Eye tracking to understand user differences in visualization processing with highlighting interventions

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Abstract. We present an analysis of user gaze data to understand if and how user characteristics impact visual processing of bar charts in the presence of different highlighting interventions designed to facilitate visualization usage. We then link these results to task performance in order to provide insights on how to design user-adaptive information visualization systems. Our results show how the least effective intervention manifests itself as a distractor based on gaze patterns. The results also identify specific visualization regions that cause poor task performance in users with low values of certain cognitive measures, and should therefore be the target of personalized visualization support.

Keywords: User characteristics, Eye Tracking, User Evaluation, Adaptive Information Visualization.

1 Introduction

Information visualization (Infoviz) systems are widely used across many domains and applications in order to explore, manage, and better understand data. Despite their increasing frequency of use and the rise of big data, these systems have typically continued to follow a one-size-fits-all approach in terms of how they account for their users. An ever increasing body of research however, has shown that individual user differences can play a role in user performance or preference for a given infoviz system [1–5]. These findings suggest that visualization effectiveness may be improved by having Infoviz systems that can detect relevant user differences during visualization processing, and adapt accordingly. Researchers have already started looking at adaptation approaches that recommend *alternative visualizations* based on detected user needs (e.g., [6, 7]). By contrast, in this paper we focus on exploring the potential of adaptive interventions aimed at improving the effectiveness of the *visualization currently used.* In particular, we use eye-tracking to evaluate the impact on visualization processing of four *highlighting interventions* which could eventually be used to provide adaptive support by dynamically redirecting the user's attention to different subsets of the visualized data as needed (e.g., when the visualization is used together with a verbal description that discusses different aspects of a dataset [1]). Previous work has already looked at the impact of these interventions on user task performance [1]. In this paper however, we analyze user gaze behavior based on eye tracking data

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collected during the study in [1], in order to gain a more fine-grained understanding of how the study factors (e.g., interventions, user differences, task complexity) impact visualization processing. For gaze data analysis, we employ the same methodology proposed in [8], consisting of several stages of data preprocessing and statistical modeling. The work in [8] looked at a simple gaze data set to understand how a set of individual differences affect visualization processing while performing a variety of tasks with two different visualizations (bar graphs and radar graphs). In this paper, we focus on bar graphs only, and extend the work in [8] by looking at (i) a larger set of individual differences; (ii) more complex data sets, and (iii) if/how the related visual processing is impacted by different highlighting interventions. We also include a new region of visualization processing (*answer input* area of interest), to track gaze behaviors within the region where users input their answers to the study tasks. The research questions we investigate in this paper are as follows:

Q1. How do the tested sets of user characteristics, highlighting interventions, and task complexity impact gaze behavior during bar graph visualization processing?

Q2. How do results in Q1 relate to results on the impact of these factors on task performance reported in [1], and what are the implications for adaptive visualizations?

In answering these research questions, our objective is to inform the next stages of design for a real-time user-adaptive information visualization system. Our results do in fact show significant impacts of user characteristics, task type, and interventions on gaze behaviors. These results are then used to shed light on why significant performance differences occurred during visualization processing as reported in [1]. Based on these outcomes, we offer design recommendations for providing adaptive visualization support for bar graph processing using highlighting interventions.

