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Mohammadreza Jelokhani-Niaraki and Jacek Malczewski

Department of Geography, Western University, London, ON, Canada

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The decision task complexity and information acquisition strategies in GIS-MCDA

Mohammadreza Jelokhani-Niaraki* and Jacek Malczewski

Department of Geography, Western University, London, ON, Canada

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This paper addresses the research question of how does the complexity of a decision task affect information acquisition strategies used by decision-makers in a GIS-based multicriteria decision analysis (MCDA)? It reports the results of an experimental study that investigated the effect of task complexity (information load) on information acquisition strategies in the use of a multicriteria spatial decision support system (MC-SDSS). The experiment involved the use of the MC-SDSS for online parking site selection (ranking) in District # 22 of Tehran, Iran at four levels of complexity. The complexity of the site selection task was manipulated in terms of the number of: (1) decision alternatives available to decision-makers and (2) the evaluation criteria (attributes) used to describe the alternatives. At each level of task complexity, the site selection process was carried out in two GIS-MCDA modes: individual and group (collaborative) modes. The findings demonstrate that: (1) an increase in task complexity tends to result in the use of non-compensatory decision strategies; (2) decision-makers using compensatory strategies spend more time acquiring information from decision tables than maps, and (3) the task complexity has no impact on the interaction between the map and table uses.

Keywords: GIS-MCDA; decision task complexity; information acquisition behavior; site selection problem

1. Introduction

The multicriteria spatial decision support systems (MC-SDSS) integrate GIS capabilities (spatial databases and analyses) and multicriteria decision analysis (MCDA) techniques to support a user or a group of users in making spatial decisions (Malczewski 1999a). Using a MC-SDSS enables decision-makers to evaluate a set of geographically defined alternatives with respect to a given set of evaluation criteria. Typically, the decision strategies determine how to evaluate alternatives or to decide which alternative is preferred to another. The decision strategies in the GIS-MCDA context involve combining the relevant spatial data (attribute map layers) and decision-makers’ preferences to provide an overall assessment (rating/ranking) of decision alternatives. The Boolean map 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 strategies in GIS-MCDA (Boroushaki and Malczewski 2010). The Boolean overlay operations are non-compensatory approaches because they do not involve trade-off among the criteria. On the other hand, the WLC strategies allow trade-off or compensation among all criteria. The weights assigned

*Corresponding author. Email: mjelokha@uwo.ca

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govern the degree to which a criterion can compensate for another criterion. These two types of combination rules can be generalized within the framework of ordered weighted averaging (OWA) (Jiang and Eastman 2000, Eldrändaly 2013). By specifying a parameter, the OWA-based method allows decision-makers to define a variety of decision strategies with different compensation levels ranging from a minimum-type/Boolean AND combination (non-compensatory) through all intermediate compensatory types (including the conventional WLC) to a maximum-type/Boolean OR combination (non-compensatory).

The studies on decision-making behavior provide both theoretical and empirical evidence about the relationship between decision strategies used by decision-makers (compensatory and non-compensatory strategies) and their information acquisition behavior. Researchers have made remarkable efforts in operationalizing information acquisition variables as a means of inferring the decision strategies used by decision-makers. For instance, the proportion, direction, variability, and time of information search in a decision table are the major variables that have been considered as the basic distinction between compensatory and non-compensatory decision strategies (Payne 1976, Roe et al. 2001, Schmeer 2003, Queen et al. 2012). Typically, the compensatory decision strategies are characterized by a higher proportion in the amount of information searched, an alternative-wise pattern of information search (where an alternative is selected and attributes/evaluation criteria are searched for that alternative), a lower level of variability in the information searched per attribute/alternative, and a higher amount of time spent on information searched.

The results of studies on human–computer interaction in the context of MC-SDSS suggest that decision situations involving different levels of task complexity affect decision-makers’ information acquisition or decision strategies (Jankowski and Nyerges 2001, Sugumaran and Degroote 2011). There is a large body of literature on the influences of task complexity on information acquisition strategies within the realm of non-spatial decisions. The studies have shown that task complexity affects the information processing demands and decision strategies of individuals (e.g., Payne 1976, Schulte-Mecklenbeck 2005). 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 (Payne et al. 1993, Schmeer 2003). With a non-compensatory strategy, compensation or trade-offs across evaluation criteria are avoided and evaluation may be qualitative rather than quantitative. Such 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 trade-off between reduced cognitive effort and potentially less than optimal decisions (non-compensatory strategies) in high-complexity decision tasks.

