# Exploring the Role of Individual Differences in Information Visualization

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## ABSTRACT
In this paper, we describe a user study aimed at evaluating the effectiveness of two different data visualization techniques developed for describing complex environmental changes in an interactive system designed to foster awareness in sustainable development. While several studies have compared alternative visualizations, the distinguishing feature of our research is that we try to understand whether *individual user differences* may be used as predictors of visualization effectiveness in choosing among alternative visualizations for a given task. We show that the cognitive ability known as *perceptual speed* can predict which one of our target visualizations is most effective for a given user. This result suggests that tailored visualization selection can be an effective way to improve user performance.

**Author Keywords**
Evaluation of visualization techniques; individual differences.

**ACM Classification Keywords**
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

## 1. INTRODUCTION
In recent years, information visualization has been gaining importance as a means of managing the often overwhelming amount of digital information available to users. From generic search engines to specialized software in areas as diverse as bioinformatics, economics and the social sciences, many applications need to be able to help users understand and manipulate bodies of data with various degrees of complexity. Research in information visualization strives to provide graphical representations that can help deal with this complexity. However, despite the many attempts to identify mappings between user needs and effective visualizations (e.g. [6], [4]) results are still partial and often conflicting (see [7]). Most of these attempts have been based on the assumption that it is possible to identify optimal visualizations given type and amount of data to be visualized as well as nature of the perceptual task involved. We argue that this assumption is one of the reasons for the lack of consistency in findings, and that there are other factors that determine a visualization's effectiveness. In particular, in this paper we explore the hypothesis that the mapping between user needs and effective visualizations is influenced by individual user differences. Given a task and corresponding data, different visualizations may work best for different users, given user traits such as cognitive skills, knowledge and personal preferences.

There is already anecdotal evidence in the literature that different users may have different visualization preferences [2], and several studies have linked individual differences to visualization effectiveness for search and navigation tasks in complex information spaces [e.g., 13,14,15]. Velez et al. [9] have shown that cognitive measures related to spatial ability correlated with performance accuracy in performing 3D mental rotations supported by 2D visualizations. Our research extends these results by analyzing how spatial abilities and other user-specific traits affect performance on two different visualizations for interpreting geographical data.

One of the ways in which visualization methods are used within Geographical Information Systems (GISs) is to show how an area of interest will change over time. Georgia Basin Quest ( GB-Quest) and QuestVis, both developed at the University of British Columbia, use different visualization methods to illustrate how a particular geographical region (the Georgia Basin in British Columbia, Canada) would change in 40 years time depending on the behaviours of its inhabitants. Anecdotal evidence (i.e., feedback from participants in environmental workshops that used GB-Quest and observations from pilot studies on QuestVis), suggests that the effectiveness of the visualization methods used by these two systems may depend on the user viewing them. If these observations were to be empirically confirmed, they could have