2 Related Work

Recent work has begun to evaluate the benefits of user-adaptation for information visualization systems. Both Grawemeyer [7], and Gotz & Wen [6] found positive results when evaluating systems that provide recommendations on a set of available visualizations based on a user's tasks, prior knowledge, and performance. While these systems adapt only to user features such as domain knowledge or performance tracked via interface-related behaviors, several studies have shown that other user characteristics can impact visualization performance. Various cognitive abilities such as perceptual speed, verbal working memory, and visual working memory have been shown to impact user performance and/or user subjective experience with Infoviz tasks [1, 2, 4, 5]. Researchers have also shown that personality traits (e.g., locus of control) can have similar impacts on performance [3]. Given this increasing evidence on the impact of user differences in visualization performance, researchers have been investigating ways to capture the relevant user traits in real-time so as to inform adaptive information visualization systems, with substantial attention being devoted to approaches leveraging gaze data. For example, Gridinger et al. [9] used group-wise similarity of gaze patterns to predict domain expertise in processing visualizations of weather patterns. Steichen et al. [10] and Toker et al. [11] predict, respectively, user characteristics and skill acquisition based solely on tracking a large set of aggregate gaze features collected during infoviz tasks. Eye-tracking has also been investigated as a promising source of information for understanding how to adapt to specific user traits for supporting effective visualization processing. For instance, several studies have shown significant differences in gaze patterns of experts and novices during visualization tasks in a variety of domains, including chemistry (e.g. [12, 13]) and general information search [14]. It should be noted however, that little work has been done to formally connect differences in gaze behaviors due to user characteristics to objective measures of task performance. Building this connection is key in order to understand how to improve visualization performance by tailoring support to specific user traits. Toker et al. [8] have begun to address this gap by running a formal analysis of eye gaze behaviors with bar and radar graph visualizations. In a previous study with these visualizations, users with low values for perceptual speed had been found to perform poorly compared to users with high perceptual speed [4]. By then analyzing the gaze data, [8] explains this performance difference in terms of the higher processing time that low perceptual speed users need to devote to the visualization's legend. Based on these findings, [8] recommended that low perceptual speed users ought to be supported by designing interventions that target the legend region. In this paper, we apply the same methodology as [8] towards the performance results from the study reported in [1] in order to gain a better understanding of how user differences impact visualization processing when highlighting interventions are available.

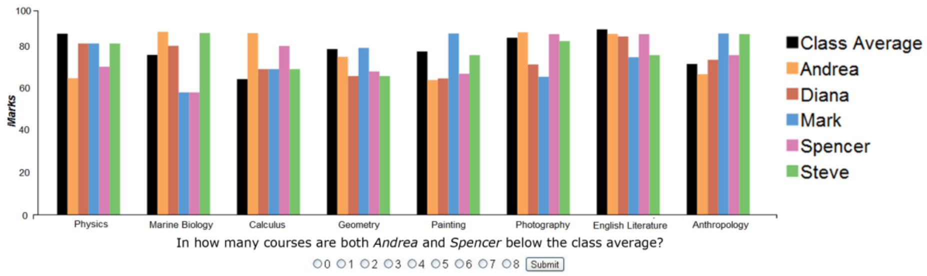

Fig. 1. Sample bar graph visualization and task administered in the study

3 User Study

The study that generated the data used in this paper investigated the effectiveness of four highlighting interventions designed to help the processing of bar graphs, as well as how this effectiveness is impacted by both task complexity and different user traits. The study was a single session, within-subjects design, lasting at most 90 minutes. 62 participants performed tasks using bar graphs (Fig.1) with a fully-automated interface, while their gaze was tracked via a Tobii T120 eye-tracker. Bars graph were chosen because they are a common visualization for which there is already evidence of the impact of individual differences and the need for adaptive support [4].

Task complexity was varied by having subjects perform 2 different types of tasks, chosen from a standard set of primitive data analysis tasks in Amar et al. [15]. The first task type was Retrieve Value (RV), one of the simplest task types in [15], which in the study consisted of retrieving the value for a specific individual in the dataset and comparing it against the group average (e.g., "Is Michael's grade in *Chemistry* above the class average?"). The second, more complex task type, was Compute Derived Value (CDV) which in the study required users to first perform a set of comparisons, and then compute an aggregate of the comparison outcomes (e.g., "In how many cities is the movie *Vampire Attack* above the average revenue and the movie *How to Date Your Friends* below it?"). All tasks involved the same number of data points (6), and series elements (8). It should be noted that these datasets were more complex than those used in a previous study on the impact of individual differences on bar graph processing [8], which involved at most three data points per series.