Although there are a number of studies that have focused on studying the effects of task complexity on information acquisition strategies within the realm of non-spatial decisions, the research efforts examining task complexity effects in the field of spatial decision-making have been rather limited. For example, the efforts in the spatial decision context have addressed the effects of task complexity on decision time and accuracy (Crossland et al. 1995), the human decision processing and performance (Swink and Speier 1999), decision efficiency and accuracy (Mennecke et al. 2000), and the use of information aids (e.g., maps and tables) (Jankowski and Nyerges 2001). Also, Jarupathirun and Zahedi (2007) manipulated the complexity of a site selection task to provide different decision situations for exploring the factors that impact perceived successful use of Web-based SDSS.
However, none of the above studies has examined the effects of task complexity on information acquisition (decision) strategies in a GIS-MCDA context. There is, therefore, a need for research to provide insights into decision-makers’ information acquisition strategies and the effect of task complexity on these strategies during the use of MC-SDSSs. The purpose of this paper is to address this need by carrying out an experimental study of information acquisition behavior in a GIS-MCDA process. Specifically, the study examines the question of whether decision-makers in an OWA-based GIS-MCDA context switch from compensatory decision strategies to non-compensatory strategies as the task complexity increases. To this end, a set of research hypotheses were developed and empirically tested. The experimental tasks involved urban and regional planning students at the two main universities in Tehran, Iran to participate and use a web-based MC-SDSS (OWA-based GIS-MCDA approach) for tackling a parking site selection problem (i.e., ranking of parking sites) at varying levels of task complexity. Using the web-based MC-SDSS, participants were able to specify their preferences with respect to the decision criteria (criteria priorities) on the basis of information provided, and the system could eventually rank the parking alternative locations according to the participants’ preferences. The students specified their preferences at four levels of task complexity in two decision-making modes: individual and group. In the individual mode, decision participants specified their preferences without knowing about the group decision, while in the group mode, they reviewed the group solution (i.e., the group ordering of alternatives) and other participants’ map-based comments, and then respecified their preferences. The information acquisition behaviors of the students were traced and measured at each level of the site selection complexity in both of the decision-making modes.

2. Information acquisition

Researchers in decision-making have long recognized the importance of information acquisition as a determinant of decision quality (e.g., Paul et al. 2005, Meng 2010). The process of information search and acquisition is critical to GIS-MCDA. The process is concerned with the examination of available decision information about the elements of a decision problem, including spatial alternatives, attributes (criteria), and the attribute values associated with the alternatives. Typically, decision-makers in GIS-MCDA processes need to seek the decision information as a basis for making trade-offs between criteria (the specification of criteria preferences/priorities/weights). Acquiring the decision information allows decision-makers to take into account the distribution of attribute values, 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 (Malczewski 1999a, 2000, Ligmann-Zielinska and Jankowski 2012). For example, it is suggested that the weights a decision-maker assigns to criteria depends on the range of attribute values (the extent to which alternatives vary on that attribute) (e.g., Malczewski 2000, Pöyhönen et al. 2001). Accordingly, this stresses the need for decision-makers to examine the decision information, and look at the attribute values when they assign their criteria/attribute preferences.

The decision table and map are two fundamental categories of decision aids for representing and organizing the information about spatial decision problems (Malczewski 1999b, Jankowski and Nyerges 2001). They represent the decision space (spatial alternatives) and the criterion outcome space (the criteria values associated with the alternatives), respectively (see Malczewski 1999b). Jankowski et al. (2001) argue that an integrated visualization of the decision and criterion outcome spaces is essential for
understanding the structure of a decision problem (see also Rinner 2007). They suggest that the concurrent representation of decision and criterion spaces opens a possibility for eliciting decision-makers’ preferences with respect to decision criteria not only on the basis of attribute data but also geography. Using maps, decision-makers are able to explore the alternatives and also the spatial distribution of the geographic entities based on which attributes are defined (Malczewski 1999a). The main purpose of using maps in GIS-MCDA should be the consideration of alternative locations during the exploration of trade-offs among the decision criteria and the search for the best solutions to the decision problem. The table-based presentation of decision information is a complementary source to the map-based presentation. Each location in the decision space (map) has its associated criterion values in the decision outcome space (decision table or criterion outcome table).