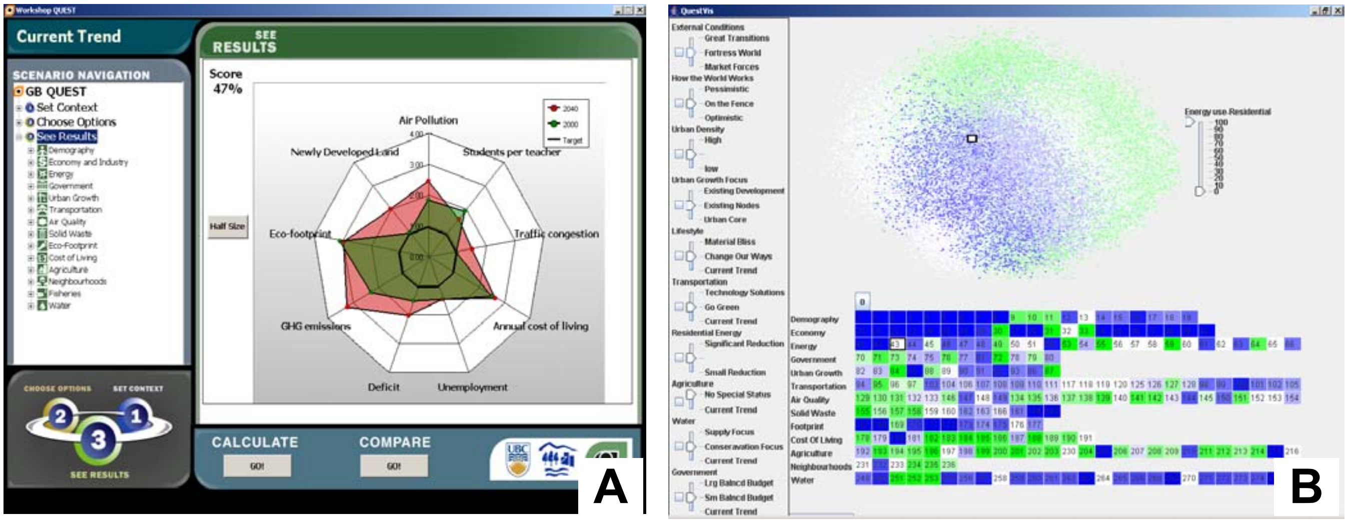



**Figure 1: Screenshots from GB-Quest (A) and QuestVis (B)**

important implications for research in information visualization, as they open the door to the idea of *user-adaptive visualizations*. These are visualizations that are tailored in real-time to the needs of each individual user, where these needs derive from specific user traits as well as user tasks. Thus, we decided to run a formal study to test the role that individual differences may play in the effectiveness of the visualizations used by GB-Quest and QuestVis.

In the rest of this paper, we first discuss related work. Next, we introduce GB-Quest and QuestVis and the visualization methods that they use. We then describe the study and its results. We conclude with a discussion of the implications of these results and plans for future work.

## 2. RELATED WORK

While most of the research on the factors that define visualization effectiveness has focused on properties of the data to be visualized or the tasks to be performed, some studies have started considering user individual differences as a promising avenue of investigation.

Most existing research in this area has focused on exploring the link between individual differences (mostly related to spatial abilities) and visualization effectiveness for information retrieval and navigation in complex information spaces [e.g. 13, 14, 15]. Baldonado et al. [2] cite differences in user profiles as one reason to have multiple individual views available in information visualization. Velez et al. [9] explored the link between five spatial abilities (selected from the Kit of Factor-referenced Cognitive Tests [5]) and proficiency in a visualization task involving the identification of a 3D object from its orthogonal projections. The data analysis in this paper is mostly based on correlations and thus does not provide insights into the actual predictive power of the target spatial abilities. It does, however, provide initial evidence that cognitive abilities may affect visualization effectiveness in a data interpretation task.

In [3], Brusilowsky et al. explore the idea of *adaptive visualizations* that are automatically tailored to the user's knowledge in the context of an educational system. This system visualizes available practice problems based on their similarity, and adaptively adds icons to each problem to indicate how suitable they are for the knowledge level of the current user. While Brusilowsky et al. [3] adapt the content of the visualization but maintain a fixed visualization technique, we investigate whether individual differences exist that may require selecting alternative visualizations for different users.

## 3. VISUALIZING ENVIROMENTAL CHANGES WITH GB-QUEST AND QUESTVIS

### 3.1 GB-Quest

Georgia Basin Quest ( GB-Quest) [8] was designed to bridge the gap between scientific research, policy making and public engagement. It has been used in workshops during which residents and policymakers are asked to identify environmental strategies to achieve their ideal future for the Georgia Basin region. These strategies are inputs to GB-Quest, which computes their effects and produces a scenario describing the environmental changes that they will cause in the region in 40 years.

In GB-Quest, each scenario is characterized by a set of 294 indicators, grouped into 9 high-level variables that represent the most salient indicators of the economic, environmental, and social health of the region (e.g. government deficit, traffic congestion, student per teacher, air pollution). GB-Quest's main tool to visualize changes to the region is the *radar graph* (see right panel in Figure 1A), which illustrates changes to the high-level variables between the present and a 40-year horizon.

