *VAT*	No	No

Note: Yes = the coefficient of correlation is significant in all of the four decision situations, No = the coefficient of correlation is not significant in all of the four decision situations, *P* = the proportion of information search, *R* = the proportion of attribute ranges examined, *AT* = the average decision time, *VAT* = the variability of information search per attribute, *VAL* = the variability of information search per alternative, *SI* = the search index, *SM* = the strategy measure.

Table 37 summarizes the effect of the task complexity and decision mode on the relationships between the time spent on the decision table and map, the number of map and table moves, the time spent viewing the group decision and the time spent on the decision table, and the time spent viewing the group decision and the time spent on the map. It can be seen from the table that both the task complexity (either in the GIS-MCDA individual mode or group mode) and decision mode have insignificant effect on the relationships. This implies that the interaction between the exploration of the geographic decision, criteria outcome spaces, and the group decision map is insignificantly influenced by the task complexity and decision mode.

Table 37. The effect of task complexity and decision mode on the relationship between information acquisition in the decision table, map, and group decision map.

	The effect of task complexity		The effect of decision mode
	Individual mode	Group mode	
The relationship between the time spent on the decision map and table	No	No	No
The relationship between the number of map and table moves	No	No	No
The relationship between the time spent viewing the group decision and the time spent on the decision table	No	No	No
The relationship between the time spent viewing the group decision and the time spent on the map	No	No	No

Note: No = the effect is not significant.

7.2 Implications

The findings emerging from this empirical study offer important implications for research in the area of spatial decision making. First, the findings broaden and deepen our understanding of collaborative spatial decision making behavior and provide details about decision process dynamics involving geographic decision aids. An understanding of how collaborating participants acquire and combine decision-related information in a decision making process provides a contribution to knowledge about decision processes and challenges (Jankowski & Nyerges, 2001b). Second, the findings make contributions to behavioral decision theory and have implications for developing the theoretical constructs and propositions of information acquisition behavior in the collaborative GIS-MCDA context. Specifically, the findings allow researchers to create theoretical frameworks explaining why information search or human-computer interaction patterns differ between low-complexity and high-complexity tasks, GIS-MCDA individual and group decision modes, and map- and table-based information aids. For example, researchers might develop theoretical reasons why the distinction between GIS-MCDA individual and group decision modes has implications for whether or not decision makers use all or only a subset of the available information in their evaluations.

Third, this research has practical implications for the development of collaborative MC-SDSSs. The findings provide a new perspective on the use of decision support aids, and also important clues for designers to develop an appropriate user-centered Web-based collaborative MC-SDSS (Meng, 2010). They enable researchers to gain insights into how information search and decision-making processes in the MC-SDSS are affected by decision contexts. A better understanding of decision making behavior would aid researchers and designers in finding ways to properly structure decision information and improve the quality of spatial decision making; it encourages certain user-centered designs of the system where system goals, objectives, context, and environment are all aligned with the users' preferences. If the decision situations do affect the search strategy employed by decision makers, and if the search strategy in turn affects the decision made, then MC-SDSS designers can foster the use of a particular decision making process via manipulation of the decision situation. For instance, the use of compensatory decision-making processes can be enhanced by limiting the amount of information provided or by reorganizing the format of presenting information through aggregation and summarization. The results that decision makers used relatively more attribute-based processing as task complexity increased provide evidence that the decision may be enhanced by developing an information structure that better supports attribute-based processing. Another result that the decision table was used much more than the map provides an important clue for MC-SDSS designers to improve the quality of map for representing the geographic decision. Such considerations would stimulate an organization (such as a municipal government) to use a system that supports a particular decision strategy or combination of strategies, which are logically justifiable and defensible (Lawrence, Goodwin, & Fildes, 2002; Gönül, Önkal, & Lawrence, 2006; Meng, 2010).

7.3 Limitations

As is the case with any research, the current research acknowledges a few limitations that should be taken into account:

One of the main limitations of this study is the choice of a Mouselab process-tracing approach (Web-based logging technique) to record the human-computer interaction data during the collaborative decision making process. Recording decision makers' information search activities in the decision table using this approach requires that the attribute values be hidden behind the cells so as to find out which specific attribute values are examined for which alternatives. Due to the recent advances in computer technology and computer vision techniques, eye tracking has gained much attention as an alternative way of keeping track of the decision process (Duchowski, 2007; Pfeiffer, 2012). Eye tracking refers to the process of measuring eye movements with eye tracker devices, such as head-mounted, stationary eye trackers, etc. With eye trackers it is unnecessary to hide information since the eye tracker system is able to precisely record fixations on information items (Reisen, Hoffrage, & Mast, 2008). However, the current eye tracking technologies are expensive, and require the test users to use a particular computer with eye tracking capabilities (Meng, 2010).

Another important limitation is to make sure that GIS-MCDA techniques are used in such a way that their fundamental assumptions are met. For instance, incorrect specification of weights is specially common error in the application of MCDA approaches to spatial decision problems (Malczewski, 2000). Any participant, whether lay or expert, should realize that assigning weights to criteria accounts for a number of factors, such as the changes in the range of variation for each attribute (the extent to which alternatives vary on that attribute) and the different degrees of importance attached to these ranges of variation (subjective evaluation of importance of that attribute). In many GIS-based studies, however, individuals assign weights to the criteria without full understanding of their meaning. Carver (1999) asserts that the participants lose confidence in any Web-based GIS applications when they do not understand the methods, technology and rationale behind that application, so that they cannot use the system efficiently. These challenges can be overcome by providing adequate Web-based learning materials on the meaning, rationale, and use of the system (Mustajoki, Hämäläinen, & Marttunen, 2004; Boroushaki, 2010).

It is suggested that the use of incentives for the decision makers may affect the decision making behavior. If decision making performance was tied to incentives or rewards, different types of behavior may have been exhibited by the decision makers (Todd, 1988). The use of incentives encourages the decision makers to make a good choice, and perhaps expend extra effort on the decision problem. For example, in an empirical study concerning the impacts of financial incentives on the decision making process, Dobbs, Miller, House, and Yards (2008) found that incentives would induce individuals to use information systems more fully and efficiently, learn faster and make better decisions, and hence turn in higher levels of performance.

Another area which needs to be addressed is the issue of generalisability or external validity. This limitation concerns the question of to what extent are the findings generalisable to other types of decision problems, political and social contexts of decision, decision makers, and decision support tools?. The choice of decision strategies is a function of characteristics of decision problems, decision or task environments, and characteristics of the decision maker (Beach & Mitchell, 1978). Meng (2010) suggested that information search in a Web-based collaborative GIS-MCDA context may vary among public participants as a result of their differences in age, education, gender, and levels of experience in web surfing, GIS use and involvement in public participatory planning. According to Sieber (2006), a participatory GIS project is not implemented in a void but rather is conditioned by the laws, culture, politics, and history of the community, city, region, or nation in which it is applied. While a collaborative MC-SDSS may be broadly accepted by all stakeholders in one community, the same system may be entirely unacceptable in another community. This also applies to our study and affects how we generalize the present findings beyond the research setting. Explicitly, this suggests that, with the lack of previous findings consistent with the one reported in this dissertation, one has to be cautious while generalizing the findings to other cases.

Finally, the present study has examined the external information search behavior during the use of the information aids (the map and table) in the collaborative MC-SDSS. However, it is suggested that, in addition to the external search, researchers should also study decision maker' internal search behaviors (search in mind) during the decision making process (see Abdul-Muhmin, 1994). An internal search is concerned with recalling relevant information from individuals' long term memories. It involves no sources other than the decision maker's own memory, prior knowledge, and experience (Lindquist & Sirgy, 2003). For example, a decision maker might deeply analyze particular places and spatial relations or specific attribute values in his/her mind while looking at the map and decision table, respectively. It is suggested that individuals with higher levels of knowledge would replace an external search with an internal one and conduct information searches more efficiently than the less knowledgeable individuals (Brucks, 1985; Wang, 2006).

7.4 Recommendations for future Work

The research presented in this thesis suggests a variety of research directions that need to be addressed:

This study focused on investigating decision-making behavior and understanding cognitive processes in the context of a parking site selection. However, further research should be undertaken to replicate the present study with a different site selection problem, spatial decision support tool, multicriteria evaluation approach, level of decision importance and consequences associated with it, region and community, and decision makers. It would be desirable to examine whether the effects of task complexity, information aids, and decision mode found in this study extend to other spatial decision making contexts.

Another important area of future research is the use of an outcome-based research paradigm for examining the effects of task complexity, information aids, and decision mode on decision quality (or accuracy). While process tracing approach allows for investigating the decision strategies using information acquisition patterns, the outcome-based approach enables the researcher to quantitatively examine decision qualities based on observed final choices. Decision quality can be measured in terms of the levels of agreement (consensus) or disagreement (Shih, Wang, & Lee, 2004). Consensus means unanimous agreement of the decision-makers involved in a decision-making process; it ensures that the best decision alternative is perceived to be acceptable by the decision makers.

The present study did not investigate the interaction effects of the decision situations on the information search behavior. Such effects describe a situation in which the effect of one of the task factors differs depending on the level of the other factor. Research on the interaction effects in a spatial decision making context suggest that there are simultaneous and additive influences of two or more decision situations on the decision making process (Chinburapa, 1991; Speier, Vessey, & Valacich, 2003; Downing, Moore, & Brown, 2005; Wilkening & Fabrikant, 2013). This opens up a great number of possibilities for future research to examine how the decision situations interactively affect information acquisition strategies in spatial multicriteria decisions. For example, an interesting research issue would be to study whether there is a significant interaction effect between task complexity and geographic information aids on information search metrics.

In this study, the complexity of a decision task was manipulated by increasing both the numbers of alternatives and attributes. Future research may consider separately examining the effects of the numbers of alternatives or attributes on information acquisition behavior. This enables us to find out which of the increases in the number of alternatives, attributes, and or both has more effect on the information search variables. The decision making task in this study's experiments involved using every available alternative and attribute to generate the decision solutions. It might be more efficient to allow the participants the option to narrow down their search by making choices among the alternatives and attributes, and then perform the decision making process using the selected alternatives and attributes.

While the present study used a within-subjects design for the experimental sessions, future research might consider employing a between-subjects design, where separate groups of individuals are involved at each level of decision situations. Using a between-subjects design allows us to overcome the potential drawback of a within-subjects design (e.g., carryover effects). A combination of the results obtained from the two experimental designs provides the robust and precise insights into the interpretations of decision making behavior.

Research on effects of complexity on decision making processes suggests that, in addition to task-based complexity, context-based complexity also affects the way that individuals acquire and combine decision information (see Payne, 1982; Biggs, Bedard, Gaber, & Linsmeier, 1985; White & Hoffrage, 2009; Pfeiffer, 2012). Payne (1982) characterizes context factors as “those factors associated with the particular values of the objects in the decision set under consideration” (p. 386). This type of complexity reflects the degree of similarity between the attribute values associated with available alternatives, the quality of the alternative set and the attributes, etc. For instance, the more similar the values, the harder it is for the decision maker to compare the attributes (higher complexity) (Pfeiffer, 2012). Therefore, there is a need for future research to examine context-based complexity effects in the use of Web 2.0-based collaborative GIS-MCDA.

Finally, although the current study used a relatively comprehensive list of metrics for examining information search behavior, one can argue that there are other relevant variables for studying decision making behavior. Future research should use additional measures of information acquisition variables for investigating the human-computer interaction patterns in collaborative GIS-MCDA.

References

Abdul-Muhmin, A. G. (1994). *A process-tracing study of external information search in multiple-item purchase decisions.* Doctoral dissertation, Institute of Marketing at the Norwegian School of Economics and Business Administration, Bergen, Norway.

Alexander, E. R. (2000). Rationality revisited: planning paradigms in a post-postmodernist perspective. *Journal of Planning Education and Research, 19*(3), 242-256.

Anderson, N. H., & Zalinski, J. (1988). Functional measurement approach to self-estimation in multiattribute evaluation. *Journal of Behavioral Decision Making, 1*(4), 191-221.

Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M. J., MacEachren, A., & Wrobel, S. (2007). Geovisual analytics for spatial decision support: setting the research agenda. *International Journal of Geographical Information Science, 21*(8), 839-857.

Andrienko, N., & Andrienko, G. (2001). Intelligent support for geographic data analysis and decision making in the Web. *Journal of Geographic Information and Decision Analysis, 5*(2), 115-128.

Atterer, R., Wnuk, M., & Schmidt, A. (2006). *Knowing the user's every move: user activity tracking for website usability evaluation and implicit interaction*. Paper presented at the Proceedings of the 15th international conference on World Wide Web, Edinburgh, Scotland. Retrieved from http://www.medien.ifi.lmu.de/pubdb/publications/pub/atterer2006www/atterer2006www.pdf

Bailey, D., Goonetilleke, A., & Campbell, D. (2003). A new fuzzy multicriteria evaluation method for group site selection in GIS. *Journal of Multi-Criteria Decision Analysis, 12*(6), 337-347.

Bakhsh, Z. (2008). *A new methodological approach to selecting and weighting criteria for the objective grading system.* Doctoral dissertation, University of Illinois, Chicago, Illinois.

Beach, L. R., & Mitchell, T. R. (1978). A contingency model for the selection of decision strategies. *The Academy of Management Review, 3*(3), 439-449.

Beattie, J., & Baron, J. (1991). Investigating the effect of stimulus range on attribute weight. *Journal of Experimental Psychology: Human Perception and Performance, 17*(2), 571-585.