3. Task complexity
Campbell (1988) argues that any structural characteristic of a decision task that places high cognitive demands on decision-makers 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 decision-makers is viewed as representing a relevant complexity factor (Payne 1976, Wang and Chu 2004, Queen et al. 2012). Accordingly, one can measure task complexity by: (1) the number of alternatives available for decision-making and (2) the number of attributes that describe those alternatives (e.g., Payne 1976, Pfeiffer 2012). The number of spatial alternatives and attributes are the major variables that affect the information acquisition behavior (decision strategy) during GIS-MCDA processes. The greater the number of alternatives and attributes in the GIS-MCDA decision task, the more difficult it will be for decision-makers to process and integrate alternative-attribute information, make trade-offs among the attributes, specify attribute/criteria preferences, and evaluate the set of alternatives.

4. Research hypotheses
The basic assumption underlying a set of hypotheses to be tested is that the information acquisition strategies shift from compensatory to non-compensatory as task complexity or the amount of information used increases. It is expected that the shift from compensatory to non-compensatory strategies manifest itself in the change of a set of information acquisition variables across the varying levels of decision complexity. Accordingly, the research hypotheses are developed based on a set of information acquisition variables. Each of the hypotheses is tested in two decision-making modes: individual and collaborative/group decision-making. In the individual mode, decision-makers evaluate alternatives without knowing the group decision; while in the group mode, decision-makers are able to review the group solution/advice (i.e., the group ordering of alternatives and the other participants’ map-based comments), and then conduct the decision-making process. Schrah et al. (2006) suggest that decision-makers may employ different information acquisition strategies in the decision modes where they are provided with advice (alternative choice recommendations) and where they are not.

Hypothesis 1: Increased task complexity will result in a decrease in the proportion of information search. The proportion of information search refers to the amount of information searched in the decision table or the amount of available information actually
considered in a decision-making process. According to Payne (1976), the proportion of information search is measured as the number of information cells examined by a decision-maker divided by the total number of information cells. 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 trade-offs, therefore the hallmarks of non-compensatory search strategy.

**Hypothesis 2a:** Increased task complexity will result in a decrease in the average amount of time spent on each piece of information (information cell). **Hypothesis 2b:** Increased task complexity will result in an increase in the total time spent acquiring information from the decision table. The time spent acquiring information from the decision table serves as an indirect measure of the amount of effort and deliberation required to make the decision (Klemz and Gruca 2001, Queen et al. 2012). The average time is calculated by dividing the total time spent examining all acquired pieces of information by the number of acquisitions. The total time is measured by the length of time during which a decision-maker examines the decision table. 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 time spent per item of information acquired in a compensatory decision strategy is greater than that in a non-compensatory decision-making process.

**Hypothesis 3a:** Increased task complexity will result in an increase in the variability information searched per attribute. **Hypothesis 3b:** Increased task complexity will result in an increase in the variability of information searched per alternative. The variability of search per alternative and/or attribute is defined as the standard deviation of the number of information pieces searched per alternative/attribute (Payne 1976, Schmeer 2003). Both the variability of search per alternative and attribute have been linked to the type of decision strategy employed. For compensatory strategies, a constant and equal amount of information will be searched per alternative/attribute, whilst for non-compensatory strategies, a variable amount of information search per alternative/attribute will be observed.

**Hypothesis 4a:** Decision-makers use a more attribute-wise strategy (direction of search) than an alternative-wise in the information acquisition process. **Hypothesis 4b:** Increased task complexity will result in a direction of search that is more attribute-wise than alternative-wise. The direction of search in the decision table is the sequence in which the information cells are examined (Payne 1976, Schrah et al. 2006, Queen et al. 2012). Typically, the search sequences are classified as alternative-wise (an alternative is selected and attributes are searched for that alternative) and attribute-wise (an attribute is selected and alternatives are searched for that attribute). An alternative-wise direction involves trade-offs among attribute values, and thus, suggests a compensatory acquisition strategy, while the attribute-wise ignores trade-offs, and therefore, presents a non-compensatory strategy. To measure whether the direction of search is alternative- or attribute-wise, one can use a search index (SI) (Payne 1976). This index is defined as a ratio of the number of alternative-wise transitions minus the number of attribute-wise transitions over the sum of those two numbers; that is, $SI = (r_{alt} - r_{att})/(r_{alt} + r_{att})$, where $r_{alt}$ is the alternative-wise transition frequency and $r_{att}$ is 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.
Hypothesis 5a: Increased task complexity will result in an increase in time spent acquiring information from map. Hypothesis 5b: Increased task complexity will result in a higher number of moves on map. Similar to the decision table, the number and time of information acquisitions could be used as the information acquisition metrics on 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-makers’ interaction with map (Jankowski and Nyerges 2001).