In the radar graph, the values of each variable in both the present time and in 40 years are displayed simultaneously along the corresponding radial line in the graph, using different colors (red for the present and green for the future in the actual application; dark grey and light grey respectively, if this paper is printed in black and white). Variable values increase with the distance from the center of the graph. Because each variable represents an indicator that is inversely correlated with quality of life, values closer to the center are more desirable.

The user is required to make a visual comparison between the two values for each variable in order to determine how it has changed. For instance, in Figure 1A the amount of newly developed land decreased in 40 years, while the annual cost of living remained unchanged. The user must also make a visual comparison of the areas outlined by all the variable values for each year in order to determine any overall trend in the current scenario. Large areas in the lighter color represent "good" scenarios in which most variables have decreased, while large areas in the darker color represent "bad" scenarios in which most of the values have increased.

Users can input alternative strategies to try and improve the scenario (i.e., the environment's evolution in the next 40 years). GB-Quest, however, does not have a dedicated mechanism to support direct scenario comparison; that is, there is no easy way to view alternative radar graphs together in order to compare them.

User surveys conducted after the workshops indicated that users generally appreciated GB-Quest as a tool to increase their environmental awareness. However, anecdotal evidence indicates that the radar graph visualization is intuitive for some users, but rather incomprehensible for others.

## 3.2 QuestVis

QuestVis [10] (see Figure 1B) is a redesign of GB-Quest aimed at facilitating the exploration and comparison of different scenarios. Here we describe the main differences with GB-Quest. Two were introduced in order to facilitate scenario generation. The first difference is that QuestVis reduces input choices to a set of 11 sliders with 2 or 3 possible choices each, replacing the more cumbersome input mechanism available in GB-Quest. The second difference is that, while GB-Quest waits until the user has finalized all choices before calculating the results, QuestVis uses a pre-computed database to show the effect of each choice as it is made. This highly reactive behavior was introduced to improve the user's sense of the connections between input choices and their effect on the region.

Another difference (the most relevant to this paper) is that QuestVis uses a new visualization to show changes to the region. This technique, known as the Multiscale Dimension Visualizer (MDV) [10], is shown in the right panel in Figure 1B, and was introduced primarily to facilitate a scenario's analysis and comparison. The only way to observe scenario changes at the level of individual indicators in GB-Quest is to abandon the radar graph view and access visualizations based on bar graphs that show the changes at the level of small subsets of related indicators. In contrast, QuestVis uses the MDV to represent all 294 of the individual indicators simultaneously. The normalized value of each indicator is color encoded to enable a compact representation of the results. The color scale uses blue and green to represent, respectively, an increase and a decrease in value relative to the present-day value. The saturation of the color represents the extent of the change, normalized relative to the minimum and maximum possible values for that particular indicator across all scenarios. The more saturated the color, the larger the change from the current value. Thus, unlike with GB Quest, the user is not required to perform a mental comparison of values in order to determine how much each variable has changed over time[1].

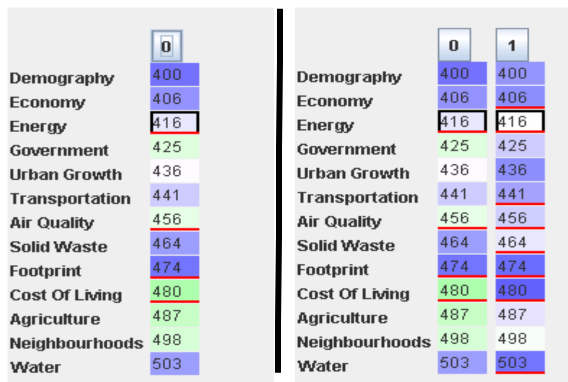



**Figure 2: QuestVis's MDV aggregated view (left) and two aggregated views side-to-side (right)**

QuestVis can also produce a summary view of a scenario by (i) aggregating the 294 indicators in the high-level variables used by GB-Quest; and (ii) using the same color conventions to represent direction and magnitude of changes over these variables, as shown on the left of Figure 2. Using this aggregated view (called *colored boxes* from now on), the user can compare multiple scenarios side by side (see Figure 2, right), something that would be hard to do with the radar graph, especially when comparing more than 2 scenarios.