Beaudreau, P., Johnson, P. A., & Sieber, R. (2011). *Creating and testing a portable template for municipal-level adoption of the Geospatial Web 2.0*. Paper presented at the Proceedings of Spatial Knowledge and Information – Canada (SKI-Canada), March 3-6, Fernie BC, Canada. Retrieved from http://rose.geog.mcgill.ca/ski/system/files/fm/2011/Beaudrea,%20Johnson,%20Sieber_0.pdf

Ben-Arieh, D., & Chen, Z. (2006). Linguistic-labels aggregation and consensus measure for autocratic decision making using group recommendations. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, 36*(3), 558-568.

Bettman, J. R., & Jacoby, J. (1976). Patterns of processing in consumer information acquisition. *Advances in consumer research, 3*(1), 315-320.

Bettman, J. R., Johnson, E. J., & Payne, J. W. (1991). Consumer decision making. In T. S. Robertson & H. H. Kassarjian (Eds.), *Handbook of consumer behavior* (pp. 50-84). Englewood Cliffs, NJ: Prentice-Hall.

Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. *Journal of consumer research, 25*(3), 187-217.

Biggs, S. F., Bedard, J. C., Gaber, B. G., & Linsmeier, T. J. (1985). The effects of task size and similarity on the decision behavior of bank loan officers. *Management science, 31*(8), 970-987.

Bockenholt, U., Albert, D., Aschenbrenner, M., & Schmalhofer, F. (1991). The effects of attractiveness, dominance, and attribute differences on information acquisition in multiattribute binary choice. *Organizational Behavior and Human Decision Processes, 49*(2), 258-281.

Böckenholt, U., & Hynan, L. S. (1994). Caveats on a process-tracing measure and a remedy. *Journal of Behavioral Decision Making, 7*(2), 103-117.

Bodily, S. E. (1985). *Modern decision making: a guide to modeling with decision support systems*. New York: McGraw-Hill.

Bonaccio, S., & Dalal, R. S. (2006). Advice taking and decision-making: an integrative literature review, and implications for the organizational sciences. *Organizational Behavior and Human Decision Processes, 101*(2), 127-151.

Borda, J. (1781). Mathematical derivation of an election system. *Isis, 44*(1-2), 42-51.

Boroushaki, S. (2010). *ParticipatoryGIS: a Web-based collaborative GIS and multicriteria decision analysis.* Doctoral dissertation, University of Western Ontario, London, Ontario.

Boroushaki, S., & Malczewski, J. (2010a). Measuring consensus for collaborative decision-making: a GIS-based approach. *Computers, Environment and Urban Systems, 34*(4), 322-332.

Boroushaki, S., & Malczewski, J. (2010b). ParcitipatoryGIS: a WebGIS-based collaborative multicriteria decision analysis. *Journal of the Urban and Regional Information Systems Association (URISA), 22*(1), 23-32.

Boroushaki, S., & Malczewski, J. (2010c). Using the fuzzy majority approach for GIS-based multicriteria group decision-making. *Computers & Geosciences, 36*(3), 302-312.

Bröder, A., & Schiffer, S. (2003). Bayesian strategy assessment in multi-attribute decision making. *Journal of Behavioral Decision Making, 16*(3), 193-213.

Broniarczyk, S. M. (2006). Product assortment. In C. P. Haugtvedt, P. M. Herr & F. R. Kardes (Eds.), *Handbook of consumer psychology* (pp. 755-779). New York: Psychology Press.

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of consumer research, 12*(1), 1-16.

Bugs, G., Granell, C., Fonts, O., Huerta, J., & Painho, M. (2010). An assessment of Public Participation GIS and Web 2.0 technologies in urban planning practice in Canela, Brazil. *Cities, 27*(3), 172-181.

Campbell, D. J. (1988). Task complexity: a review and analysis. *Academy of management review, 13*(1), 40-52.

Carrigan, N., Gardner, P., Conner, M., & Maule, J. (2007). The impact of structuring the interface as a decision tree in a treatment decision support tool. In A. Holzinger (Ed.), *HCI and Usability for Medicine and Health Care* (pp. 273-288). Berlin: Heidelberg.

Carsjens, G. J., & Ligtenberg, A. (2007). A GIS-based support tool for sustainable spatial planning in metropolitan areas. *Landscape and Urban Planning, 80*(1–2), 72-83.

Carver, S. (1999). Developing Web-based GIS/MCE: improving access to data and spatial decision support tools. In J. C. Thill (Ed.), *Spatial Multicriteria Decision-making and Analysis* (pp. 49-75). Aldershot, England: Ashgate.

Carver, S., & Peckham, R. (1999). Using GIS on the Internet for planning. In J. Stillwell, S. Geertman & S. Openshaw (Eds.), *Geographical Information and Planning* (pp. 371-390). Berlin Springer Berlin Heidelberg.

CEMAT. (1983). The European Regional/Spatial Planning Charter (Torremolinos charter), *Strasbourg, Council of Europe*.

Chakhar, S., & Martel, J.-M. (2003). Enhancing geographical information systems capabilities with multi-criteria evaluation functions. *Journal of Geographic Information and Decision Analysis, 7*(2), 47-71.

Chang, K.-P. (1997). *The design of a web-based geographic information system for community participation.* Master's thesis.

Chen, Y., Jiang, Y., & Li, D. (2007). A decision support system for evaluation of the ecological benefits of rehabilitation of coal mine waste areas. *New Zealand Journal of Agricultural Research, 50*(5), 1205-1211.

Chestnut, R. W., & Jacoby, J. (1976). Analytical techniques for examining process data. *Purdue Papers in Consumer Psychology, 160*.

Chinburapa, V. (1991). *Physician prescribing decisions: the effects of situational involvement and task complexity on information acquisition and decision-making.* Doctoral dissertation, The University of Arizona, Tucson, Arizona.

Church, R. L., Loban, S. R., & Lombard, K. (1992). An interface for exploring spatial alternatives for a corridor location problem. *Computers & Geosciences, 18*(8), 1095-1105.

Chuvakin, A., Schmidt, K., & Phillips, C. (2012). *Logging and log management: the authoritative guide to dealing with syslog, audit logs, events, alerts and other it 'noise'*. Rockland, United States: Syngress Media Inc.

City of Dover Inc. (2008). Downtown parking facility and management study.

Conlon, B., Dellaert, B. G., & Soest, A. v. (2001). *Complexity and accuracy in consumer choice: the double benefits of being the consistently better brand*. Netherlands: Tilburg University (CentER Discussion Paper).

Contractor, N. S., & Seibold, D. R. (1993). Theoretical frameworks for the study of structuring processes in group decision support systems. *Human Communication Research, 19*(4), 528-563.

Crossland, M. D., Wynne, B. E., & Perkins, W. C. (1995). Spatial decision support systems: an overview of technology and a test of efficacy. *Decision Support Systems, 14*(3), 219-235.

Dai, F. C., Lee, C. F., & Zhang, X. H. (2001). GIS-based geo-environmental evaluation for urban land-use planning: a case study. *Engineering Geology, 61*(4), 257-271.

Däne, S., & Van Den Brink, A. (2007). Perspectives on citizen participation in spatial planning in Europe. In A. Van Den Brink, R. Van Lammeren, R. Van De Velde & S. Dane (Eds.), *Imaging the future: geo-visualisation for participatory spatial planning in Europe* (pp. 33-51). Wageningen: Wageningen Academic Publishers.

Dennis, A. R., & Carte, T. A. (1998). Using geographical information systems for decision making: extending cognitive fit theory to map-based presentations. *Information Systems Research, 9*(2), 194-203.

Desanctis, G., & Gallupe, R. B. (1987). A foundation for the study of group decision support systems. *Management science, 33*(5), 589-609.

DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: adaptive structuration theory. *Organization Science, 5*(2), 121-147.

Dessì, N., Garau, G., & Pes, B. (2012). *Web 2.0 technologies empowering spatial decision making*. Paper presented at the IEEE 21st International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE). Retrieved from http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6269780

Dhar, R., Nowlis, S. M., & Sherman, S. J. (2000). Trying hard or hardly trying: an analysis of context effects in choice. *Journal of Consumer Psychology, 9*(4), 189-200.

DiNucci, D. (1990). Fragmented Future (1999). *Print, 53*(4), 32.

Dobbs, I. M., Miller, A. D., House, C., & Yards, H. (2008). *The impact of financial incentives on decision making: further evidence*. Edinburgh: Institute of Chartered Accountants of Scotland.

Downing, R. E., Moore, J. L., & Brown, S. W. (2005). The effects and interaction of spatial visualization and domain expertise on information seeking. *Computers in Human Behavior, 21*(2), 195-209.

Dragićević, S. (2004). The potential of Web-based GIS. *Journal of Geographical Systems, 6*(2), 79-81.

Dragićević, S., & Balram, S. (2004). A Web GIS collaborative framework to structure and manage distributed planning processes. *Journal of Geographical Systems, 6*(2), 133-153.

Duchowski, A. T. (2007). *Eye tracking methodology: theory and practice*. London: Springer-Verlag.

Eastman, J. (1997). *IDRISI for Windows, version 2.0: tutorial exercises graduate* Worcester,Massachusetts Clark University.

Eastman, J. (2006). *IDRISI Andes tutorial*. Worcester,Massachusetts Clark University.

Eastman, J. R., Jin, W., Kyem, P. A. K., & Toledano, J. (1995). Raster procedures for multi-Criteria/multi-objective decisions. *Photogrammetric Engineering and Remote Sensing (PE&RS), 61*(5), 539-547.

Esnard, A.-M., & MacDougall, E. B. (1997). Common ground for integrating planning theory and gis topics. *Journal of Planning Education and Research, 17*(1), 55-62.

Evans, A. J., Kingston, R., & Carver, S. (2004). Democratic input into the nuclear waste disposal problem: the influence of geographical data on decision making examined through a Web-based GIS. *Journal of Geographical Systems, 6*(2), 117-132.

Farzanmanesh, R., Naeeni, A. G., & Abdullah, A. M. (2010). Parking site selection management using fuzzy logic and multi criteria decision making. *Environ Asia, 3*, 109-116.

Feick, R., & Hall, B. (2004). A method for examining the spatial dimension of multi-criteria weight sensitivity. *International Journal of Geographical Information Science, 18*(8), 815-840.

Feick, R., & Hall, G. B. (2001). Balancing consensus and conflict with a GIS-based multi-participant, multi-criteria decision support tool. *GeoJournal, 53*(4), 391-406.

Feick, R. D., & Hall, G. B. (1999). Consensus building in a multiparticipant spatial decision support system. *Journal of the Urban and Regional Information Systems Association (URISA), 11*(2), 17-23.

Fischer, G. W. (1995). Range sensitivity of attribute weights in multiattribute value models. *Organizational Behavior and Human Decision Processes, 62*(3), 252-266.

Fischer, M. M., & Nijkamp, P. (1993). *Geographic information systems, spatial modelling and policy evaluation*. Berlin: Springer-Verlag

Ford, J. K., Schmitt, N., Schechtman, S. L., Hults, B. M., & Doherty, M. L. (1989). Process tracing methods: contributions, problems, and neglected research questions. *Organizational Behavior and Human Decision Processes, 43*(1), 75-117.

Ganapati, S. (2010). *Using geographic information systems to increase citizen engagement* (pp. 1-46). Washington, DC: IBM Center for the Business of Government.

Ghanbari, S., & Ghazi Asgar, A. (2011). Evaluation of different methods of site selection in management of public parking construction in central business of Esfahan using GIS. *Geography and Environmental Planning, 22*(2), 183-198.

Gino, F., & Moore, D. A. (2007). Effects of task difficulty on use of advice. *Journal of Behavioral Decision Making, 20*(1), 21-35.

Glaholt, M. G. (2010). *Biases in looking behaviour during visual decision making tasks.* Doctoral dissertation.

Gönül, M. S., Önkal, D., & Lawrence, M. (2006). The effects of structural characteristics of explanations on use of a DSS. *Decision Support Systems, 42*(3), 1481-1493.

Goodchild, M. (2007). Citizens as sensors: the world of volunteered geography. *GeoJournal, 69*(4), 211-221.

Haklay, M., Singleton, A., & Parker, C. (2008). Web mapping 2.0: the neogeography of the GeoWeb. *Geography Compass, 2*(6), 2011-2039.

Hall, B., & Leahy, M. G. (2006). Internet-based spatial decision support using open source tools. In S. Balram & S. Dragićević (Eds.), *Collaborative Geographic Information Systems* (pp. 237-262). Hershey: Idea Group Publishing.

Harte, J. M., & Koele, P. (2001). Modelling and describing human judgement processes: the multiattribute evaluation case. *Thinking & reasoning, 7*(1), 29-49.

Herrera-Viedma, E., Herrera, F., & Chiclana, F. (2002). A consensus model for multiperson decision making with different preference structures. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, 32*(3), 394-402.

Heywood, D. I., Cornelius, S., & Carver, S. (2002). *An introduction to Geographical Information Systems*. Harlow, England: Prentice-Hall.

Hodge, G. (2003). *Planning Canadian communities: an introduction to the principles, practice, and participants*. Toronto: Nelson Thomson Learning.

Hossack, I., Robertson, D., Tucker, P., Hursthouse, A., & Fyfe, C. (2004). A GIS and Web-based decision support tool for the management of urban soils. *Cybernetics and Systems, 35*(5-6), 499-509.

Jacoby, J., Speller, D. E., & Kohn, C. A. (1974). Brand choice behavior as a function of information load. *Journal of Marketing Research, 11*(1), 63-69.

Janis, I. L. (1989). *Crucial decisions: Leadership in policymaking and crisis management*. New York: Free Press.