Hypothesis 6a: There is a significant relationship between the type of information aid (table and map) and the time spent acquiring the decision information. It is anticipated that significantly more time will be spent on the decision table than on map in both the GIS-MCDA individual and group modes. Hypothesis 6b: Increased task complexity has a significant impact on the relationship between the time spent on map and the time spent acquiring information from decision table. Speier (2006) argues that data visualized using such techniques as tables and maps allows decision-makers to shift some of the cognitive processing burden to perceptual operations that typically occur automatically and result in significantly lower mental workload. Therefore, it is reasonable to expect that the types of decision aids offered (decision table vs. map) in the GIS-MCDA environment have a significant influence on the way and number of times that they are used (Jankowski and Nyerges 2001).

5. Method
5.1. Experimental design
Using task complexity as the independent factor and the information acquisition metrics as the dependent variables, this study adopted a repeated-measures experimental design to test the hypotheses advanced in Section 4. The experimental activities centered on using a web-based MC-SDSS for parking site selection (ranking) in Tehran, Iran (for details see Jelokhani-Niaraki 2013). The complexity of parking site selection task in the MC-SDSS was manipulated at four levels: (1) five alternatives and two attributes; (2) ten alternatives and four attributes; (3) fifteen alternatives and six attributes; and (4) twenty alternatives and eight attributes. Each increase in the number of alternatives and attributes incorporated the previous available alternatives and attributes as a subset. In this way, the procedure ensured that even the most limited information load would involve at least some attributes (e.g., land cost) which would seem necessary to making a realistic choice (Payne 1976). To avoid carryover or order effects in the experiment, the order of presentation of the decision situations (task complexity) was counterbalanced across participants.

5.2. Subjects
Experimental tasks required that subjects have an adequate level of knowledge about GIS, MCDA, and urban planning. To this end, the study involved both graduate and undergraduate students in the urban planning departments at the two main universities in Tehran (University of Tehran and Shahid Beheshti University) in the experiment. Students in these departments had studied the basic and advanced concepts, theories, practices, and techniques associated with GIS and urban planning in different courses. They were
already involved in various GIS-based course works and research projects in Tehran’s municipalities that have given them experience using GIS-based applications for urban planning. For these reasons, the students were used as the potential subjects in the experiment. Each student was able to participate in the experiment after registering online as a user in order to track the information acquisition activities. A total of 55 volunteers participated throughout the parking site selection process. From the data available through online registration form in the website (see http://collaborativesdss.com), it was evident that over 80% of the participating students were in the graduate level, aged 22–30, and most of them had a relatively good knowledge about GIS and urban planning. This, to some extent, reduces the experimental uncertainty associated with the subjects’ knowledge in performing the decision tasks.

5.3. Decision-making procedure

Using the MC-SDSS, the participants performed the task of parking site selection at each level of complexity in the GIS-MCDA individual and group modes (see http://collaborativesdss.com). Figures 1 and 2 show an example of the user interfaces for the complexity level 15 alternatives × 6 attributes in the individual and group decision-making modes, respectively. In the individual mode, the MC-SDSS provides participants with a decision table and map for exploring the decision information and allows them to determine the criteria preferences, and evaluates the alternatives according to the participants’ criteria preferences. The information cells in the decision table contain the attribute values associated with alternatives as well as the range values of the attributes.

The method used in this study to monitor the users’ interaction with the decision table is based on a well-known method called Mouselab process-tracing approach (Payne et al. 1993). This approach has been widely used in the research efforts focusing on tracing...
information acquisition behavior in a decision table (e.g., see Klemz and Gruca 2001, Willemsen and Johnson 2010, Van Kerckhove et al. 2012, Trudel and Murray 2013). Based on this method, in the beginning, only attribute and alternative labels are visible, and all the attribute values are hidden in the cells. To access and examine the information in each cell, participants need to move the mouse cursor into the cell and click on it. When participants click on another cell, the information in the previous cell disappears and the new cell’s value comes into view. 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. If only one cell can be opened at a time and it is closed when another cell is opened, the Mouselab places constraints on working memory, because pieces of information must be remembered until the search process is terminated. Despite this limitation, the study did not adopt a design that permanently leaves cells open once they have been selected by the subject. Although leaving the cells open has the advantage that subjects face a reduced memory burden, Gabaix et al. (2006) argue that it has the disadvantage that subjects have the option to quickly open many cells, and only afterward analyze their content. In this case, as participants analyze the cell contents later, their real information acquisition behavior is characterized with their eye fixations later, not early, in the opening of the cells. Gabaix et al. (2006) assert that leaving cells open implies that we lose the ability credibly to infer the user’s attention at each point in time.