[1] The numbers in the boxes in Figure 1 and 2 relate to variables, they do not represent additional information about the scenario.

**Table 1. The cognitive abilities tested in our study**

| Name | Description |
|---|---|
| Visual Memory (VM) | The ability to remember the configuration, location, and orientation of figural material |
| Spatial Visualization (SV) | The ability to manipulate or transform the image of spatial patterns into other arrangements |
| Perceptual Speed (PS) | Speed in comparing figures or symbols, scanning to find figures or symbols, or carrying out other very simple tasks involving visual perception |
| Disembodiment (D) | The ability to hold a given visual percept or configuration in mind so as to disembed it from other well defined perceptual material |
| Need for Cognition (N4C) | The tendency to engage in and enjoy tasks that require thinking |
| Learning Style (LS) | Preferences for the manner in which information is received and learned, i.e., preference for: |
| Active/Reflective (A/R) | • proactive participation to the learning process vs. passive reception of instruction |
| Sensing/Intuitive (S/I) | • concrete, well defined learning objects/strategies vs. discovering possibilities and relationships |
| Visual/Verbal (V/V) | • receiving information visually vs. verbally |
| Sequential/Global(S/G) | • learning in linear, logical steps vs. learning in large non-methodical jumps, absorbing material almost randomly and then suddenly "getting it." |

# 4. COMPARING THE RADAR GRAPH AND THE *COLORED BOXES* VIEW

The MDV technique in QuestVis has two obvious advantages compared with GB-Quest: it supports the explicit comparison of alternative scenarios and it includes a flexible, integrated mechanism to observe scenarios at different levels of detail.

However, it is not obvious that the MDV colored boxes visualization is better at providing an overview of the changes in terms of high-level variables. As with the radar graph, observations from informal pilot studies indicate that not all users find the colored boxes intuitive. These observations suggest the hypothesis that the colored boxes and the radar graph could be used more effectively as alternative visualizations within the same system, and that the choice between the two may need to be based on knowledge of individual user differences.

The study described in the rest of the paper was designed to shed light on this issue. In particular, we wanted to investigate the following questions: (1) Is one visualization more effective than the other for all users? (2) If not, can the most effective visualization for a given participant be predicted from specific individual traits? In the rest of this section, we first describe the individual traits we chose to investigate in our study. We then describe the tasks and design details of the study, and finally discuss the data analysis and related results.

## 4.1 Individual traits explored in the study

A variety of individual traits could influence a user's perception of different visualizations, including cognitive abilities, expertise with visualization techniques and affective elements such as personality. For this study, we chose to focus on cognitive abilities. We selected four that have been previously linked to visualization capabilities [9], as well as five additional abilities that, to our knowledge, have never been considered in the context of information visualization research. The four previously explored abilities come from Velez et al.[9] (see Section 2) and are listed in the first four rows of Table 1. The rest of the rows show the new cognitive abilities that we introduced, i.e., *need for cognition* along with four indicators that define a person's *learning style*.

## 4.2 Experimental tasks

Because we want to study the effectiveness of the radar graph and colored boxes as alternative means to visualize the same information, an evaluation involving interaction with the complete system would be confounded by the different interaction styles and functionalities of QuestVis and GB-Quest. Therefore, for this study we used a series of basic tasks that would allow us to compare user performance with each visualization in isolation from the system in which it is embedded. The tasks were based on a set of low-level analysis tasks that Amar et al. [1] identified as largely capturing people's activities while employing information visualization tools for understanding data. In consultation with one of the researchers involved in the design of QuestVis (who was also highly familiar with GB-Quest and its radar graph visualization), we chose a subset of Amar et al.'s tasks that are most relevant for interacting with visualizations of scenarios for environmental changes. Tasks were left out when they required knowledge of absolute values instead of unmarked scales (e.g., "Retrieve value" of a variable in a single scenario, "Determine Range" of a variable's values), because neither the radar graph nor the colored boxes represent absolute values. The