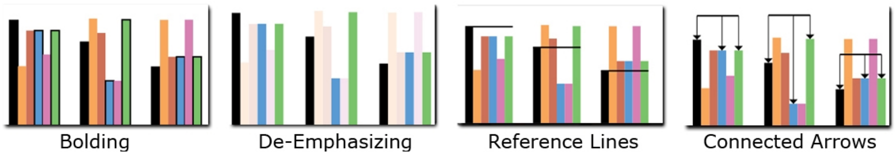

Fig. 2. The four highlighting interventions evaluated in the study

Each intervention evaluated in the study (shown in **Fig. 2**) was designed to highlight graph bars that were relevant to answer the current question, to guide a user's focus to a specific subset of the visualized data while still retaining the overall context of the data as a whole [16]. The *Bolding* intervention draws a thickened box around the relevant bars; *De-Emphasis* fades all non-relevant bars; *Average Reference Line*s draws a horizontal line from the top of the left-most bar (representing the average) to the last relevant bar; *Connected Arrows* involves a series of connected arrows pointing downwards to the relevant bars. Participants began by completing a set of tests that measured the 5 user characteristics evaluated in the study which included: (1) *Perceptual speed*, a measure of speed when performing simple perceptual tasks [17]; (2) *Visual Working Memory*, a measure of storage and manipulation capacity of visual and spatial information [18]; (3) *Verbal Working Memory*, a measure of storage and manipulation capacity of verbal information [19]; (4) *Bar Graph Expertise*, a self-reported measure of a user's experience with using bar graphs; (5) *Locus of Control*, a personality trait measuring whether individuals tend to take responsibility for their circumstances or blame them on external factors. These measures were selected because they had been previously shown to influence user performance or satisfaction in bar graph studies [1, 2, 4, 5] or other visualizations [3]. Next, each participant performed each of the two task types (RV & CDV) with each of the 4 interventions as well as *No Intervention* as a baseline for comparison, in a fully randomized manner.

4 Eye Tracking Pre-processing & Analysis

Following the same approach in [8], the eye tracking data is processed in three stages. First, we generate a set of gaze features from the raw data. Next, principal component analysis (PCA) is performed on these features to obtain a set of factors which will act as the dependent measures for statistical analysis. Lastly, mixed models are used to evaluate the impact of the study factors and user characteristics on the eye tracking components.

4.1 Generate Low-Level Eye Tracking Features.

Eye tracking data consists of fixations (i.e., gaze points on the screen), and saccades (i.e., paths between fixations). We processed the raw gaze data from the study using EMDAT, an open-source toolkit[1] which computes gaze features including sums, averages, and standard deviations of a variety of gaze measures, such as fixation rate and duration, saccade length, and absolute/relative saccade angles. These features can be computed with respect to the overall screen, using no information on the displayed content (e.g., mean fixation duration, sum lengths of saccades, average angles of saccades), and there are 14 such features, called *High-level* features, from now on. Features can also be computed for specific areas of interest (AOI) in the interface (*AOI-level* features). These include both proportionate measures indicating relative attention to each AOI (e.g., proportion of time/fixations spent looking at an AOI), as well as transition measures indicating how a user's attention shifts between two AOIs (e.g., transition from AOI *x* to AOI *y*). This ensemble of features constitute the building blocks for comprehensive gaze processing [20]. The set of AOIs for the bar graph used in the study consists of: (1) 'High' AOI, a rectangular area that covers the top half of the vertical bars; (2) 'Low' AOI covers the lower half of the vertical bars, (3) 'Labels' AOI: covers the series elements labels, (4) 'Legend' AOI: covers the legend, (5) 'Question' AOI: covers the text describing the task to be performed, and (6) 'Input' AOI: covers the radio buttons and submit button, (refer to Fig. 1).

4.2 Generate Components using Dimensional Reduction

The goal of this step is to use principal component analysis (PCA) in order to identify and combine groups of inter-related gaze features into components more suitable for data analysis [21]. We first group the gaze features into three non-overlapping families: *High-level family*, *AOI-proportionate family*, and *AOI-transitions family*. We then conduct a separate PCA on each family, of which the results are described next. In the subsequent tables, '**' indicates features that are negatively correlated within their component. Since [8] used the same families of gaze features for their PCAs, we will comment on the similarities and differences with our results to show where the consistencies exist across different visualization contexts.

Table 1. PCA results for high-level family.