The system allows a two-way dynamic and interactive link between the decision table and map views whereby the search moves in one view are immediately propagated to the other view (Jankowski et al. 2001). If the participant clicks on a particular decision
alternative (parking site) on the map, then the corresponding information cells (the blank cells not the cell values) in the decision table are highlighted. Also, by clicking on a particular information cell in the decision table, the system highlights the corresponding alternative on the map (see Figures 1 and 2). This level of interactivity allows the participant to simultaneously explore the alternatives in both the geographic and criterion outcome spaces, thus facilitating information acquisition during the decision-making process. Similar to the individual mode, the MC-SDSS in the group mode enables the participants to examine the decision table and map, express their criteria preferences, and generate the alternatives’ rankings. The only difference is that, in the group mode, participants can review the other participants’ comments and also the group rankings of alternatives as a kind of choice recommendations using the group decision tool.

5.4. Collecting data and hypothesis testing
The data on the participants’ information acquisition activities during the experiment was traced and recorded using a database-logging approach. The log data included the information that the participants examined on the map and decision table, how much information was examined, how long the information was examined for, as well as the sequence in which they were looked at in the decision table. These data were date and time stamped, and when reviewed, provided a picture of the user interaction with the system. After computing the information acquisition metrics from the log data, repeated measures analysis of variance (ANOVA) and linear mixed model (LMM) tests at a significance level of $\alpha = 0.05$ were carried out to test the hypotheses. The set of hypotheses 1, 2, 3, 4, and 5 were tested using ANOVA, with the task complexity as the independent factor and each of the information acquisition metrics as the dependent variable. The hypothesis 6 was examined using LMM test, where the time spent on the map was considered as the dependent variable and the time spent on the decision table as the covariate, and the factor was task complexity.

6. Results and discussion
Hypothesis 1: The results indicate that the mean proportion of information search in both the GIS-MCDA individual and group modes declines as the task complexity increases (see Table 1). The ANOVA test shows that the null hypothesis of no difference in the proportion of information search between the low- and high-complexity decision situations should be rejected. Consistent with the expectations, the participants searched a significantly higher proportion of available information in the lower levels of task complexity in both of the decision modes. This result provides a support 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, Schrah et al. 2006, Queen et al. 2012).

The significant effect of task complexity on the proportion of information search can be explained in terms of the high-cognitive demands on decision-makers for searching more information as well as more variations of range values across the attributes. The range values for each attribute (the extent to which alternatives vary on that attribute) are the key to specification of the criteria preferences in the GIS-MCDA context. When the task complexity increases, the addition of alternatives and attributes
Table 1. The descriptive statistics and ANOVA results for the effect of task complexity.

<table>
<thead>
<tr>
<th>Decision mode</th>
<th>Individual mode</th>
<th>Group mode</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Task complexity</strong></td>
<td><strong>5 × 2</strong></td>
<td><strong>10 × 4</strong></td>
</tr>
<tr>
<td><strong>The proportion of information search</strong></td>
<td>Mean</td>
<td>0.271</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>0.312</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(2, 104) = 23.49, P = 0.000 &lt; 0.05$</td>
</tr>
<tr>
<td><strong>The average amount of time spent acquiring per item of information (sec)</strong></td>
<td>Mean</td>
<td>4.540</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(2, 84) = 1.45, P = 0.239 &gt; 0.05$</td>
</tr>
<tr>
<td><strong>The total time spent on the decision table (sec)</strong></td>
<td>Mean</td>
<td>20.92</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>33.37</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(3, 162) = 1.06, P = 0.368 &gt; 0.05$</td>
</tr>
<tr>
<td><strong>The variability of information search per attribute</strong></td>
<td>Mean</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(3, 84) = 5.50, P = 0.002 &lt; 0.05$</td>
</tr>
<tr>
<td><strong>The variability of information search per alternative</strong></td>
<td>Mean</td>
<td>0.474</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>0.306</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(2, 52) = 0.75, P = 0.468 &gt; 0.05$</td>
</tr>
<tr>
<td><strong>The direction of search (SI)</strong></td>
<td>Mean</td>
<td>−0.284</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>0.551</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(2, 66) = 1.085, P = 0.352 &gt; 0.05$</td>
</tr>
<tr>
<td><strong>The total time spent on the map (sec)</strong></td>
<td>Mean</td>
<td>1.32</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>6.81</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(2, 133) = 0.55, P = 0.612 &gt; 0.05$</td>
</tr>
<tr>
<td><strong>The number of moves on the map</strong></td>
<td>Mean</td>
<td>0.309</td>
</tr>
<tr>
<td></td>
<td>Standard deviation</td>
<td>1.65</td>
</tr>
<tr>
<td></td>
<td>ANOVA result</td>
<td>$F(1, 99) = 1.48, P = 0.233 &gt; 0.05$</td>
</tr>
</tbody>
</table>
to the initial set of alternatives is more likely to expand the variations of ranges across the attributes. Several studies show that the greater the attribute ranges, and thus the less similar the alternative, the lower is the proportion of search (e.g., Pfeiffer 2012). With an increased task complexity, the proportion of attribute values and ranges examined by decision-makers decreases as a kind of unintentional cognitive shortcut. This means that decision-makers avoid a full compensation or trade-off between attributes by considering an only subset of available attribute values, and therefore it is an indication of a non-compensatory strategy.