**Table 2: The ten task types in the study and related sample questions**

**One Scenario**

| Task | Sample Question |
|---|---|
| Filter | Find the variables that increased in the scenario. |
| Compute derived value | Taken as a whole, how much did the scenario increase or decrease? |
| Find extremum | Name the variable that decreased the most. |
| Sort | Rank the following variables, putting the greatest increase first. |
| Characterize distribution | Describe the distribution of values within the scenario (choose all options that you think apply). |

**Two Scenarios**

| Task | Sample Question |
|---|---|
| Retrieve value | For each of the following variables, do you think it is larger in the scenario on the left or on the right. |
| Filter | Find the variables whose values decreased in the scenario on the right compared to the scenario on the left. |
| Compute derived value | As a whole, how much did the scenario on the right increase/decrease compared to the scenario on the left. |
| Find extremum | Find the variable whose value in the scenario on the right decreased the most compared to the one on the left. |
| Sort | Rank the following variables in terms of greatest increase in the scenario on the right compared to the scenario on the left. |

tasks were framed as a series of questions that participants had to answer while viewing a single scenario or pair of scenarios, and they are listed in Table 2. The scenarios and corresponding questions were presented via automated software developed specifically for this study. Note that we changed the radar graph's original red-green color scheme to avoid complications due to color-blindness.

Participants repeated each of the tasks in Table 2 on four different scenario "types" that varied in terms of the skewness of the distribution of variable values. Two of the four types are shown in Table 3 (with only the Radar graph for brevity). Distribution skew was varied to make participants perform each task type at different levels of difficulty. For instance, performing the sorting task "Rank the following variables, putting the greatest increase first" is easier with the spiky distribution shown at the top of Table 3 than with the uniform distribution shown at the bottom of the table.

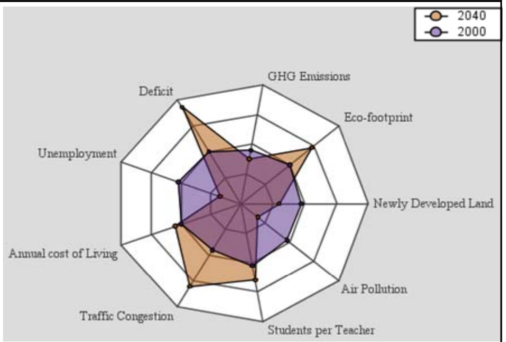
## 4.3 Design and procedure

The study was a within-subject factorial design with visualization type (Radar Graph or Colored Boxes) as the primary factor and visualization order as a between-subjects control variable. There were 45 participants, 18 male, 27 female, all students at a local university. Students were paid $30 for their time and came from a variety of departments, including commerce, engineering, and dentistry. The experiment was designed and pilot-tested to fit in a single session lasting at most 2 hours (average session length was 1h 45'). Participants took part in the study in small groups of 1 to 4 people. The study took place in a room set up with 4 separate stations, each equipped with a laptop computer with the testing software pre-loaded for immediate use.

Each session started with the participant taking pencil-and-paper tests for the six cognitive traits in Table 1, with a 5-minute break after the first three tests. For spatial abilities we used the Kit of Factor-referenced Cognitive Tests [5]; for need for cognition we used the test described in [12]; and for learning style we used the the ILS inventory [11]). After completing the tests, participants took a second break, received a brief training on the two visualizations and the testing software, and finally started interacting with the software. Each participant performed a block of basic visualization tasks twice, once with each visualization method. A task block was structured as follows: First, subjects were presented with a single scenario and had to answer the five questions listed in the "One Scenario" portion of Table 2. Then subjects were presented with two scenarios and had to answer the five questions listed in the "Two Scenarios" portion of Table 2. Participants repeated the above cycle four times, once for each of the four distribution types described earlier. Visualization order was fully counterbalanced to account for learning effects, making visualization order a between-subject control variable in our design

## 4.4 Measures

We measure visualization effectiveness in terms of accuracy on the visualization tasks, computed as the number of correct answers generated for the questions in the testing software. More specifically, accuracy on each of the 10 task types in Table 2 is computed by summing all correct answers to the related questions across the four distribution types.