Jankowski, P. (1995). Integrating geographical information systems and multiple criteria decision-making methods. *International Journal of Geographical Information Systems, 9*(3), 251-273.

Jankowski, P. (2009). Towards participatory geographic information systems for community-based environmental decision making. *Journal of Environmental Management, 90*(6), 1966-1971.

Jankowski, P., Andrienko, N., & Andrienko, G. (2001). Map-centred exploratory approach to multiple criteria spatial decision making. *International Journal of Geographical Information Science, 15*(2), 101-127.

Jankowski, P., & Nyerges, T. (2001a). *Geographic information systems for group decision-making: towards a participatory, geographic information science*. New York: Taylor & Francis.

Jankowski, P., & Nyerges, T. (2001b). GIS-supported collaborative decision making: results of an experiment. *Annals of the Association of American Geographers, 91*(1), 48-70.

Jankowski, P., Nyerges, T. L., Smith, A., Moore, T. J., & Horvath, E. (1997). Spatial group choice: a SDSS tool for collaborative spatial decisionmaking. *International Journal of Geographical Information Science, 11*(6), 577-602.

Jankowski, P., & Stasik, M. (2006). An experimental study using SDS tools for a participatory approach to local land use planning. In S. Balram & S. Dragićević (Eds.), *Collaborative Geographic Information Systems* (pp. 150-166). Hershey: Idea Group Publishing.

Jankowski, P., Zielinska, A.-L., & Swobodzinski, M. (2008). Choice modeler: a Web-based spatial multiple criteria evaluation tool. *Transactions in GIS, 12*(4), 541-561.

Jiang, H., & Eastman, J. R. (2000). Application of fuzzy measures in multi-criteria evaluation in GIS. *International Journal of Geographical Information Science, 14*(2), 173-184.

Jiaxi, L. (2003). *Multi-functioned parking facility's site selection in tourist towns: case study of Changyang, China.* Master's dissertation.

Joerin, F., Desthieux, G., Beuze, S. B., & Nembrini, A. (2009). Participatory diagnosis in urban planning: proposal for a learning process based on geographical information. *Journal of Environmental Management, 90*(6), 2002-2011.

Joerin, F., Thériault, M., & Musy, A. (2001). Using GIS and outranking multicriteria analysis for land-use suitability assessment. *International Journal of Geographical Information Sciences, 15*(2), 153-174.

Kantowitz, B. H., Roediger III, H. L., & Elmes, D. G. (2009). *Experimental psychology*. Belmont: Cengage Learning.

Karimi, V., Ebadi, H., & Ahmady, S. (2009). Modeling of parking site selection by using gis with emphasis on weighting and integrating layers. *Journal of Faculty of Eng, 38*(3), 11-21.

Karnatak, H., Saran, S., Bhatia, K., & Roy, P. S. (2007). Multicriteria spatial decision analysis in Web GIS environment. *GeoInformatica, 11*(4), 407-429.

Karnatak, H. C., Shukla, R., Sharma, V. K., Murthy, Y. V. S., & Bhanumurthy, V. (2012). Spatial mashup technology and real time data integration in geo-web application using open source GIS – a case study for disaster management. *Geocarto International, 27*(6), 499-514.

Katz, I., Bereby-Meyer, Y., Assor, A., & Danziger, S. (2010). Children's adaptive pre-decisional search behavior: effects of memory and number of alternatives. *Journal of Economic Psychology, 31*(1), 17-24.

Keeney, R. L., & Raiffa, H. (1976). *Decisions with multiple objectives: preferences and value trade-offs*. New York: Wiley.

Kim, J., Hahn, J., & Hahn, H. (2000). How do we understand a system with (so) many diagrams? Cognitive integration processes in diagrammatic reasoning. *Information Systems Research, 11*(3), 284-303.

Kim, P. S., Halligan, J., Cho, N., Oh, C. H., & Eikenberry, A. M. (2005). Toward participatory and transparent governance: report on the sixth global forum on reinventing government. *Public Administration Review, 65*(6), 646-654.

Kingston, R. (2002). Web-based PPGIS in the United Kingdom. In W. Craig, T. Harris & D. Weiner (Eds.), *Community participation and geographic information systems* (pp. 127-138). London: Taylor & Francis.

Klayman, J. (1983). Analysis of predecisional information search patterns. In P. Humphreys, O. Svenson & A. Vári (Eds.), *Advances in Psychology* (pp. 401-414). Amsterdam: North-Holland.

Klayman, J. (1985). Children's decision strategies and their adaptation to task characteristics. *Organizational Behavior and Human Decision Processes, 35*(2), 179-201.

Klemz, B. R., & Gruca, T. S. (2001). Managerial assessment of potential entrants: processes and pitfalls. *International Journal of Research in Marketing, 18*(1), 37-51.

Klosterman, R. E. (1997). Planning support systems: a new perspective on computer-aided planning. *Journal of Planning Education and Research, 17*(1), 45-54.

Koele, P., & Westenberg, M. R. (1995). A compensation index for multiattribute decision strategies. *Psychonomic bulletin & review, 2*(3), 398-402.

Krek, A. (2005). *Rational ignorance of the citizens in public participatory planning*. Paper presented at the Proceedings of the 10th Symposium on Information and Communication Technologies in Urban Planning and Spatial Development and Impacts of ICT on Physical Space, Vienna, Austria. Retrieved from http://www.hcu-hamburg.de/fileadmin/documents/Professoren_und_Mitarbeiter/Alenka_Poplin/Rational_Ignorance_of_the_Citizens_in_Public_Participatory_Planning_CORP__krek_rational_ignorance_in_participatory_planning.pdf

Krygier, J. B. (2002). A praxis of public participation GIS and visualization. In W. J. Craig, T. M. Harris & D. Weiner (Eds.), *Community participation and geographic information systems* (pp. 330-345). London: Taylor and Francis.

Kyem, P. A. K. (2001). An application of a choice heuristic algorithm for managing land resource allocation problems involving multiple parties and conflicting interests. *Transactions in GIS, 5*(2), 111-129.

Kyem, P. A. K. (2004). Of intractable conflicts and participatory gis applications: the search for consensus amidst competing claims and institutional demands. *Annals of the Association of American Geographers, 94*(1), 37-57.

Laaribi, A., Chevallier, J. J., & Martel, J. M. (1996). A spatial decision aid: a multicriterion evaluation approach. *Computers, Environment and Urban Systems, 20*(6), 351-366.

Larson, A., & Ribot, J. (Eds.). (2005). *Democratic decentralisation through a natural resource lens: an introduction*. London: Routledge.

Lawrence, M., Goodwin, P., & Fildes, R. (2002). Influence of user participation on DSS use and decision accuracy. *Omega, 30*(5), 381-392.

Leahy, M. G. (2011). *Adaptation of public participation GIS for community irrigation planning in rural New Zealand*. Waterloo,Ontario: Wilfrid Laurier University.

Lee, B. K., & Lee, W. N. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing, 21*(3), 159-183.

Ligmann-Zielinska, A., & Jankowski, P. (2012). Impact of proximity-adjusted preferences on rank-order stability in geographical multicriteria decision analysis. *Journal of Geographical Systems, 14*(2), 167-187.

Limayem, M., & DeSanctis, G. (2000). Providing decisional guidance for multicriteria decision making in groups. *Information Systems Research, 11*(4), 386-401.

Lindquist, J. D., & Sirgy, J. (2003). *Shopper, buyer, and consumer behavior: theory, marketing applications, and public policy implications*. Cincinnati, OH: Atomic Dog Publishing.

Lovan, W. R., Murray, M. R., & Shaffer, R. (Eds.). (2004). *Participatory governance: planning, conflict mediation and public decision making in civil society*. Aldershot: Ashgate Publishing.

Lurie, N. H., & Swaminathan, J. M. (2009). Is timely information always better? The effect of feedback frequency on decision making. *Organizational Behavior and Human Decision Processes, 108*(2), 315-329.

Macdonald, S. (2008). Data visualization tools: part 2-spatial data in a Web 2.0 environment and beyond, *DISC-UK data share project*.

MacEachren, A. M., Gahegan, M., Pike, W., Brewer, I., Cai, G., Lengerich, E., & Hardisty, F. (2004). Geovisualization for knowledge construction and decision support. *IEEE Computer Graphics and Applications, 24*(1), 13-17.

Makropoulos, C., Butler, D., & Maksimovic, C. (2003). Fuzzy logic spatial decision support system for urban water management. *Journal of Water Resources Planning and Management, 129*(1), 69-77.

Malczewski, J. (1996). A GIS-based approach to multiple criteria group decision-making. *International Journal of Geographical Information Systems, 10*(8), 955-971.

Malczewski, J. (1999a). *GIS and multicriteria decision analysis*. New York, NY: John Wiley & Sons.

Malczewski, J. (1999b). Visualization in multicriteria spatial decision support systems. *Geomatica, 53*(2), 139-147.

Malczewski, J. (2000). On the use of weighted linear combination method in GIS: common and best practice approaches. *Transactions in GIS, 4*(1), 5-22.

Malczewski, J. (2004). GIS-based land-use suitability analysis: a critical overview. *Progress in Planning, 62*(1), 3-65.

Malczewski, J. (2006a). GIS-based multicriteria decision analysis: a survey of the literature. *International Journal of Geographical Information Science, 20*(7), 703-726.

Malczewski, J. (2006b). Multicriteria decision analysis for collaborative GIS. In S. Balram & S. Dragićević (Eds.), *Collaborative Geographic Information Systems* (pp. 167-185). Hershey: Idea Group Publishing.

Malczewski, J. (2006c). Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis. *International Journal of Applied Earth Observation and Geoinformation, 8*(4), 270-277.

Malczewski, J., Chapman, T., Flegel, C., Walters, D., Shrubsole, D., & Healy, M. A. (2003). GIS-multicriteria evaluation with ordered weighted averaging (OWA): case study of developing watershed management strategies. *Environment and Planning A, 35*(10), 1769-1784.

Malczewski, J., & Rinner, C. (2005). Exploring multicriteria decision strategies in GIS with linguistic quantifiers: a case study of residential quality evaluation. *Journal of Geographical Systems, 7*(2), 249-268.

Markieta, M., & Rinner, C. (2012). *Using web map overlay for visual multi-criteria analysis - the example of the Ontario human influence index.* Paper presented at the GEOIDE Annual Scientific Conference, Quebec City, Canada.

Marttunen, M. (2011). *Interactive multi-criteria decision analysis in the collaborative management of watercourses*. Helsinki, Finland: Aalto University.

Massam, B. H. (1988). Multi-Criteria Decision Making (MCDM) techniques in planning. *Progress in Planning, 30, Part 1*(0), 1-84.

Matkan, A., Shakiba, A., Pourali, S., & Ebadi, I. (2009). Crisp and fuzzy decision making in multistore public parking lots. *Environmental Sciences, 6*(3), 207-222.

Mau-Crimmins, T., de Steiguer, J. E., & Dennis, D. (2005). AHP as a means for improving public participation: a pre–post experiment with university students. *Forest Policy and Economics, 7*(4), 501-514.

McCall, M. K., & Dunn, C. E. (2012). Geo-information tools for participatory spatial planning: fulfilling the criteria for ‘good’ governance? *Geoforum, 43*(1), 81-94.

Mellers, B. A., & Chang, S. J. (1994). Representations of risk judgments. *Organizational Behavior and Human Decision Processes, 57*(2), 167-184.

Mellers, B. A., & Cooke, A. D. (1994). Trade-offs depend on attribute range. *Journal of Experimental Psychology: Human Perception and Performance, 20*(5), 1055-1067.

Menegolo, L., & Peckham, R. J. (1996). A fully integrated tool for site planning using multi criteria evaluation techniques within a GIS. In M. Rumor, R. McMillan & H. F. L. Ottens (Eds.), *Geographical information* (pp. 621-630). Amsterdam: IOS Press.

Meng, Y. (2010). *Evaluating web-based public participatory GIS for multicriteria site selection analysis: a case study in Canmore Alberta.* Doctoral dissertation, Departement of Geography, University of Western Ontario, London, Ontario.

Meng, Y., & Malczewski, J. (2010). Web-PPGIS usability and public engagement: a case study in Canmore, Alberta, Canada. *Journal of the Urban and Regional Information Systems Association (URISA), 22*(1), 55-64.

Miller, C. C. (2006). A beast in the field: the Google Maps Mashup as GIS/2. *Cartographica, 41*(3), 187-199.

Minch, R. P., & Sanders, G. L. (1986). Computerized information systems supporting multicriteria decision making. *Decision Sciences, 17*(3), 395-413.

Monat, J. P. (2009). The benefits of global scaling in multi-criteria decision analysis. *Judgment and Decision Making, 4*(6), 492-508.

Musser, J., & O'Reilly, T. (2006). *Web 2.0 principles and best practices.O'Reilly radar report*. Sebastopol, CA: O'Reilly Media Inc.

Mustajoki, J., Hämäläinen, R. P., & Marttunen, M. (2004). Participatory multicriteria decision analysis with Web-HIPRE: a case of lake regulation policy. *Environmental Modelling & Software, 19*(6), 537-547.

Nidumolu, U. B., de Bie, C., van Keulen, H., Skidmore, A. K., & Harmsen, K. (2006). Review of a land use planning programme through the soft systems methodology. *Land Use Policy, 23*(2), 187-203.

Norese, M. F., & Toso, F. (2004). Group decision and distributed technical support. *International Transactions in Operational Research, 11*(4), 395-417.

O'Sullivan, D., & Unwin, D. J. (2003). *Geographic information analysis*. Hoboken, NJ: John Wiley & Sons.