**Hypothesis 2a:** Contrary to the expectations, the mean times (the average amount of time spent examining information cells) in both the individual and group GIS-MCDA modes are not in a descending order (see Table 1). The ANOVA test also fails to reject the null hypothesis of no difference in the average amount of time between the low- and high-complexity situations. Thus, the main effect of task complexity on the average amount of decision time is insignificant. The findings in both of the decision modes are inconsistent with the results of research by Ford et al. (1989) and Klemz and Gruca (2001). 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, 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 method) for the evaluation of geographic alternatives based on the individual preferences.

**Hypothesis 2b:** The results suggest that, in both of the decision modes, the amounts of total time spent on the decision table are not in the hypothesized direction, as was the case for the average amount of time (see Table 1). The ANOVA results show that there is a statistically insignificant difference in the total times among the decision situations. Therefore, one can conclude that task complexity has an insignificant effect on the total time spent acquiring information from decision table. The results of this study are inconsistent with the findings reported by Smelcer and Carmel (1997) and Jankowski and Nyerges (2001). These two studies found that the amount of time spent looking at the information in the table increases with an increase in task complexity. The possible reasons for the discrepancy between these results might be attributed to the factors described in Section 6: Hypothesis 2a.

**Hypothesis 3a:** The results show a positive relationship between task complexity and the variability of information search per attribute in the individual mode. Therefore, the direction of these values is consistent with the hypothesis (see Table 1). The ANOVA result indicates that task complexity has a significant effect on the variability of information searched per attribute. 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. Unlike the individual mode, the variability values in the GIS-MCDA group mode are not in the same direction as predicted by the hypothesis. In addition, the ANOVA test shows that the main effect of task complexity on the variability of search per attribute is statistically insignificant.
Hypothesis 3b: The mean values of variability per alternative in both of the decision modes are not in the hypothesized direction (see Section 4). The ANOVA test fails to reject the null hypothesis of no difference in the variability among the low- and high-complex decision situations (see Table 1). As a result, the main effect of task complexity on the variability of search per alternative is statistically insignificant. 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, the hypothesis is not supported by the evidence.

Hypothesis 4a: In both the GIS-MCDA individual and group modes, participants were expected to use a more attribute-wise strategy than an alternative-wise in the information search process. The results show that the SI values are negative in all of the four decision situations in both the GIS-MCDA individual and group modes. This indicates that the participants used attribute-wise strategies, thus providing a support for the hypothesis (see Section 4). The attribute-wise strategies require less cognitive effort as the comparisons and trade-off among evaluation attributes are avoided. Consequently, when decision-makers are faced with a choice between reduced cognitive effort and making trade-off among criteria (alternative-wise strategy), they often choose attribute-wise strategies, and therefore non-compensatory strategies.

Hypothesis 4b: Clearly, the mean SI values in both of the decision modes are not in the direction suggested by the hypothesis (see Section 4). The ANOVA test fails to reject the null hypothesis of no difference in the direction of information search (the SI values). Therefore, there is a statistically insignificant difference in the direction of search among the decision situations. This implies that, in both the GIS-MCDA individual and group modes, participants do not necessarily switch from an alternative-wise to attribute-wise direction as task complexity increases.

Hypothesis 5a: The results show that the time spent on the map in both the decision modes do not increase as task complexity increases (see Section 4). In addition, the ANOVA results indicate that there are statistically insignificant differences in the mean times. These results are inconsistent with previous studies by Smelcer and Carmel (1997), Swink and Speier (1999), and Jankowski and Nyerges (2001). In this study, time spent on the map neither increases nor decreases as the task complexity increases. While both the studies by Smelcer and Carmel (1997) and Swink and Speier (1999) revealed that increasing the task complexity leads to an increase in time spent examining information on the map. One of the potential reasons for the discrepancy between the findings may be the fact that this study examines the time spent on the map in a GIS-MCDA context, while the two studies investigated the time spent on the map in a simple evaluation/determination of alternative locations (locations of facilities) (see also Section 6: Hypothesis 2b). On the other hand, Jankowski and Nyerges (2001) reported that the maps were used more in the simple task than in the complex task. Although both Jankowski and Nyerges (2001) and this research investigated the effect of task complexity on information acquisition times in the use of GIS-MCDA, the difference between the findings could be explained by the use of different GIS-MCDA techniques, spatial decision problems, and/or decision-making platforms (web-based vs. desktop-based).