<table>
<tr><th colspan="2">Table 3: Two of the four distributions in the study</th></tr>
<tr><td>Spiky</td><td>
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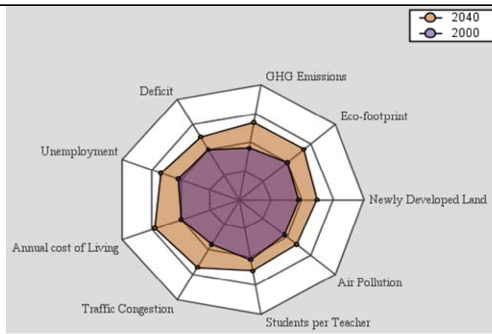
<tr><td>Uniform</td><td>
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# 5. DATA ANALYSIS AND RESULTS

## 5.1 Cognitive abilities as predictors of the most effective visualization

Recall that the main goal of this study is to verify whether one of our two visualizations dominates the other over any of the target tasks, or whether best visualization depends on one or more of the cognitive abilities in Table 1.

To answer these questions, we use an analysis based on General Linear Models (GLM). We started the analysis by running a repeated-measures 2 (visualization type) by 10 (task) by 2 (visualization order) GLM with the 9 cognitive test measures as covariates and task accuracy as the dependent variable. In this and all subsequent GLM, we applied the Greenhouse-Geisser adjustment for non-spherical data. We report statistical significance at the 0.05 level (unless otherwise specified), as well as partial eta-squared ($\eta^2$), a measure of effect size. To interpret this value, .01 is a small effect size, .06 is medium, and .14 is large [7].

The salient findings from this first GLM include:

- No significant main effect of visualization type on accuracy
- No main or interaction effects of visualization order, indicating that the counterbalancing of visualization presentation successfully avoided ordering effects
- A significant interaction of visualization type with the cognitive ability related to *perceptual speed* (PS) ($F(1,34)=4.8$, $p = 0.035$, $\eta^2= .124$). This interaction means that perceptual speed has a significant effect in determining which visualization generates better accuracy for each individual user. In other words, PS is a significant predictor of the *difference* in accuracy between the two visualizations.
- No other cognitive ability had a significant interaction with visualization type
- A significant main effect of task ($F(9,26)= 5.951$, $p < 0.01$, $\eta^2= .149$), indicating that accuracy outcome significantly varies with task type.

Because only perceptual speed (PS from now on) generated a significant interaction with visualization type, we will focus on this ability in the rest of the analysis. To better understand the relationships among visualization type, perceptual speed and task type, we ran a series of GLMs with task accuracy as the dependent variable, visualization type as the main factor and perceptual speed as covariate, one for each of the ten tasks in Table 2 (we applied a Bonferroni adjustment for 10 post-hoc comparisons, bringing the alpha level for significance down to 0.005). Note that we no longer include visualization order in the analysis, because it did not show any significant effect in the overall model.

For nine of the tasks, there was no significant difference in accuracy between the two visualizations, and no significant effect of perceptual speed on accuracy. In contrast, the GLM for accuracy on the “Compute Derived Value” task with two scenarios generated a significant interaction between visualization type and perceptual speed, with a high effect size ($F(1,43) = 14.442$, $p < 0.005$, $\eta^2= .251$).