Parnell, G., Figueira, J., Bennett, S., Bobylev, N., Pup, M., Ganoulis, J., . . . Schnelle, D. (2007). Decision analysis tools for safety, security, and sustainability of ports and harbors. In I. Linkov, R. Wenning & G. Kiker (Eds.), *Managing Critical Infrastructure Risks* (pp. 245-260). Netherlands: Springer

Paul, S., Saunders, C. S., & Haseman, W. D. (2005). A question of timing: the impact of information acquisitions on group design making. *Information Resources Management Journal, 18*(4), 81-99.

Payne, J. W. (1976). Task complexity and contingent processing in decision making: an information search and protocol analysis. *Organizational Behavior and Human Performance, 16*(2), 366-387.

Payne, J. W. (1982). Contingent decision behavior. *Psychological Bulletin, 92*(2), 382-402.

Payne, J. W., Bettman, J. R., Coupey, E., & Johnson, E. J. (1992). A constructive process view of decision making: multiple strategies in judgment and choice. *Acta Psychologica, 80*(1), 107-141.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge: Cambridge University Press.

Peng, Z. R., & Tsou, M. H. (2003). *Internet GIS: distributed geographic information services for the internet and wireless networks*. New York: John Wiley & Sons.

Pennington, M. (2004). Citizen participation, the -knowledge problem- and urban land use planning: An austrian perspective on institutional choice. *The Review of Austrian Economics, 17*(2-3), 213-231.

Pfeiffer, J. (2012). Fundamentals on decision-making behavior. In J. Pfeiffer (Ed.), *Interactive Decision Aids in E-Commerce* (pp. 15-45). Berlin: Springer-Verlag.

Phua, M.-H., & Minowa, M. (2005). A GIS-based multi-criteria decision making approach to forest conservation planning at a landscape scale: a case study in the Kinabalu Area, Sabah, Malaysia. *Landscape and Urban Planning, 71*(2–4), 207-222.

Pickles, J. (Ed.). (1995). *Ground truth: the social implications of geographic information systems*. New York: Guilford Press.

Pöyhönen, M., Vrolijk, H., & Hämäläinen, R. P. (2001). Behavioral and procedural consequences of structural variation in value trees. *European Journal of Operational Research, 134*(1), 216-227.

Queen, T. L., Hess, T. M., Ennis, G. E., Dowd, K., & Gruhn, D. (2012). Information search and decision making: effects of age and complexity on strategy use. *Psychol Aging, 27*(4), 817-824.

Rao, M., Fan, G., Thomas, J., Cherian, G., Chudiwale, V., & Awawdeh, M. (2007). A Web-based GIS decision support system for managing and planning USDA's Conservation Reserve Program (CRP). *Environmental Modelling & Software, 22*(9), 1270-1280.

Redlawsk, D. P. (2004). What voters do: information search during election campaigns. *Political Psychology, 25*(4), 595-610.

Reisen, N., Hoffrage, U., & Mast, F. W. (2008). Identifying decision strategies in a consumer choice situation. *Judgment and Decision Making, 3*(8), 641-658.

Renn, O., Webler, T., Rakel, H., Dienel, P., & Johnson, B. (1993). Public participation in decision making: a three-step procedure. *Policy Sciences, 26*(3), 189-214.

Riabacke, M., Danielson, M., & Ekenberg, L. (2012). State-of-the-Art prescriptive criteria weight elicitation. *Advances in Decision Sciences, 2012*.

Riedl, R., Brandstätter, E., & Roithmayr, F. (2008). Identifying decision strategies: a process-and outcome-based classification method. *Behavior Research Methods, 40*(3), 795-807.

Rinner, C. (2001). Argumentation maps: GIS-based discussion support for on-line planning. *Environment and Planning B: Planning and Design, 28*(6), 847-863.

Rinner, C. (2006). Argumentation mapping in collaborative spatial decision making. In S. Balram & S. Dragićević (Eds.), *Collaborative Geographic Information Systems* (pp. 85-102). Hershey: Idea Group Publishing.

Rinner, C. (2007). A geographic visualization approach to multi-criteria evaluation of urban quality of life. *International Journal of Geographical Information Science, 21*(8), 907-919.

Rinner, C., & Jankowski, P. (2002). Web-based spatial decision support-technical foundations and applications. In C. B. Medeiros (Ed.), *The Encyclopedia of Life Support Systems (EOLSS), Theme 1.9 – Advanced Geographic Information Systems* (pp. 209-234). Oxford: UNESCO / Eolss Publishers.

Rinner, C., Keßler, C., & Andrulis, S. (2008). The use of Web 2.0 concepts to support deliberation in spatial decision-making. *Computers, Environment and Urban Systems, 32*(5), 386-395.

Rinner, C., & Malczewski, J. (2002). Web-enabled spatial decision analysis using Ordered Weighted Averaging (OWA). *Journal of Geographical Systems, 4*(4), 385-403.

Rittel, H. J., & Webber, M. (1973). Dilemmas in a general theory of planning. *Policy Sciences, 4*(2), 155-169.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative decision field theory: a dynamic connectionist model of decision making. *Psychol Rev, 108*(2), 370-392.

Roschelle, J., & Teasley, S. (1995). The construction of shared knowledge in collaborative problem solving. In C. O'Malley (Ed.), *Computer Supported Collaborative Learning* (pp. 69-97). Berlin: Springer-Verlag.

Roshan, G., Zanganeh, S. Z., Sauri, D., & Borna, R. (2010). Urban sprawl and climatic changes in Tehran. *Iranian Journal of Environmental Health Science & Engineering, 7*(1), 43-52.

Rosmuller, N., & Beroggi, G. E. G. (2004). Group decision making in infrastructure safety planning. *Safety Science, 42*(4), 325-349.

Rowe, G., & Frewer, L. J. (2000). Public participation methods: a framework for evaluation. *Science, Technology & Human Values, 25*(1), 3-29.

Sadagopan, G. D. (2000). *Web-based geographic information systems: public participation in virtual decision making environment.* Master's dissertation, Virginia Polytechnic Institute and State University, Blacksburg, Virginia.

Sakamoto, A., & Fukui, H. (2004). Development and application of a livable environment evaluation support system using Web GIS. *Journal of Geographical Systems, 6*(2), 175-195.

Sani, A., & Rinner, C. (2011). A scalable GeoWeb tool for argumentation mapping. *Geomatica, 65*(2), 145-156.

Saunders, C., & Miranda, S. (1998). Information acquisition in group decision making. *Information & Management, 34*(2), 55-74.

Schmeer, S. (2003). *The effects of accountability on information search, evaluation and integration in multiattribute decision making*. Doctoral dissertation.

Schrah, G. E., Dalal, R. S., & Sniezek, J. A. (2006). No decision-maker is an island: Integrating expert advice with information acquisition. *Journal of Behavioral Decision Making, 19*(1), 43-60.

Schram, A., & Sonnemans, J. (2011). How individuals choose health insurance: an experimental analysis. *European Economic Review, 55*(6), 799-819.

Schroeder, P. (1996). *Criteria for the design of a GIS/2*. Paper presented at the Specialists' meeting for NCGIA Initiative 19: GIS and Society. Retrieved from http://www.commoncoordinates.com/ppgis/criteria.html

Schulte-Mecklenbeck, M. (2005). *Tracing the decision maker.* Doctoral dissertation, University of Fribourg, Fribourg , Switzerland.

Sharifi, M. A., van den Toorn, W., Rico, A., & Emmanuel, M. (2002). Application of GIS and multicriteria evaluation in locating sustainable boundary between the tunari National Park and Cochabamba City (Bolivia). *Journal of Multi-Criteria Decision Analysis, 11*(3), 151-164.

Shields, M. D. (1980). Some effects on information load on search patterns used to analyze performance reports. *Accounting, Organizations and Society, 5*(4), 429-442.

Shih, H.-S., Wang, C.-H., & Lee, E. S. (2004). A multiattribute GDSS for aiding problem-solving. *Mathematical and Computer Modelling, 39*(11–12), 1397-1412.

Sidlar, C. L., & Rinner, C. (2007). Analyzing the usability of an argumentation map as a participatory spatial decision support tool. *Journal of the Urban and Regional Information Systems Association (URISA), 19*(1), 47-55.

Sieber, R. (2006). Public participation geographic information systems: a literature review and framework. *Annals of the Association of American Geographers, 96*(3), 491-507.

Sikder, I. U., & Gangopadhyay, A. (2002). Design and implementation of a Web-Based collaborative spatial decision support system: organizational and managerial implications (pp. 33-47): IGI Global.

Simão, A., Densham, P. J., & Haklay, M. (2009). Web-based GIS for collaborative planning and public participation: an application to the strategic planning of wind farm sites. *Journal of Environmental Management, 90*(6), 2027-2040.

Simon, H. A. (1977). *The new science of management decision*. New Jersey: Prentice-Hall.

Sipilä, M., & Tyrväinen, L. (2005). Evaluation of collaborative urban forest planning in Helsinki, Finland. *Urban Forestry & Urban Greening, 4*(1), 1-12.

Smelcer, J. B., & Carmel, E. (1997). The effectiveness of different representations for managerial problem solving: comparing tables and maps. *Decision Sciences, 28*(2), 391-420.

Speier, C. (2006). The influence of information presentation formats on complex task decision-making performance. *International Journal of Human-Computer Studies, 64*(11), 1115-1131.

Speier, C., Vessey, I., & Valacich, J. S. (2003). The effects of interruptions, task complexity, and information presentation on computer-supported decision-making performance. *Decision Sciences, 34*(4), 771-797.

Stafford, B. A. (2007). *Cognitive components, information search processes, and outcomes in a decision making task.* Master's dissertation.

Statistical Center of Iran. (2006). *National census of 2006: Tehran Province*. Tehran: SCI Press.

Stillwell, W. G., Seaver, D. A., & Edwards, W. (1981). A comparison of weight approximation techniques in multiattribute utility decision making. *Organizational Behavior and Human Performance, 28*(1), 62-77.

Stokmans, M. (1992). Analyzing information search patterns to test the use of a two-phased decision strategy. *Acta Psychologica, 80*(1), 213-227.

Sugumaran, R., Meyer, J. C., & Davis, J. (2004). A Web-based environmental decision support system (WEDSS) for environmental planning and watershed management. *Journal of Geographical Systems, 6*(3), 307-322.

Svenson, O. (1979). Process descriptions of decision making. *Organizational Behavior and Human Performance, 23*(1), 86-112.

Takemura, K., & Selart, M. (2007). Decision making with information search constraints: a process tracing study. *Behaviormetrika, 34*(2), 111-130.

Tang, K., & Waters, N. (2005). The internet, GIS and public participation in transportation planning. *Progress in Planning, 64*(1), 7-62.

Tang, M. Y. (2006). *Design and implementation of a GIS-enabled online discussion forum for participatory planning* Master's dissertation, University of New Brunswick Fredericton, New Brunswick,Canada.

Taranu, J. (2009). *Building consensus using a collaborative spatial multi-criteria analysis system.* Master's dissertation.

Thill, J. C. (1999). *Spatial multicriteria decision making and analysis: a geographic information sciences approach*. New York: Ashgate.

Todd, P. A. (1988). *An experimental investigation of the impact of computer based decision aids on the process of preferential choice*. Doctoral dissertation.

Tomlin, C. D. (1990). *Geographic information systems and cartographic modeling*. New Jersey: Prentice-Hall.

Tran, T. (2007). *Google Maps Mashups 2.0. Google Lat-Long Blog* Retrieved from http://google-latlong.blogspot.ca/2007/07/google-maps-mashups-20.html

Udell, S. (2008). *Beginning Google Maps mashups with mapplets, KML, and GeoRSS: from novice to professional*. Berkeley, CA: Apress.

Usluel, Y. K., & Mazman, S. G. (2009). Adoption of Web 2.0 tools in distance education. *Procedia - Social and Behavioral Sciences, 1*(1), 818-823.

Valente, M., Sarli, C. C., Valente, L. M., Amlani, A. M., Oeding, K., Finnell, J., . . . Huart, S. (2011). *The audiology capstone: research, presentation, and publication*. New York: Thieme Medical Publishers.

Vandenberghe, E. S. (2011). Behavioral approaches to contract law. In G. De Geest (Ed.), *Contract Law and Economics* (pp. 401-424). Cheltenham: Edward Elgar Publishing.

Von Nitzsch, R., & Weber, M. (1993). The effect of attribute ranges on weights in multiattribute utility measurements. *Management science, 39*(8), 937-943.

Voss, A., Denisovich, I., Gatalsky, P., Gavouchidis, K., Klotz, A., Roeder, S., & Voss, H. (2004). Evolution of a participatory GIS. *Computers, Environment and Urban Systems, 28*(6), 635-651.

Wang, H., & Chu, P. C. (2004). The impact of problem size on decision processes: an experimental investigation on very large choice problems with support of decision support systems. *Expert Systems, 21*(2), 104-118.

Wang, T. (2006). *The impact of the internet adoption on the information search for high and low involvement products: an empirical study based in Taiwan.* Master's dissertation, University of Nottingham, Nottingham, England.

White, C. M., & Hoffrage, U. (2009). Testing the tyranny of too much choice against the allure of more choice. *Psychology and Marketing, 26*(3), 280-298.

Wilkening, J., & Fabrikant, S. I. (2013). How users interact with a 3D geo-browser under time pressure. *Cartography and Geographic Information Science, 40*(1), 40-52.

Witlox, F. (2005). Expert systems in land-use planning: an overview. *Expert Systems with Applications, 29*(2), 437-445.