Component Name	High-level family gaze features
Sum-Measures	*Total-num-fixations, Sum-rel.-saccade-angles, Sum-abs-saccade-angles, Sum-saccade-length, Sum-fixation-durations*
Fixation-Measures	*Mean-fixation-durations, Std-dev-fixation-durations, Fixation-rate***
Saccade-Length	*Mean-saccade-length, Std-dev-saccade-length*
Saccade-Angles	*Mean-rel.-saccade-angles, Std-dev-rel.-saccade-angles, Std-dev-abs-saccade-angles*
Mean-Abs-Saccade-Angles	*Mean-abs-saccade-angles*

[1] Eye Movement Data Analysis Toolkit, available at: http://www.cs.ubc.ca/~skardan/EMDAT/

Performing PCA on the 14 high-level gaze features generated five components ($x^2 = 22035.01$, df = 91, $p < .001$, explained variance 88.31%), shown in Table 1. The names for the components are based on commonalities among their features. These 5 components are identical to those found in [8], even though the underlying gaze features were generated from two different studies (one using radar graphs and bar graphs, and one using only bar graphs and interventions). This is initial yet strong evidence that the relationships between the 14 High-level gaze features are consistent regardless of the task context.

Table 2. PCA results for AOI-proportionate family

Component Name	AOI-proportionate family gaze features
prop-Question/High	*Question-prop-total-duration, Question-prop-total-fixations, High-prop-total-duration**, High-prop-total-fixations***
prop-Low	*Low-prop-total-duration, Low-prop-total-fixations*
prop-Labels	*Labels-prop-total-duration, Labels-prop-total-fixations*
prop-Input	*Input-prop-total-duration, Input-prop-total-fixations*
prop-Legend	*Legend-prop-total-duration, Legend-prop-total-fixations*

Performing PCA on the 12 features in the *AOI-proportionate* family produced five components ($x^2 = 15271.10$, df = 66, $p < .001$, explained variance 93.71%), shown in Table 2. Although the 'Input' AOI was not examined in [8], there are still strong similarities between their PCA results and ours. In both PCAs, proportionate measures of total-duration and total-fixations for any AOI always appear together in some component, indicating that these features are strongly correlated. Furthermore, the components related to proportionate attention to ‘Label’, ‘Low’, and ‘Legend’ AOI are identical to those in [8]. One obvious difference with [8] is that here we included an additional AOI, whose proportionate features were grouped by PCA in the same component (prop-Input in Table 2). A second difference is that in [8] the 'Question' and 'High' AOI-proportionate gaze features produced separate components, whereas here they were combined into one component (prop-Question/High in Table 2). This is an indication that unlike High-level gaze features, certain AOI related gaze behaviors are likely dependent on interaction contexts (e.g., visualization type, task complexity).

Performing PCA on the 36 gaze features in the AOI-transition family generated five components ($x^2 = 22755.8$, df = 630, $p < .001$, explained variance 48.2%), shown in Table 3. Unlike [8], where each transition component included features related mostly to one specific AOI, here the transition components are a lot more noisy, meaning that there is more overlap between which AOI(s) primarily comprise a given component. These findings indicate that of the 3 families of gaze features examined, transitions features are the least similar across interaction contexts, which is likely due to the finer granularity of interaction with the visualization that they capture.

Table 3. PCA resutls for AOI transitions faimly

Component Name	AOI-transitions family gaze features
trans-Label/Low	*Low→label, Label→low, Label→labels, Question→label, Label→question, Label→legend, Legend→label, Legend→low, Low→low, Low→legend, Question→low, Question→question, Low→question*
trans-High/ Legend/Question	*High→legend, Legend→high, Legend→question, Question→legend, High→ question, High→high, Question→question, Question→high, Legend→legend*
trans-Input	*Legend →input, Input→legend, Input→input, Question→input, Input→question, Input→low, Low→input*
trans-Low	*Low→high, High→low, Low→low, Question→low, Low→question*
trans-Label/Question	*Input→label, Label→high, Label→input, High→high, Label→question, Question→label, Input→question*

4.3 Mixed Model Analysis

The final step of our analysis involves running a formal statistical model (mixed-model) to evaluate the impact of our study parameters (task complexity, interventions) and user characteristics on gaze components. For each of the three families of gaze features described in the previous section, we run a set of mixed models on each component (for a total of 15 sets of mixed models). Each mixed model is a 2 (task type) by 5 (intervention) with the respective component as the dependent measure. Additionally, as was done in [1], each of the five covariates (perceptual speed, verbal WM, visualWM, expertise, locus of control) are separately analyzed by running an additional mixed model for each covariate and the experimental factors. Given the high number of covariates, this approach ensures that we do not over-fit the models. To account for multiple comparisons within each family of gaze features, each mixed model is adjusted using a Bonferroni correction equal to the number of components in each family. Statistical significance is thus reported post-correction at the .05 level.