Hypothesis 5b: Similar to the time spent on the map, the mean values of map moves are not in the hypothesized direction (see Section 4). The ANOVA results for this hypothesis indicate that there is an insignificant difference in the number of map moves among the
four decision situations (see Table 1). Therefore, the hypothesis is not supported by the evidence.

**Hypothesis 6a**: As can be seen from Table 1, in both of the decision modes, the time spent examining the information pieces in the decision table is higher than that on the map. This assertion is also supported by the percentage of participants who spent more time acquiring the decision information from the decision table than the map (see Table 2). The LMM test results indicate that one should reject the null hypothesis of no difference in the amount of time spent between the decision table and map. In other words, participants spent a significantly higher amount of time on information acquired in the decision table than the map (see also Smelcer and Carmel 1997, Jankowski and Nyerges 2001). A main conclusion that emerges from these results is that decision-makers using compensatory strategies are more likely to spend more time on decision tables than maps in spatial decision-making processes.

The possible reasons for using the decision table more than the map could be the importance of information that decision table represents, and the way that it represents the information. Although the map and table representations complement each other, they contain different information (geographic decision space vs. criteria outcome 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. Smelcer and Carmel (1997) suggest that maps generally produce faster problem solving than tables and are more efficient for a variety of levels of task complexity. Since a map contains an integrated view of the relevant data, it is a more accurate representation of geographic features, and keeps the information that a user must consider smaller in one display. It provides a decision-making environment that more consistently fits the cognitive requirements of decision-makers and thereby reduces cognitive load.

**Hypothesis 6b**: The LMM results suggest that, in both of the GIS-MCDA individual and group modes, an increase in task complexity has an insignificant effect on the relationship between the times spent on the map and table (see Table 3). This is an indication that the interaction between the exploration of the geographic and criteria outcome spaces (the

Table 2. The percentage of participants and LMM results for the usage of table more than map.

<table>
<thead>
<tr>
<th>Task complexity</th>
<th>Individual mode</th>
<th>Group mode</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 × 2</td>
<td>10 × 4</td>
</tr>
<tr>
<td>Table usage more than map usage (%)</td>
<td>98.11</td>
<td>100</td>
</tr>
<tr>
<td>LMM result</td>
<td>$F = 62.29, P = 0.000 &lt; 0.05$</td>
<td>$F = 56.13, P = 0.000 &lt; 0.05$</td>
</tr>
</tbody>
</table>

Table 3. The LMM results for the effect of task complexity on the relationship between the time spent on the decision table and map.

<table>
<thead>
<tr>
<th></th>
<th>Individual mode</th>
<th>Group mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>LMM result</td>
<td>$F = 0.82, P = 0.485 &gt; 0.05$</td>
<td>$F = 1.51, P = 0.221 &gt; 0.05$</td>
</tr>
</tbody>
</table>
interaction between the number of map and table uses) is not affected by the complexity of decision task (see also Jankowski and Nyerges 2001). Accordingly, one can conclude that, in every complexity level, decision-makers adopting compensatory strategies tend to use decision tables more than maps.

7. Conclusion
The main purpose of this study was to examine the information acquisition strategies within a web-based MC-SDSS. Specifically, the study investigated the following research question: how does decision task complexity affect information acquisition strategies used by decision-makers individually and collaboratively? The results suggest that there are statistically significant relationship between the task complexity and the following information acquisition metrics: the proportion of information search and the variability of information search per attribute. 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 impact of the task complexity on the other metrics were neither significant nor in the direction suggested by the relevant hypotheses.

This study also revealed that decision-makers use a more attribute-wise than alternative-wise strategies in all of the complexity levels. The attribute-wise strategies require less cognitive effort as the comparisons and trade-off among evaluation criteria/attributes are avoided. This is an indication for the use of non-compensatory strategies in GIS-MCDA processes. In other words, decision-makers adopt a more non-compensatory information acquisition strategy for combining spatial attribute values in their decision strategies.