Wohlgemuth, M. (1999). Entry barriers in politics, or: why politics, like natural monopoly, is not organised as an ongoing market-process. *The Review of Austrian Economics, 12*(2), 175-200.

Wu, H., He, Z., & Gong, J. (2010). A virtual globe-based 3D visualization and interactive framework for public participation in urban planning processes. *Computers, Environment and Urban Systems, 34*(4), 291-298.

Yager, R. (1997). On the inclusion of importances in OWA aggregations. In R. R. Yager & J. Kacprzyk (Eds.), *The Ordered Weighted Averaging Operators* (pp. 41-59). Boston: Kluwer Academic Publishers.

Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on Systems, Man and Cybernetics, 18*(1), 183-190.

Yager, R. R. (1996). Quantifier guided aggregation using OWA operators. *International Journal of Intelligent Systems, 11*(1), 49-73.

Yang, F., Zeng, G., Du, C., Tang, L., Zhou, J., & Li, Z. (2008). Spatial analyzing system for urban land-use management based on GIS and multi-criteria assessment modeling. *Progress in Natural Science, 18*(10), 1279-1284.

Yeung, C. W., & Soman, D. (2005). Attribute evaluability and the range effect. *Journal of consumer research, 32*(3), 363-369.

Zhang, Z. (2007). Human computer interaction research in Web design and evaluation. In P. Zaphiris & S. Kurniawan (Eds.), (pp. 209-228). Hershey, PA: Idea Group Publishing.

Zhu, X., & Dale, A. P. (2001). JavaAHP: a web-based decision analysis tool for natural resource and environmental management. *Environmental Modelling and Software with Environment Data News, 16*(3), 251-262.

Zhu, X., McCosker, J., Dale, A. P., & Bischof, R. J. (2001). Web-based decision support for regional vegetation management. *Computers, Environment and Urban Systems, 25*(6), 605-627.

Appendices

Appendix A: The sample source code for developing the Web 2.0-based MC-SDSS

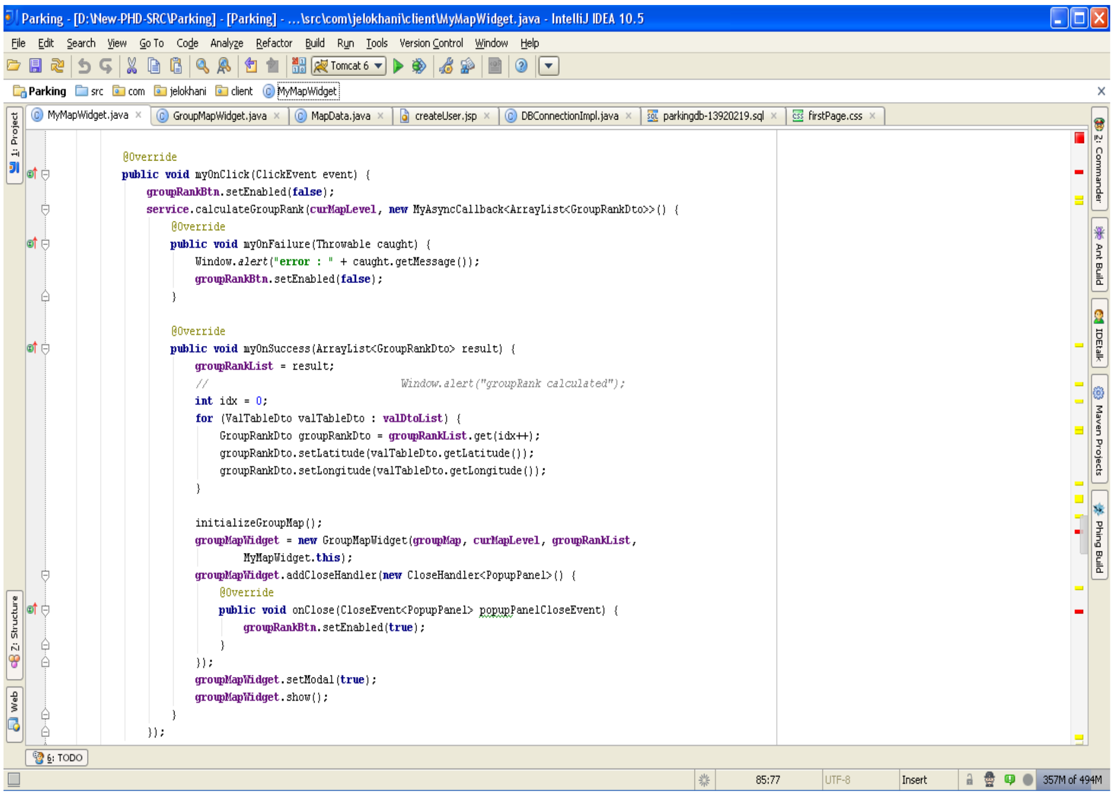


Figure A1. A part of source code in the in the Java IDE environment IntelliJ IDEA 10.5.

Appendix B: The tutorial of the Web 2.0-based collaborative MC-SDSS (in Persian)

محل بهتر است.

نزدیکی به مراکز تجاری(متر) : هر چه قدر فاصله کمتر باشد، محل بهتر است.

نزدیکی به پایانه های حمل و نقل(متر) : هر چه قدر فاصله کمتر باشد، محل بهتر است.

نزدیکی به مراکز اداری(متر) : هر چه قدر فاصله کمتر باشد، محل بهتر است.

در این پروژه، کاربران درچهارحالت مختلف تصمیم گیری مشارکت می نمایند. این حالات به شرح زیر می باشند:

- حالت اول تصمیم گیری: اولویت بندی ۵ محل بر مبنای ۲ معیار
- حالت دوم تصمیم گیری: اولویت بندی ۱۰ محل بر مبنای ۴ معیار
- حالت سوم تصمیم گیری: اولویت بندی ۱۵ محل بر مبنای ۶ معیار
- حالت چهارم تصمیم گیری: اولویت بندی ۲۰ محل بر مبنای ۸ معیار

در هریک از حالات فوق، کاربران به دو شکل مختلف در تصمیم گیری شرکت می نمایند: تصمیم گیری فردی و تصمیم گیری گروهی.

مراحل شرکت در تصمیم گیری فردی

در حالت تصمیم گیری فردی، کاربران ارجحیت معیارها و همچنین عدد تعامل پذیری بین معیارها را مشخص می نمایند و سپس سیستم مورد نظر محل ها را بر اساس ارجحیت و همچنین عدد تعامل پذیری تعیین شده، اولویت بندی می نماید. ارجحیت یک معیار نمایانگر تقدم یک معیار نسبت به معیار دیگر در تصمیم گیری می باشد.کاربران ارجحیت معیارها را با در نظر گرفتن اهمیت نسبی آنها و همچنین مقادیر آنها در محل های مختلف

(مقادیر در جدول تصمیم گیری)، تعیین می نمایند. علاوه بر اهمیت نسبی معیارها، مقادیر یک معیار در محل های مختلف نقش عمده ای را در تعیین ارجحیت ان معیار ایفا می کند. کاربران ممکن است کمترین مقدار یک معیار در بین محل های مختلف، بیشترین مقدار یک معیار در بین محل های مختلف، کمترین مقدار مورد نظر خود در بین محل های مختلف، بیشترین مقدار مورد نظر خود در بین محل های مختلف و محدوده تغییرات مقادیر معیار را در تعیین ارجحیت معیارها در نظر بگیرند. به عنوان مثال، فرض کنید که مقدار معیار "نزدیکی پارکینگ به راه اصلی" تا سه محل به ترتیب "۱۰ متر" و "۲۰ متر" و "۱۵ متر" می باشد و مقدار معیار "اندازه پارکینگ" برای سه محل به ترتیب "۵۰۰ مترمربع" و "۱۰۰۰ مترمربع" و "۳۰۰۰ مترمربع" می باشد. محدوده تغییرات مقادیر برای معیار "نزدیکی پارکینگ به راه اصلی" کم است، یعنی از ۱۰ تا ۲۰ متر است. از انجاییکه محدوده تغییرات مقادیر "نزدیکی پارکینگ به راه اصلی" کم است، بین سه محل فرق مهمی از لحاظ این معیار، وجود ندارد. در حالی که محدوده تغییرات مقادیر برای معیار "اندازه پارکینگ" زیاد است، یعنی ۵۰۰ تا ۳۰۰۰ مترمربع است و بین سه محل فرق مهمی از لحاظ این معیار وجود دارد. در نتیجه از نظر کاربر، ممکن است معیار "اندازه پارکینگ" مهمتر از معیار "نزدیکی پارکینگ به راه اصلی" باشد.

عدد تعامل پذیری بین معیارها نمایانگر میزان اهمیت نسبی مقادیر معیارهای یک محل نسبت به یکدیگر می باشد. این عدد بین صفر تا یک می باشد.

- با افزایش تدریجی این عدد از ۰,۵ به سمت ۱ ، مقادیر بالاتر معیارهای یک محل در اولویت بندی به

طور نسبی مهمتر و مهمتر می شوند و مقادیر پایین تر ان کم اهمیت تر می شوند. به گونه ای که وقتی کاربر عدد ۱ را انتخاب می کند، تنها بالاترین مقدار در اولویت بندی محل به شمار می اید.

- با کاهش تدریجی این عدد از ۰,۵ به سمت ۰ ، مقادیر پایین تر یک محل در اولویت بندی به طور نسبی مهمتر و مهمتر می شوند و مقادیر بالاتر کم اهمیت تر می شوند. به گونه ای که وقتی کاربر عدد ۰ را انتخاب می کند، تنها کمترین مقدار در اولویت بندی محل به شمار می اید.

شکل ۱ مراحل تصمیم گیری فردی را نمایش می دهد. این مراحل به شرح زیر می باشند:

۱- جستجو ی مقادیر معیارها در جدول تصمیم گیری و جستجوی فضای نقشه

همانگونه که قبلا یاد شد، لازمه تعیین ارجحیت معیارها و عدد تعامل پذیری بین معیارها، جستجوی مقادیر معیارها در جدول تصمیم گیری می باشد. در جدول تصمیم گیری، ستون ها نمایانگر معیارها، ردیفها نمایانگر محل ها و هرخانه جدول نمایانگر مقدار یک معیار برای یک محل خاص می باشد. ردیف آخر در این جدول نمایانگر محدوده تغییرات مقادیر برای هر معیار می باشد. به عنوان مثال، جدول تصمیم گیری در شکل ۱، مقادیر دو معیار را برای ۳ محل نمایش می دهد. با کلیک کردن بر روی هر خانه در جدول ، مقدار یک معیار برای یک محل مشخص، ظاهر می شود و وقتی کاربر بر روی یک خانه دیگر در جدول کلیک می نماید، مقدار خانه قبلی ناپدید شده و مقدار خانه جدید ظاهر می شود. همچنین کاربران قادرند، محل ها متناظر با خانه های

انتخاب شده در جدول را با رنگ سبز بر روی نقشه Google map مشاهده نمایند. کاربران می توانند عوارض مکانی مختلف مانند (خیابان اصلی، مراکز خرید و غیره)را نیز در قسمت بالای نقشه انتخاب نمایند و توزیع عوارض را در فضای نقشه مشاهده کنند.

۲-باز نمودن پنجره تعیین ارجحیت و تعامل پذیری معیارها

پس از جستجو ی مقادیر معیارها در جدول تصمیم گیری و جستجوی فضای نقشه، کاربران ارجحیت و عدد تعامل پذیری بین معیارها را تعیین می نمایند. با کلیک بر روی دکمه تصمیم گیری، پنجره تعیین ارجحیت و تعامل پذیری معیارها باز می شود. لازم به ذکر است که با بسته شدن پنجره، اطلاعات کاربران همچنان در این پنجره باقی خواهد ماند. بنابراین کاربران می توانند در حین تعیین ارجحیت و عدد تعامل پذیری بین معیارها، پنجره را بسته و اطلاعات موجود را در جدول و نقشه جستجو نمایند و دوباره وارد پنجره شوند و کار خود را ادامه دهند.

۳- تعیین ارجحیت معیارها

از طریق پنجره باز شده، کاربران ارجحیت معیارها را با بالا و پایین بردن معیارها، تعیین می نمایند (شکل ۱ را ببینید).