5 Results

In this section, we report a selection of results from the gaze analysis, organized into three parts: results on effects relating to user characteristics; results relating to highlighting interventions; and results that relate to task type (i.e., CDV/RV) but that do not directly involve user characteristics.

5.1 Impact of User Characteristics on Gaze Patterns

The user differences for which we found significant effects on gaze data are perceptual speed (PS), visual working memory (VisualWM), and verbal working memory (VerbalWM). These are also the user characteristics that were found to significantly impact user performance in [1]. In particular, users with low measures of PS and VisualWM were significantly slower when completing harder tasks (CDV) than users with high VerbalWM. Users with low VerbalWM were significantly slower than high VerbalWM users regardless of task type. In the following sections, we link differences in task performance (previous results presented in [1]) to gaze behaviors (new results in this paper), which together offer explanations as to where/how poor performance is occurring within a task, as well as how this knowledge can inform the design of user-adaptive support. Results for user characteristics are presented based on a median split of users along these measures (e.g., low vs. high perceptual speed).

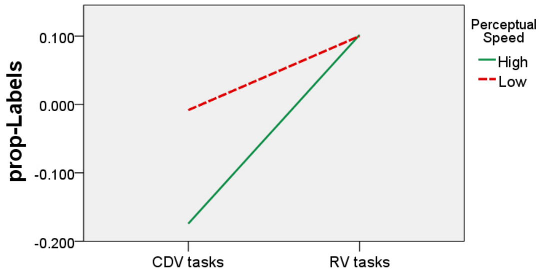

Fig. 3. Interaction effect between PS and TaskType on *prop_Labels*.

Interaction Effect - PerceptualSpeed * TaskType. We found an interaction effect between PS and TaskType on *prop-Labels* ($p < .001$, $R^2 = .009$), shown in Fig 3. This effect indicates that, for harder tasks (CDV), users with low PS are spending more of their time looking at the labels of the bar graph. Similar results were also reported in [8], where they found that users with low PS transitioned more often to the labels when working on harder tasks. Given that low PS users showed poorer performance in harder tasks [2], these results reinforce the need to consider offering adaptive interventions that can help low PS users to process graph labels. For instance, we may want to extend our set of highlighting interventions to apply to labels.

Interaction Effect - VisualWM * TaskType. We found interaction effects for visualWM*TaskType on features in both the AOI-transitions and AOI-proportionate families, specifically on the *prop-Input* ($p < .001$, $R^2 = .014$) and on *trans-Input* components ($p < .001$, $R^2 = .016$), shown in Fig. 4.

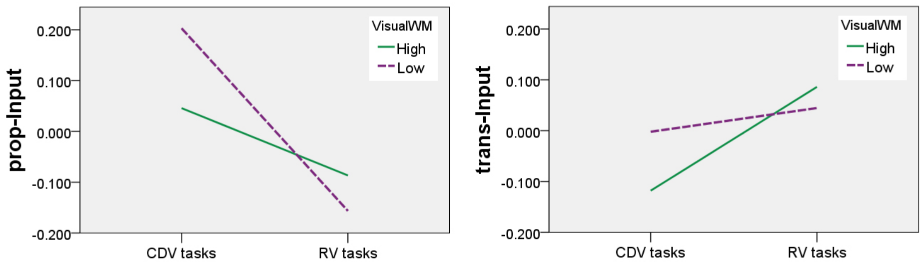

Fig. 4. Interaction between visualWM and TaskType for two 'Input' AOI related components.

These effects indicate that for harder tasks, users with low visualWM spend more of their time looking at the 'Input' AOI and are also transitioning more frequently to it, compared to users with high visualWM. The latter finding on transition frequency specifically suggests that low visualWM users likely have difficulty connecting the answer options in the input area with the information in the graph, which causes them to go back and forth between the input and the other graph areas more often than high visualWM users do. This behavior can explain why in [2] low visualWM users were found to be slower at solving the tasks than their high visualVW counterparts. This combination of findings suggest that we may want to experiment with designing adaptive support for low visualWM users that focuses on facilitating processing of the input options in relation to the task (e.g., experiment with different input methods or visual representations of radio buttons).