In addition, it was found that decision-makers spend more time on acquiring information from the decision table than the map. The overall picture that emerges from this result is that decision-makers using compensatory strategies are more likely to spend more time acquiring information from decision tables than maps in spatial decision-making processes. Finally, the present study explored the question whether task complexity affect the relationship between the information acquisition from the decision table and map? The results indicated that task complexity has no impact on the interaction between the map and table uses (the interaction between the geographic decision and criteria outcome spaces).

The findings emerging from this empirical study offer important implications for research in the area of spatial decision-making. They broaden our understanding of spatial decision-making behavior and provide details about decision process dynamics involving geographic decision aids. An understanding of how decision-makers acquire and combine decision-related information in a decision-making process provides a contribution to knowledge about decision processes. In addition, the findings make contributions to behavioral decision theory and have implications for developing the theoretical constructs and propositions of information acquisition behavior in the GIS-MCDA context. Specifically, the findings allow researchers to create theoretical frameworks explaining why information search patterns differ between low- and high-complexity tasks.

The findings have practical implications for the development of MC-SDSSs, providing a new perspective on the use of decision support aids, and also important clues for designers to develop an appropriate user-centered MC-SDSS. A better understanding of decision-making behavior would aid researchers and designers in finding ways to properly structure the decision information and improve the quality of spatial decision-making. If different levels of task complexity do affect information acquisition strategies employed
by decision-makers, and if the strategy in turn affects the decision made, then MC-SDSS designers can foster the use of a particular decision-making process via the manipulation of decision complexity. 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. The results that decision-makers used relatively more attribute-based processing provide the evidence that decisions may be enhanced by developing an information structure that better supports alternative-based processing. 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 (Gönül et al. 2006, Meng 2010).

This research also suggests opportunities for using intelligent decision aids for helping decision-makers during the information acquisition process (Mennecke et al. 2000). For example, as we attain a better understanding of how the various levels of task complexity impact the cognitive loads of decision-makers, and in turn the proportion of information search in the GIS-MCDA, the MC-SDSS developers may adopt the intelligent software agents that could assist decision-makers in the information search activities. The agents could automatically and intelligently carry out some set of information search operations on behalf of decision-makers based on the specified goals and desires, and effectively support users’ information needs. This would be particularly useful when decision-makers are novice/less knowledgeable or a high volume of information is available for the decision problem (complex decision situation).

As is the case with any empirical research, the findings in this study are subject to some limitations. One of the limitations is the choice of a Mouselab-based approach to monitor the information acquisition behavior during the decision-making process. Using this approach, decision-makers could open only one cell at a time. However, this approach may have artificially reduced the accuracy of the results since subjects may have been unable to retain all of the relevant information in memory as required in our study. A future experiment needs to be designed in such a way that allows participants to continually view the cell values of decision table once these cells have been selected. In addition, eye tracking systems can be used as an alternative way of keeping track of decision processes. With eye trackers, it is unnecessary to hide information since the eye tracker system is able to precisely record fixations on information items (Pfeiffer 2012).

The issue of generalizability or external validity is another area which needs to be addressed. This limitation concerns the question to what extent are the findings generalizable to other types of decision problems, decision-makers, and decision support tools? In this study, participation was limited to the students of urban planning departments in Tehran. Although students were from urban planning departments and had a relatively good knowledge about GIS and urban planning, the results may still be subject to uncertainties which arise from the improper use of the GIS-MCDA application. For example, one likely source of uncertainty in the results may be related to the improper specification of criteria preferences/weights/priorities in the GIS-based MCDA (see Malczewski 1999a, 2000, Borouchaki and Malczewski 2010). Some participants might largely ignore acquiring information from both the decision table and map during the specification of criteria weights, and inaccurately assign the criteria weights mainly based on the subjective evaluations of importance of criteria (see Malczewski 2000, Monat, 2009, Ligmann-Zielinska and Jankowski 2012). Any participant should realize that assigning weights to criteria requires the examination of information about the distribution of values for a given criterion, the range of criteria values, and so on (see Section 2). In the GIS-MCDA studies, however, decision-makers may assign weights to criteria based
largely on the subjective evaluation of importance of criteria without a full consideration of the available information. In such a context, the information acquisition strategies may be biased in terms of properly and completely acquiring the decision information during the specification of criteria weights. These challenges can be overcome by providing adequate web-based learning materials on the meaning, rationale, and use of GIS-MCDA tools, as well as using professional planners in the experiment. Future research may involve professional planners as subjects in the experiment to generate more robust and valid results for the hypotheses.

In this study, the complexity of 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. One source of weakness is also related to the choice of the number of alternatives and attributes in manipulating the levels of complexity in the experimental study.

References