Recall, from Table 2, that “compute derived value” with two scenarios requires users to compare the scenarios in terms of how much they changed as a whole. The eta-square value reported above indicates that variation in PS can explain 25.1% of the variance in accuracy difference between the two visualizations for this task. An analysis of the relationship between PS and accuracy with each visualization on this task shows that PS is a significant negative predictor of accuracy with radar graph ($\beta$ correlation coefficient = -.475, $t = -3.6$, $p = .001$). It is also positively correlated with (although not a significant predictor of) accuracy with the colored boxes for this task. Figure 3 shows the interaction between PS and visualization type if PS is converted to a categorical variable with values HIGH and LOW determined by the median of the original covariate

These results indicate that users with high PS will be more accurate when comparing scenarios in terms of how much they changed as a whole if they use the colored boxes rather than the radar graph, and that PS can be used as a factor to decide which of our two target visualizations will be more effective for accomplishing this particular value-derivation task. This predictive ability is especially important in the context of systems focused on sustainable development like GB-Quest and QuestVis, because evaluation of overall environmental changes is a focal concept for these systems

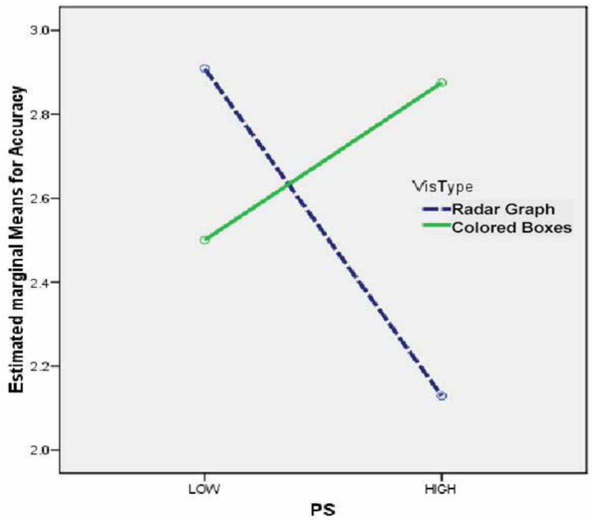


**Figure 3: Interaction between PS and Visualization Type**

and was one of the main targets in the GB-Quest workshops described earlier. Thus, adaptive visualization selection based on this predictor could have direct applications in the activities that GB Quest or QuestVis will be used for.

**Table 4: Linear Regression results for Individual Accuracies. "Pred." stands for "Predictors"; "$R^2$" stands for adjusted $R^2$**

| Task | Measure | Pred. | β | Linear Model |
|---|---|---|---|---|
| **One Scenario** | | | | |
| Sort | AccCB | N4C, V/V; | .445 -.282 | F=6.91, p=.003, $R^2$= .150 |
| Characterize Distribution | AccCB | SV | .434 | F=9.97, p=.003, $R^2$= .169 |
| **Two Scenarios** | | | | |
| Filter | AccCB | VM | .443 | F=9.91, p=.003, $R^2$= .168 |
| Compute Derived Value | AccRadar | PS A/R | -.47 -.36 | F=8.33,p=.001, $R^2$= .25 |

Although we don't have a conclusive explanation for the direction of the relationships that we found among perceptual speed, accuracy with the radar graph and accuracy with the colored boxes, our results for the radar graph visualization are consistent with the negative correlation found by Velez et al. between perceptual speed and accuracy in deriving 3D shapes from 2D projections. In the radar graph, scenario change is derived by performing a visual comparison of the areas outlined by the individual variables. Thus, both this task and the derivation of 3D shapes from 2D projections studied by Velez et al. require comparing 2D shapes. This commonality is a plausible explanation of why we found the same negative correlation as Velez et al. between perceptual speed and task accuracy.