۴- تعیین عدد تعامل پذیری بین معیارها

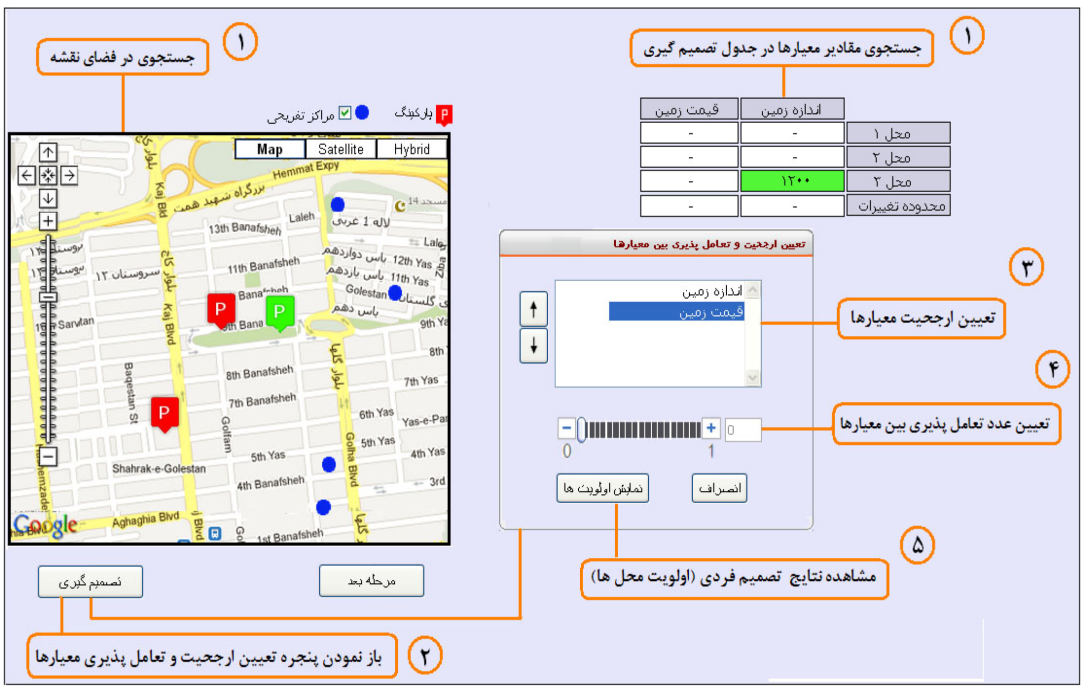
پس از مشخص نمودن ارجحیت معیارها، کاربران عدد تعامل پذیری بین معیارها را با حرکت دادن موس بر روی نوار افقی درون پنجره تعیین ارجحیت و تعامل پذیری معیارها، تعیین می نمایند (**شکل ۱** را ببینید).

۵- مشاهده نتایج تصمیم فردی (اولویت محل ها)

پس از تعیین نمودن ارجحیت معیارها و عدد تعامل پذیری،

کاربران می توانند اولویت محل ها را بر روی نقشه مشاهده نمایند. جهت نمایش اولویت محل ها، کاربران باید بر روی دکمه نمایش اولویت ها کلیک نمایید. علاوه بر اولویت محل ها، کاربران می توانند میزان امتیاز تصمیم بدست امده برای هر محل را نیز با کلیک بر روی ان محل، مشاهده نمایند (**شکل ۲** را ببینید).

پس از پایان مراحل تصمیم فردی، کاربران با کلیک بر روی دکمه مرحله بعد، وارد مرحله تصمیم گیری گروهی می شوند.



شکل ۱ : مراحل تصمیم گیری فردی

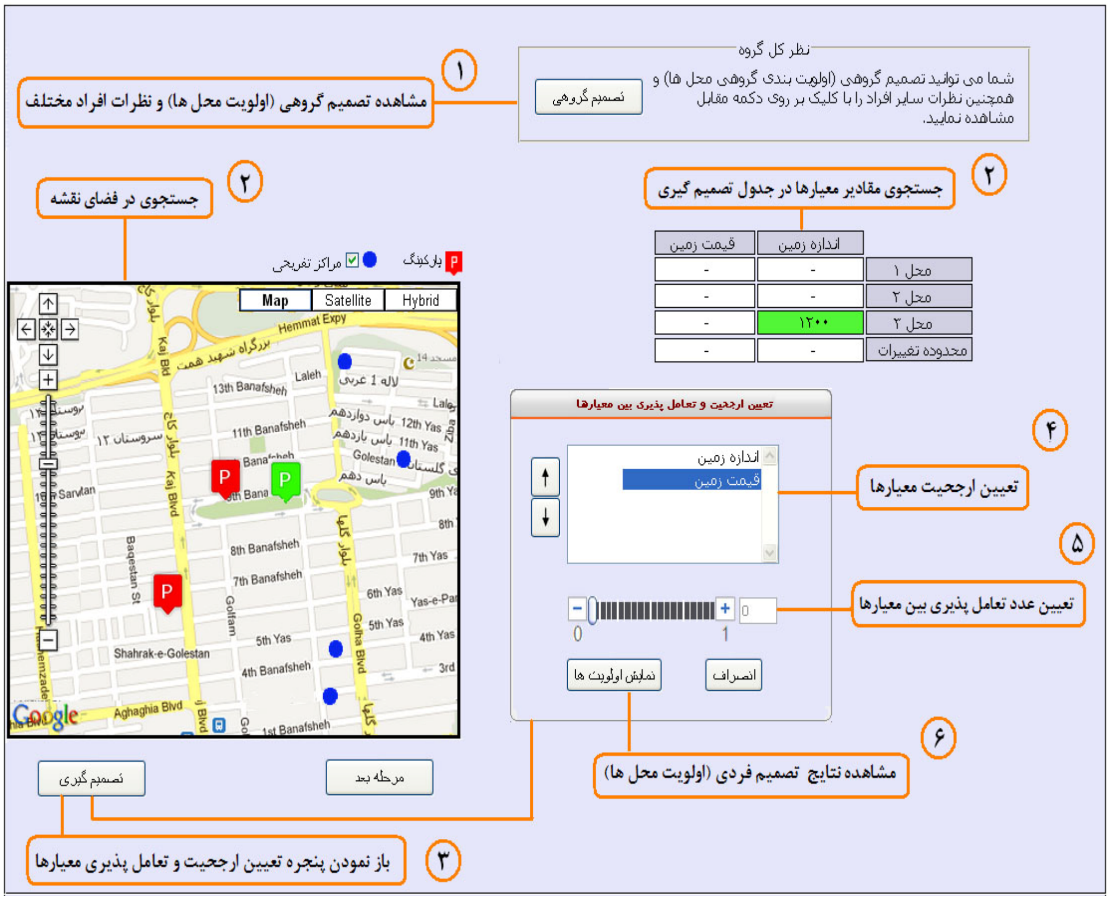
شکل ۲ : نتایج تصمیم فردی (اولویت محل ها)

مراحل شرکت در تصمیم گیری گروهی

مراحل شرکت در تصمیم گیری گروهی عینا مشابه مراحل تصمیم گیری فردی می باشد. تنها تفاوت ان در این است که در حالت تصمیم گیری گروهی، کاربران می توانند ابتدا تصمیم گروهی (میانگین اولویتهای بدست امده توسط کاربران مختلف) و همچنین نظرات سایر افراد را با کلیک بر روی دکمه تصمیم گروهی مشاهده نمایند و سپس نتایج تصمیم خود (اولویت فردی محل ها) و نتایج تصمیم گروهی را بر روی نقشه مقایسه نموده و دوباره مرحله تصمیم گیری خود (مراحل ذکر شده در بالا) را تکرار می نمایند (شکل ۳ را ببینید).

علاوه بر مشاهده تصمیم گروهی، کاربران قادرند نظرات خود را در مورد محل های موجود پارکینگها و یا مکانهای مناسب دیگر برای ایجاد پارکینگها بر روی نقشه وارد نمایند (شکل ۴ را ببینید). به عنوان مثال، ممکن است بعضی از کاربران، محل های

دیگری را برای ایجاد پارکینگ پیشنهاد نمایند. پس از وارد نمودن نظرات، کاربران باید بر روی دکمه ذخیره کلیک نمایند. با کلیک بر روی دکمه بازگشت، کاربران به صفحه تصمیم گیری برگشته و دوباره فرایند تصمیم گیری فردی خود را تکرار می نمایند. پس از پایان این مرحله، کاربران با کلیک بر روی دکمه مرحله بعد وارد حالت بعدی تصمیم گیری می شوند.



شکل ۳ : مراحل تصمیم گیری گروهی

شکل ۴ : مشاهده تصمیم گروهی (اولویت گروهی محل ها) و نظرات افراد

Appendix C: The GUIs for the GIS-MCDA individual and group modes in the four decision situations (in Persian)

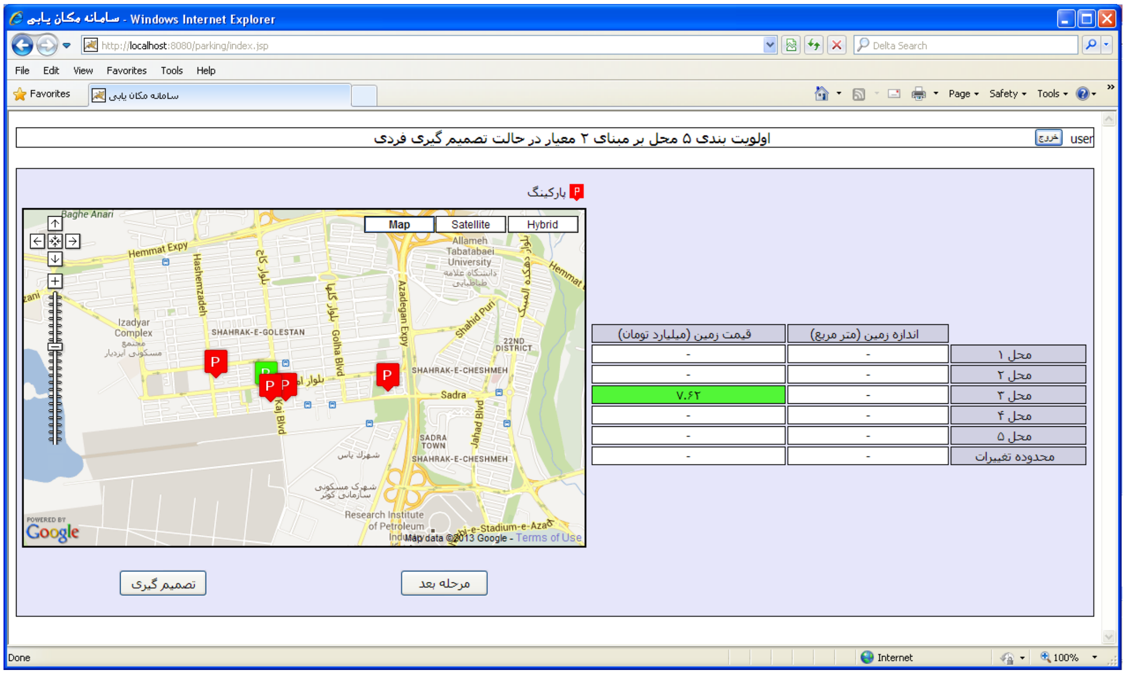


Figure C2. The GUI for the GIS-MCDA individual mode in decision situation “5×2”.

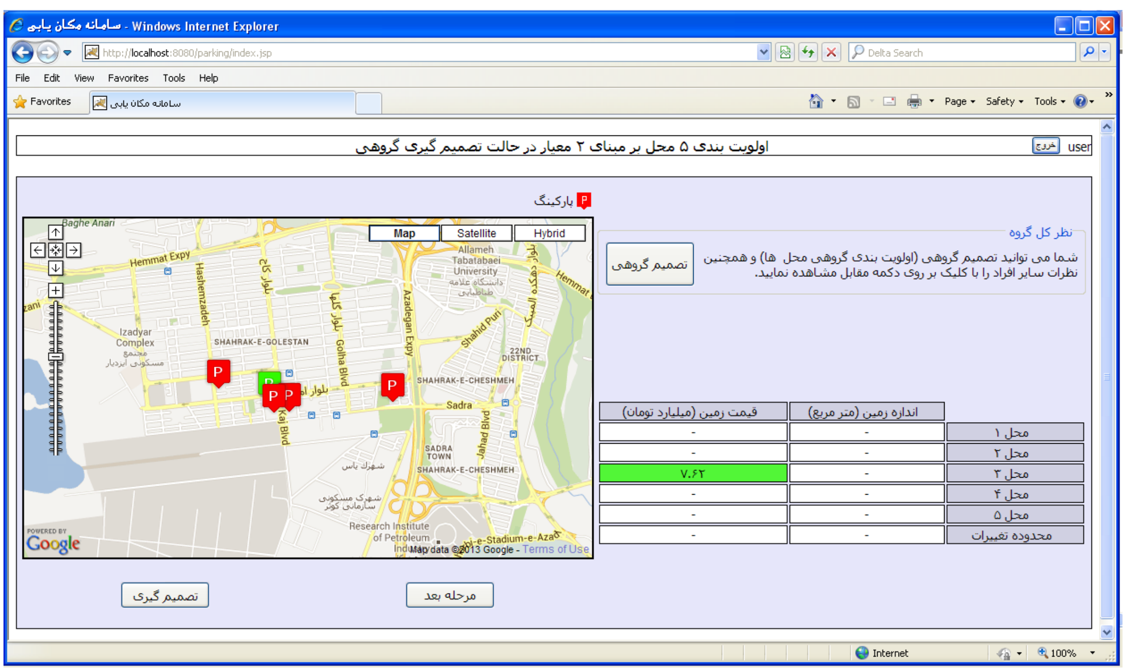


Figure C3.The GUI for the GIS-MCDA group mode in decision situation “5×2”.