We also found an interaction effect between visualWM and TaskType on the *Saccade-Length* component ($p < .05$, $R^2 = .008$) indicating that, for harder tasks, users with low visualWM had longer saccades and a greater standard deviation of saccade lengths. This is akin to these users taking 'broader strokes' as they look about the screen, as well as having less consistently sized saccades. This finding may be an additional manifestation of the difficulty these users experience with harder tasks, further explaining why they were slower at completing them. Interestingly, no links between visualWM and gaze behaviors were found in [8]. One explanation is that the more complex datasets used for the visualizations targeted in this paper provided an increase in visual complexity which drew out the impact of visualWM capacity.

Main Effect - VerbalWM. We found a main effect of verbalWM on the AOI-transitions family, specifically on the *trans-High/Legend/Question* component ($p = .01$, $R^2 = .005$). This effect indicates that users with low verbalWM transitioned over the 'High', 'Legend', and 'Question' AOIs more often than users with high verbalWM. Both legend and question are textual elements, thus this finding is consistent with the fact that users with lower verbal capacity may need to review these textual elements more often. Similarly, [8] reported a main effect of verbalWM on the proportion of time users spent looking at the main textual elements of the visualization. They were, however, unable to establish whether these behaviors affected performance and may warrant adaptive interventions. In contrast, we can link the main effect discussed here to the increase in task completion time for low VisualWM reported in [1], indicating that it is worthwhile to investigate adaptive interventions that aid the processing of a visualization's textual component for these users.

5.2 Impact of Interventions on Visualization Processing

Previous results in [1] show that three of the four highlighting interventions described in Section 3 led to better task performance compared to having no interventions, whereas the Avg.Ref.Line intervention did not. The eye tracking results in this subsection may help shed some light on this finding.

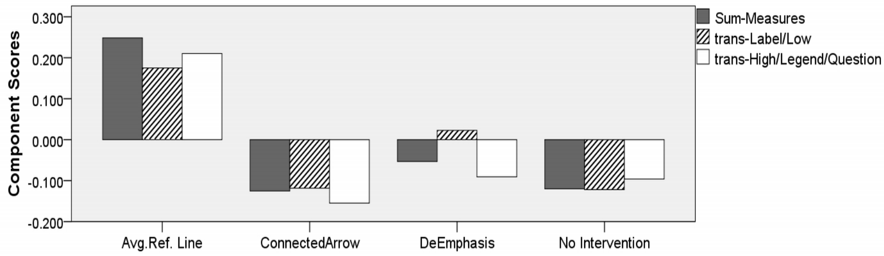

Fig. 5. Main effect of intervention on three different gaze components.

We found main effects of intervention type on three different gaze components: *Sum-Measures* (a component of the High-level family consisting of sums over measures for overall fixations and saccade angles), as well as two components of the AOI-transitions family, *trans-Label/Low* and *trans-High/Legend/Question*. Pairwise comparisons indicated that for all three gaze components, Avg.Ref.Line has significantly higher values than ConnectedArrow and DeEmphasis (see Fig. 5). In [1], Avg.Ref.Line was suggested to be a visual *distractor* that interferes with visualization processing because to its poor performance. Our results seem to confirm this suggestion, by showing that this intervention generated significant additional visual work (i.e., increased sum measures and gaze transitions). It is interesting to note that, even though in [1] Avg.Ref.Line is comparable to No Intervention in terms of task performance, pairwise comparisons also indicated that the three gaze components values for No Intervention are significantly lower than Avg.Ref.Line, and are in fact more comparable to the other 3 interventions. Thus, it appears that for No Interventions, users still perform poorly, but not because of visual distraction. Since no other significant results were found based on the interventions, this eye-gaze analysis cannot account for why [1] found that three of the interventions were better than No Intervention.

5.3 Impact of TaskType on AOI processing

In this section, we report the most compelling results relating exclusively to main effects of TaskType. These results are interesting because under some conditions, an adaptive system may not have reliable information on its user's cognitive abilities. Our results show that gaze behavior may help an adaptive system ascertain the complexity of the task at hand (e.g., easier vs. harder task), which by itself can be a valuable basis for providing adaptive support.