### 5.2 Cognitive abilities as predictors of accuracy with individual visualizations

While the main goal of this study was to understand whether user cognitive abilities can predict which visualization is most effective for each user, there is also value in exploring whether these abilities can predict task accuracy with each visualization. Towards this end, we ran a series of 20 linear regression analyses for each of the two available visualizations, with accuracy on each task as the dependent variable and the cognitive test scores as predictors. Table 4 summarizes the results of this analysis as follows. The first column lists all the tasks for which we found a significant ($p < 0.0025$ with adjustment for multiple tests) or marginally significant ($p < 0.005$)[2] linear model for predicting accuracy. The second column reports, for each task, which accuracy measure we can predict (AccCB = Accuracy with Colored boxes; ACCRadar = Accuracy with Radar). The third column reports the significant or marginally significant predictors in the model. The fourth column lists their correlation coefficients. The fifth column summarizes the model statistics.A relevant result from Table 4 is that the new cognitive abilities we added in this study compared to the study by Velez et al. (2005) (i.e. need for cognition and the four linear scales for learning styles) do play a role as predictors of visualization accuracy. In fact, they are the only predictors for the visualization accuracy of sorting with one scenario with the colored boxes (see first row in Table 4). Furthermore, they are comparable to the spatial abilities from the Velez et al. study in terms of the amount of accuracy variance they can explain (see $R^2$ values in the 5th column of Table 4).

It should be noted, however, that the variance accounted for by all our linear models is rather low, ranging from 12.9% to 25%. This result suggests that other user traits should be explored to understand how individual differences affect visualization effectiveness. One promising candidate is expertise with visualizations, which we could not include in our study due to the difficulty of finding a reasonable number of visualization experts in the user population available to us.

## 6. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a study aimed at exploring whether user's individual differences can be used as predictors to select the most effective visualization for different users. The study involved a variety of tasks that can be accomplished using two alternative visualizations

[2] We include results with close marginal significance because they are most likely due to not having sufficient subjects to run a linear regression with nine predictors

for representing value changes in a set of variables: one is the Radar Graph, which relies on both spatial elements (linear distance and area) and color to represent change; the other is the Multiscale Dimension Visualizer (called *Colored Boxes* in the paper), which uses primarily color.

Our data analysis shows that, while there is no significant difference in task accuracy with the two visualization for 9 of the task types performed during the study, for the 10$^{th}$ task type (comparing how the values of two sets of variables change as a whole) the best visualization depends on the user's Perceptual Speed (PS). That is, users with high perceptual speed perform this task better if they can see the relevant data via the colored boxes, while users with low perceptual speed perform better with the radar graph. This finding suggests the idea of having a system that can display both visualizations but that adaptively selects which one to recommend based on the user perceptual speed, if one of the tasks to be performed involves comparing overall changes in variables of interest. Information of the user's perceptual speed could be obtained at the onset of the interaction by administering to the user a test for this cognitive ability [5]. If the test is administered on-line, then its results can be automatically computed by the software and used in real time to suggest the optimal visualization.

Our data analysis also provided initial evidence that some cognitive abilities can be used as predictors for the effectiveness of each individual visualization. The predictive power of cognitive abilities related to spatial reasoning had already been identified by previous research. Our contribution lies in the identification of additional predictors not related to spatial processing, specifically *need for cognition* and measures related to learning style. These findings could be used to provide users with further automatic support to ensure effective visualization processing. While using a specific visualization, the user may receive help or clarifications from the system if the system detects that this user scores low on the cognitive abilities that predict success in using the current visualization. For instance, one of our findings was that Need for Cognition is a positive predictor of user accuracy in sorting variables with the colored boxes. If a system detects that the user has a low need for cognition, it can offer help in interpreting the visualizations during this task.

However, in order to provide effective help, the system also needs to know what type of problems a user with low scores on the relevant cognitive measures may have when using a specific visualization. We plan to investigate this issue in the context of the visualization systems discussed in this paper by running further studies specifically designed to uncover these problems. We also plan to investigate additional individual traits that may function as predictors of visualization effectiveness, including abilities related to color perception and user expertise.

## ACKNOWLEDGEMENTS

This research was funded by the GEOIDE network grant P31HS20. We would like to thank John Robinson, the project leader, for his continuous support and Tamara Munzner for her help with the study design.

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