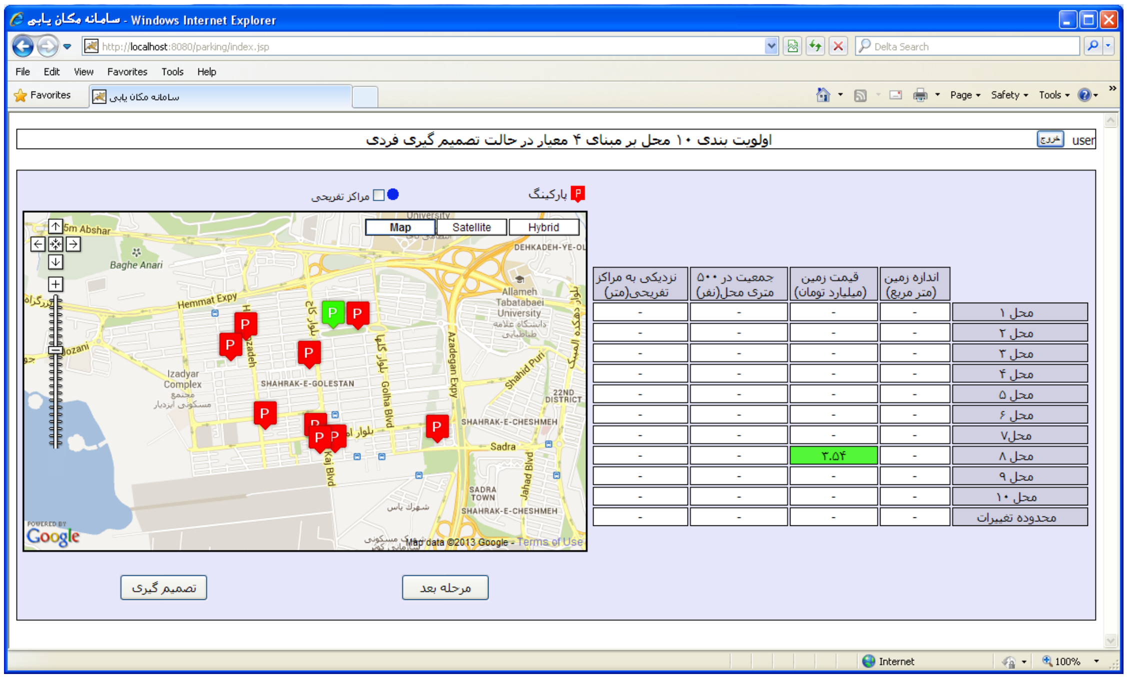


Figure C4. The GUI for the GIS-MCDA individual mode in decision situation“10×4”.

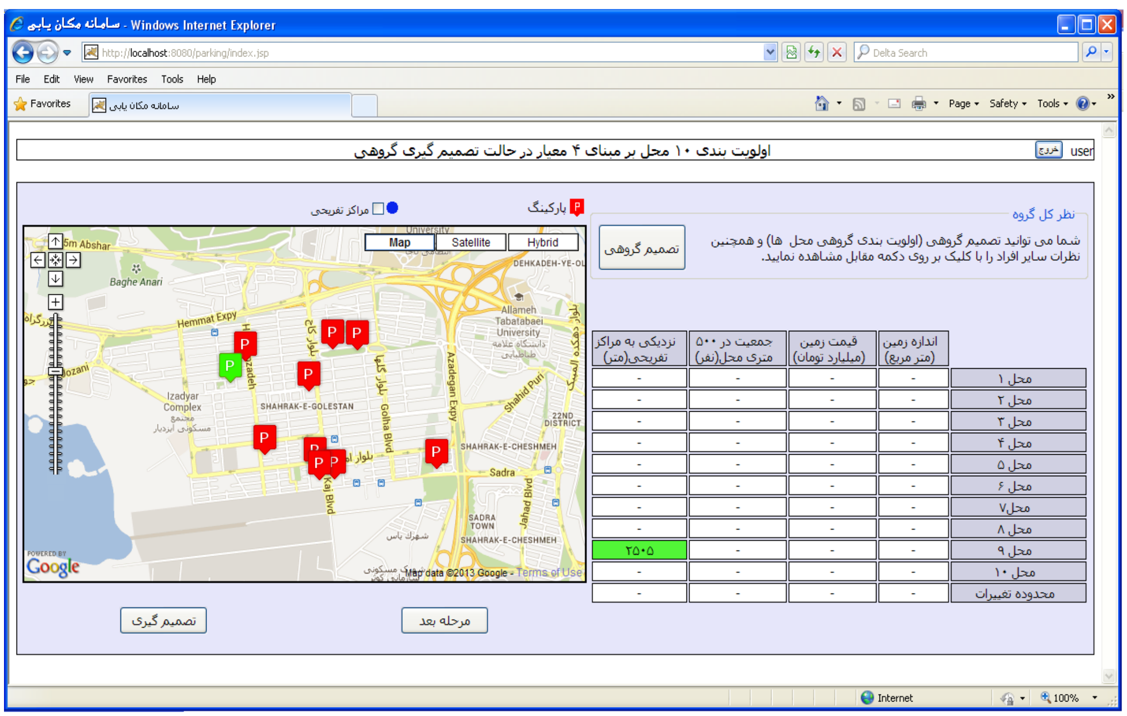


Figure C5. The GUI for the GIS-MCDA group mode in decision situation “10×4”.

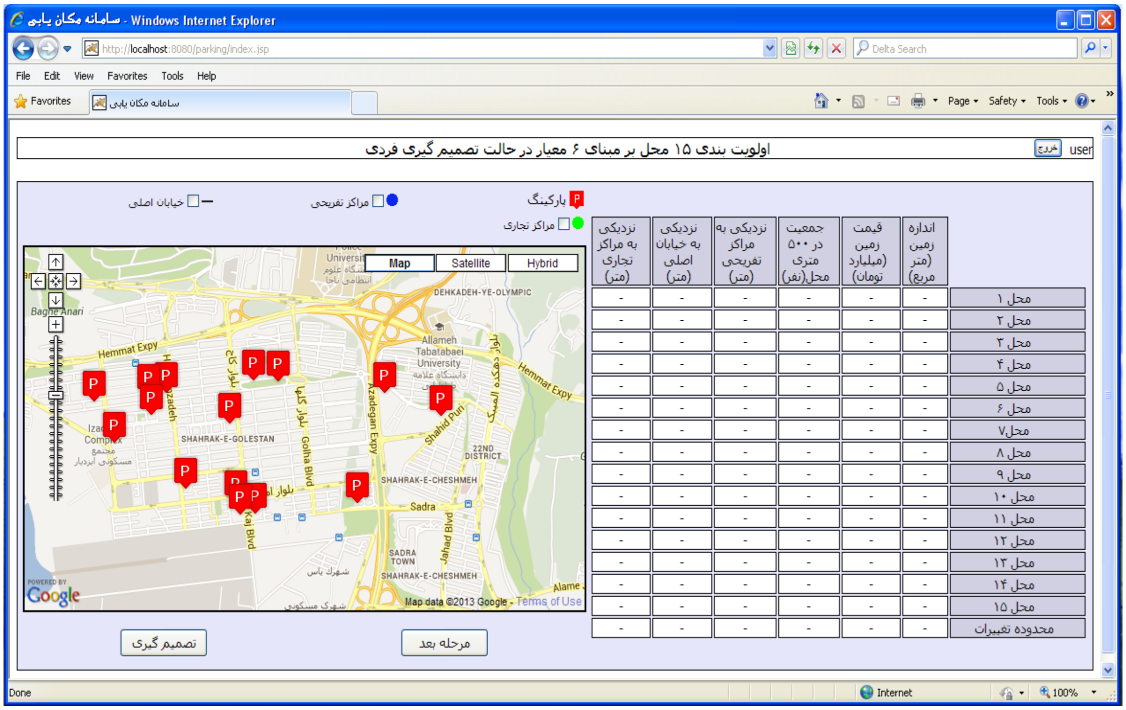


Figure C6. The GUI for the GIS-MCDA individual mode in decision situation “15×6”.

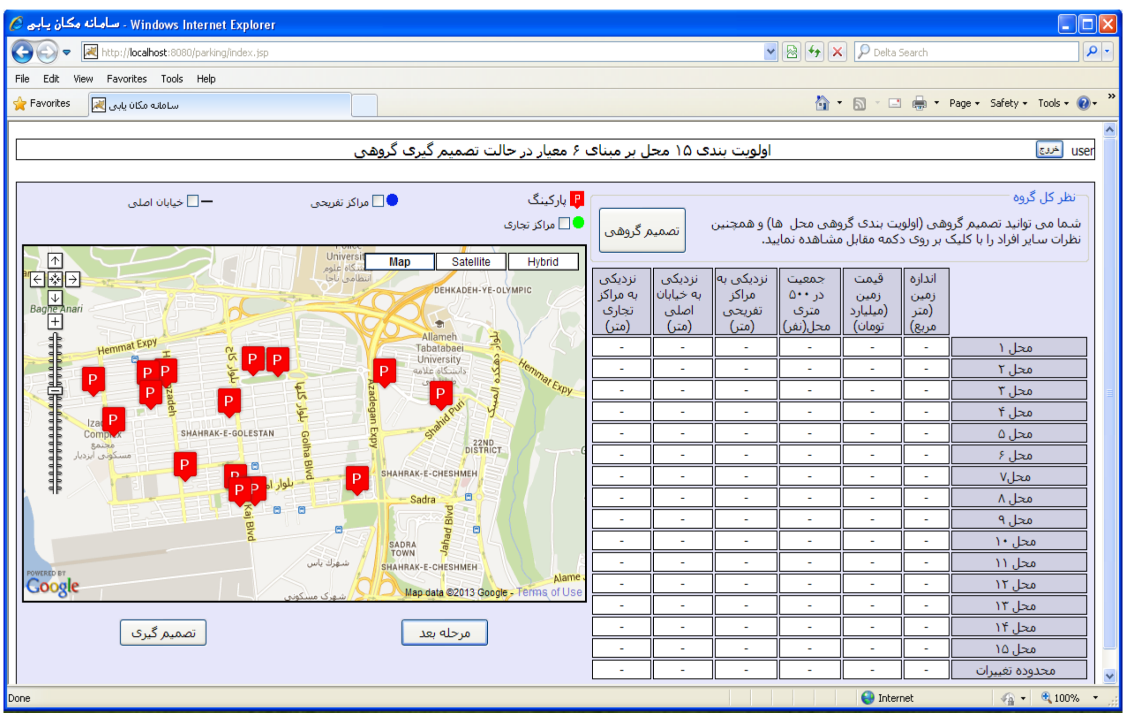


Figure C7. The GUI for the GIS-MCDA group mode in decision situation “15×6”.

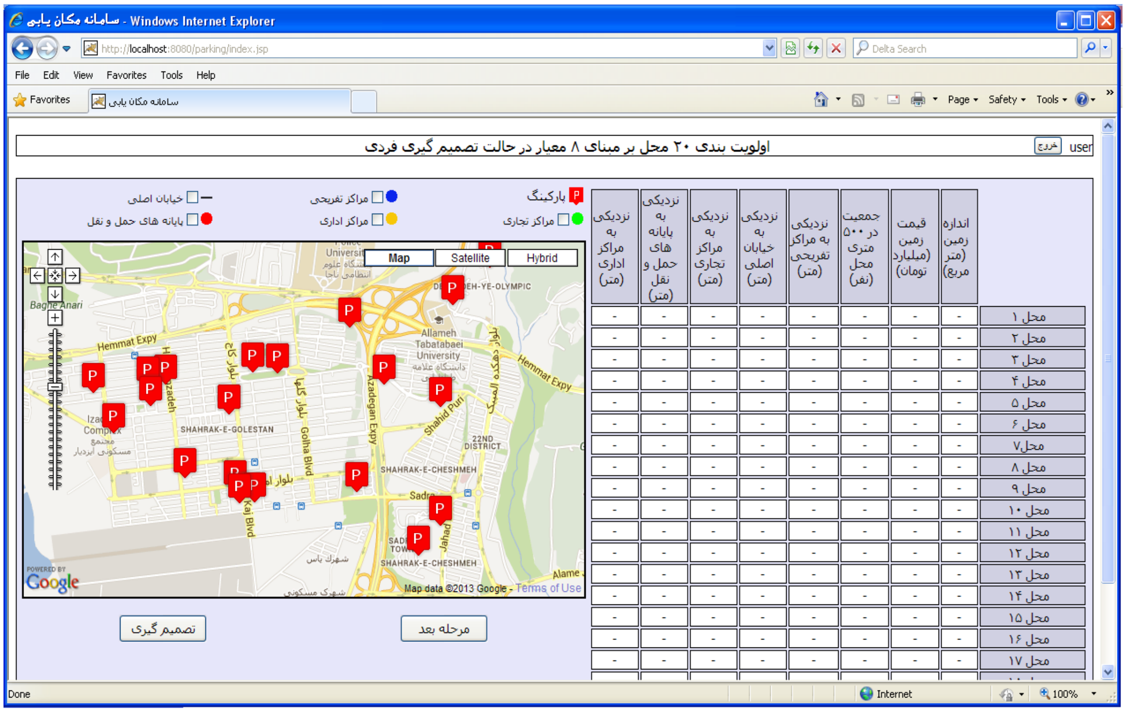


Figure C8. The GUI for the GIS-MCDA individual mode in decision situation “20×8”.

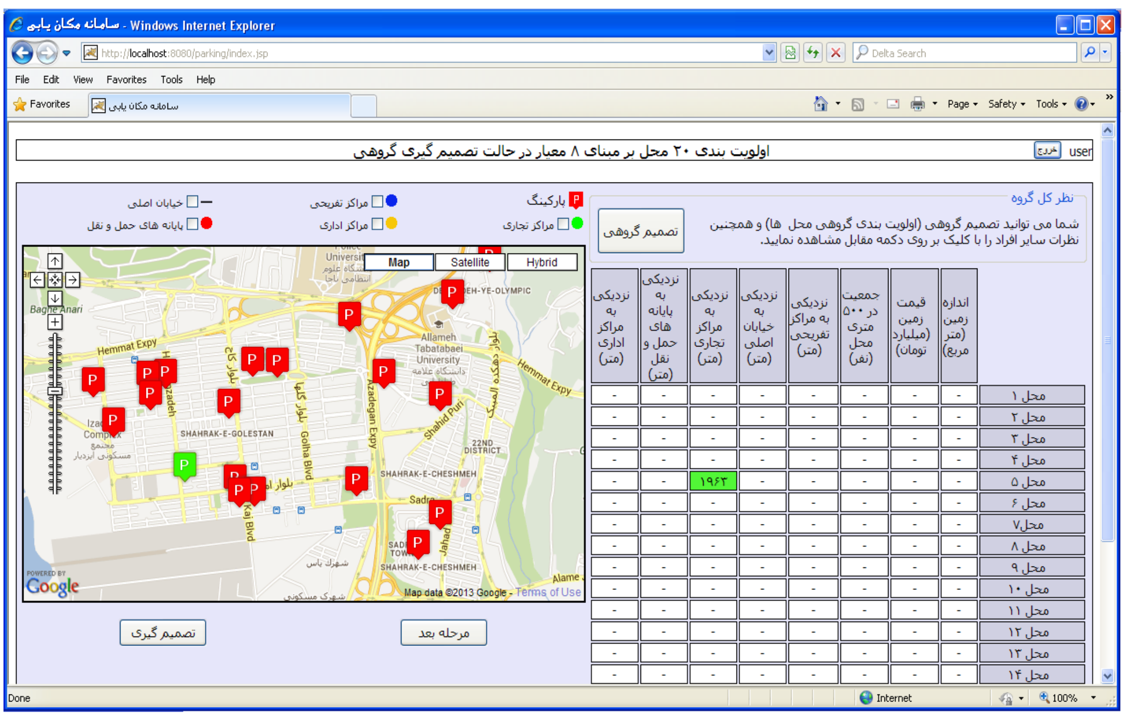


Figure C9. The GUI for the GIS-MCDA group mode in decision situation “20×8”.

Figure C10. The windows for specifying the criteria priorities and ORness value in the four decision situations “5×2”, “10×4”, “15×6”, and “20×8”.

Appendix D: The log event data

[Table] logtb @parkingdb (localhost)

File Edit View Window

Import Wizard | Export Wizard | Filter Wizard | Grid View | Form View | Memo | Hex | Image | Sort Ascending | Sort Descending | Remove Sort

id	userId	userName	logDate	level	isGroupLevel	actionName	actionCode	newVal	lat	lang	oldVal
4632	97	user1	2013-05-12 19:33:27	(Null)	(Null)	ایجاد کاربر	3	97 user1	(Null)	(Null)	(Null)
4633	97	user1	2013-05-12 19:33:41	(Null)	(Null)	کلیک دکمه	100	start	(Null)	(Null)	(Null)
4634	97	user1	2013-05-12 19:34:09	1	1	کلیک خانه جدول	30	(Null)	1	1	(Null)
4635	97	user1	2013-05-12 19:34:10	1	1	کلیک خانه جدول	30	(Null)	2	2	(Null)
4636	97	user1	2013-05-12 19:34:11	1	1	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4637	97	user1	2013-05-12 19:34:14	1	1	بالا بردن مشخصه	40	قیمت زمین	(Null)	(Null)	Up
4638	97	user1	2013-05-12 19:34:19	1	1	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4639	97	user1	2013-05-12 19:34:23	1	1	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4640	97	user1	2013-05-12 19:34:26	1	2	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4641	97	user1	2013-05-12 19:34:29	1	2	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4642	97	user1	2013-05-12 19:34:30	1	2	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4643	97	user1	2013-05-12 19:34:31	1	2	کلیک دکمه	100	yes	(Null)	(Null)	(Null)
4644	97	user1	2013-05-12 19:34:33	2	1	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4645	97	user1	2013-05-12 19:34:34	2	1	بالا بردن مشخصه	40	نزدیکی به مراکز تفریحی	(Null)	(Null)	Up
4646	97	user1	2013-05-12 19:34:36	2	1	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4647	97	user1	2013-05-12 19:34:39	2	1	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4648	97	user1	2013-05-12 19:34:39	2	2	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4649	97	user1	2013-05-12 19:34:40	2	2	بالا بردن مشخصه	40	نزدیکی به مراکز تفریحی	(Null)	(Null)	Up
4650	97	user1	2013-05-12 19:34:40	2	2	بالا بردن مشخصه	40	نزدیکی به مراکز تفریحی	(Null)	(Null)	Up
4651	97	user1	2013-05-12 19:34:43	2	2	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4652	97	user1	2013-05-12 19:34:44	2	2	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4653	97	user1	2013-05-12 19:34:45	2	2	کلیک دکمه	100	yes	(Null)	(Null)	(Null)
4654	97	user1	2013-05-12 19:34:50	3	1	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4655	97	user1	2013-05-12 19:34:50	3	1	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4656	97	user1	2013-05-12 19:34:50	3	1	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4657	97	user1	2013-05-12 19:34:50	3	1	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4658	97	user1	2013-05-12 19:34:52	3	1	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4659	97	user1	2013-05-12 19:34:54	3	1	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4660	97	user1	2013-05-12 19:34:54	3	2	کلیک دکمه	100	تصمیم گروهی	(Null)	(Null)	(Null)
4661	97	user1	2013-05-12 19:34:59	3	2	ایجاد کامنت جدید	32	(Null)	35.752503	51.249075	(Null)
4662	97	user1	2013-05-12 19:34:59	3	2	تغییر اطلاعات اضافی گروه	51	groupComment	(Null)	(Null)	false
4663	97	user1	2013-05-12 19:35:17	3	2	کلیک دکمه	100	ذخیره	(Null)	(Null)	(Null)
4664	97	user1	2013-05-12 19:35:20	3	2	جابجایی نقشه گروه	9	(Null)	35.750483	51.24341	(Null)
4665	97	user1	2013-05-12 19:35:23	3	2	ایجاد کامنت جدید	32	(Null)	35.747418	51.231909	(Null)
4666	97	user1	2013-05-12 19:35:48	3	2	کلیک دکمه	100	ذخیره	(Null)	(Null)	(Null)
4667	97	user1	2013-05-12 19:35:57	3	2	ایجاد کامنت جدید	32	(Null)	35.750483	51.257401	(Null)
4668	97	user1	2013-05-12 19:36:13	3	2	کلیک دکمه	100	ذخیره	(Null)	(Null)	(Null)
4669	97	user1	2013-05-12 19:36:14	3	2	کلیک دکمه	100	بازگشت	(Null)	(Null)	(Null)
4670	97	user1	2013-05-12 19:36:16	3	2	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4671	97	user1	2013-05-12 19:36:17	3	2	کلیک دکمه	100	yes	(Null)	(Null)	(Null)
4672	97	user1	2013-05-12 19:36:19	4	1	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4673	97	user1	2013-05-12 19:36:20	4	1	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4674	97	user1	2013-05-12 19:36:21	4	1	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4675	97	user1	2013-05-12 19:36:23	4	1	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4676	97	user1	2013-05-12 19:36:25	4	2	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4677	97	user1	2013-05-12 19:36:27	4	2	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4678	97	user1	2013-05-12 19:36:27	4	2	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4679	97	user1	2013-05-12 19:36:27	4	2	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4680	97	user1	2013-05-12 19:36:28	4	2	بالا بردن مشخصه	40	نزدیکی به مراکز تجاری	(Null)	(Null)	Up
4681	97	user1	2013-05-12 19:36:32	4	2	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4682	97	user1	2013-05-12 19:36:39	4	2	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4683	97	user1	2013-05-12 19:36:41	4	2	کلیک دکمه	100	end	(Null)	(Null)	(Null)
4684	97	user1	2013-05-12 19:36:41	4	2	خروج	2	97 user1	(Null)	(Null)	(Null)
4685	98	aaa	2013-05-12 19:37:35	(Null)	(Null)	ایجاد کاربر	3	98 aaa	(Null)	(Null)	(Null)
4686	98	aaa	2013-05-12 19:37:40	(Null)	(Null)	کلیک دکمه	100	start	(Null)	(Null)	(Null)
4687	98	aaa	2013-05-12 19:37:51	1	1	کلیک دکمه	100	تصمیم گیری	(Null)	(Null)	(Null)
4688	98	aaa	2013-05-12 19:37:53	1	1	بالا بردن مشخصه	40	قیمت زمین	(Null)	(Null)	Up
4689	98	aaa	2013-05-12 19:38:01	1	1	کلیک دکمه	100	نمایش اولویت ها	(Null)	(Null)	(Null)
4690	98	aaa	2013-05-12 19:38:02	1	1	کلیک دکمه	100	مرحله بعد	(Null)	(Null)	(Null)
4691	98	aaa	2013-05-12 19:38:34	1	2	کلیک دکمه	100	تصمیم گروهی	(Null)	(Null)	(Null)
4692	98	aaa	2013-05-12 19:38:38	1	2	تغییر اطلاعات اضافی گروه	51	groupComment	(Null)	(Null)	false
4693	98	aaa	2013-05-12 19:38:41	1	2	کلیک آیکون کامنت جدید	31	(Null)	35.747418	51.231909	(Null)
4694	98	aaa	2013-05-12 19:38:50	1	2	کلیک دکمه	100	ذخیره	(Null)	(Null)	(Null)
4695	98	aaa	2013-05-12 19:38:58	1	2	ایجاد کامنت جدید	32	(Null)	35.75703	51.228905	(Null)
4696	98	aaa	2013-05-12 19:39:12	1	2	کلیک دکمه	100	ذخیره	(Null)	(Null)	(Null)
4697	98	aaa	2013-05-12 19:39:17	1	2	جابجایی نقشه گروه	9	(Null)	35.74693	51.239033	(Null)
4698	98	aaa	2013-05-12 19:39:18	1	2	کلیک دکمه	100	بازگشت	(Null)	(Null)	(Null)

ELECT * FROM `logtb` LIMIT 0,1000

Record 67 of 1000 in Page 1

Figure D11. The sample log event data in MySQL database.

Curriculum Vitae

Mohammadreza Jelokhani-Niaraki

Education

PhD in Geography **09/2009-Present**
Western University, Ontario, Canada

Thesis: Web 2.0-based Collaborative Multicriteria Spatial Decision Support System: A Case Study of Human-Computer Interaction Patterns

Graduation date: 12/2013

M.Sc. in Civil Engineering- Geographic Information System (GIS) **09/2006-02/2009**
K. N. Toosi University of Technology, Tehran, Iran

Thesis: The design and implementation of GIS-based Data Model for Managing Roads Maintenance Information in Iran

B.Sc. in Civil Engineering-Surveying (Geomatics) **09/2002-07/2006**
Azad University (South Tehran Branch), Tehran, Iran

Publications

Journal papers

- Malczewski, J., & **Jelokhani-Niaraki, M.R.**, (2012). An ontology-based multicriteria spatial decision support system: a case study of house selection. *Geo-spatial Information Science,* 15(3), pp. 177-185.

- **Jelokhani-Niaraki, M.R.,** & Malczewski, J. (2012). A web 3.0-driven collaborative multicriteria spatial decision support system. *Cybergeo: European Journal of Geography* Article 620, http://cybergeo.revues.org/25514.

- **Jelokhani-Niaraki, M.R.**, Sadeghi-Niaraki, A., & Kyehyun, K. (2012). An ontology-based approach for managing spatio-temporal linearly referenced road event data. *Road & Transport Research*, 21(4), pp.38-49.

- **Jelokhani Niaraki, M.R.**, Alesheikh, A.A., Sadeghi, A., & Alimohammadi, A. (2011). An approach for automatic update of GIS road segments for a pavement management system (PMS). *Journal of Spatial Science*, 56 (2), pp.253-267.

- **Jelokhani-Niaraki, M.R.**, Alesheikh, A.A., Alimohammadi, A., & Sadeghi-Niaraki, A. (2010). Towards a rule driven approach for updating dynamic road segments. *Promet – Traffic &Transportation Journal*, 22(6), pp.405-411.

- **Jelokhani-Niaraki, M.R.**, Alesheikh, A.A., & Sadeghi-Niaraki, A. (2010). An efficient approach for historical storage and retrieval of segmented road data in Geographic Information System for Transportation. *Chinese geographical science Journal*, 20 (3), pp. 236-242.

Presentations and conference papers

- Jelokhani-Niaraki, M.R. and Malczewski, J. 2012. A user-centered multicriteria spatial decision analysis model for participatory decision making: An ontology-based approach. In Proceedings of GSDI 13, Quebec City. (Online Proceedings-http://www.gsdi.org/gsdiconf/gsdi13 /prog_details.html).

- Jelokhani-Niaraki, M.R. and Malczewski, J. 2012. Web 2.0-based Semantic Spatial Multicriteria Decision Analysis (MCDA) Framework for Collaborative Decision Making. In Proceedings of CAG (Canadian Association of Geographers), Waterloo.

- Jelokhani-Niaraki, M.R., A.A. Alesheikh, A. Alimohammadi, A. Sadeghi-Niaraki, (2009). "Designing Road Maintenance data Model Using Dynamic Segmentation Technique". Springer-Verlag Lecture Notes in Computer Science (LNCS) Series, Volume 5592/2009, 442-452.

- Jelokhani Niaraki, M.R., Golnarkar, A. and Alesheikh, A.A., 2008. "Integration of GIS and GPS for Water Utility Disaster Management". Map India 2008, 6-8 February, New Delhi, India.

- Golnarkar, A., Jelokhani Niaraki, M.R. and Hamrah, M., 2008. "An Approach to the Selection of a Suitable Interpolation Method". Map India 2008, 6-8 February, NewDelhi, India.

- Jelokhani Niaraki, M.R., Alesheikh, A.A., Sadeghi, A., 2008. "Evaluation of dynamic segmentation process for roads network data models". Geomatics 87 Conference, May 2008, NCC, Tehran, Iran.