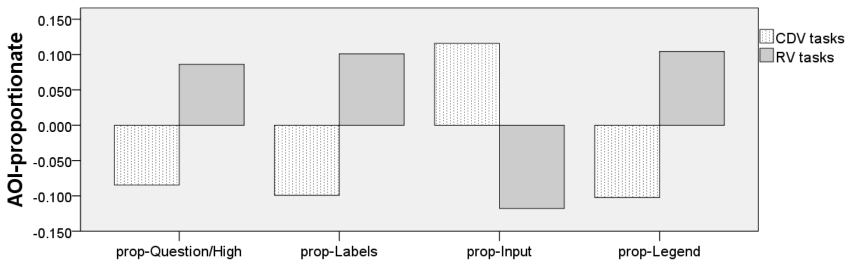

Fig. 6. Main effect of TaskType on four of the five AOI-proportionate family components.

There are significant main effects of TaskType on four of the five components in the AOI-proportionate family (Fig. 6). For three of these components (*prop-Question/High, prop-Labels,* and *prop-Legend*), values are lower for easier (RV) than for harder (CDV) tasks. Recall that the *prop-Question/High* component includes 'High' AOI features with a negative correlation (see Table 2), thus in terms of attention to the corresponding AOIs, these effects mean that when performing harder tasks, users spend less time (in proportion) in the 'Legend', 'Label', and 'Question' AOIs, and more time in the 'High' AOI. This result is quite intuitive considering that this is the region were the actual data values are displayed, and thus users may need more time to process this information for more complex tasks. Adaptive interventions like the ones targeted in these papers may help alleviate this problem. For the fourth component, *prop-Input*, values increase during harder tasks, indicating that for these tasks users also devote a higher proportion of their attention to the 'Input' AOI, as they do for the 'High' AOI. These findings offer further evidence that the input region may play an important role in supporting optimal user performance, thus making it worthwhile to investigate forms of adaptations that target not only user differences (as discussed in a previous section), but also task complexity.

6 Conclusions and Future Work

We presented an analysis of user gaze data to understand if and how user characteristics impact visual processing of bar charts in the presence of different highlighting interventions designed to facilitate visualization usage. We then linked these results to task performance, obtained from a previous study, in order to provide insights on how to design user-adaptive information visualization systems.

Our first research question (Q1) asked if and how our tested sets of user differences, highlighting interventions, and task complexity impact gaze behavior during bar graph visualization processing. We found several positive answers. For instance, with harder tasks, users with low perceptual speed (PS) spent more time processing the 'Label' AOI, whereas users with low visualWM spent more time looking at the 'Input' AOI and transitioning between that AOI and other parts of the screen. Similarly, users with low verbalWM spend more time processing some of the textual elements of the graph. Similar results for PS were obtained in [8], however, the findings related to verbalWM and visualWM are unique of our work. All users, regardless of cognitive abilities, spent more time processing the 'High' AOI as well as the 'Input' AOI when dealing with harder tasks. As for the highlighting interventions, Avg.Ref.Line caused significantly more transitions as well as an increase in fixations and saccades.

Our second research question (Q2) asked how the above findings can be related to user performance results reported in [1], and the implications for adaptive visualizations. We found that most of our significant effects on gaze behaviors mirrored effects found on task performance in [1], allowing us to explain poor performance in terms of both specific gaze patterns, as well as the user differences that caused them. These connections indicate several new avenues of investigation for adaptive interventions, in addition to those discussed, for instance, in [8]. In particular, adaptive support may benefit users with low visualWM on harder tasks by targeting the input regions of bar graphs. Low verbalWM users may benefit from interventions that facilitate processing the textual information related to the task questions and legend. We also discussed evidence as to why the Avg.Ref.Line intervention was distracting and did not improve performance, which provides preliminary abstract guidelines on what constitutes a distraction (e.g., increased Sum-Measures and AOI-transitions).

In future work, we will evaluate pupil dilation data from the same study to understand how the study factors and user differences affect cognitive load. We will also design and evaluate adaptive interventions based on the results in this paper (e.g., various types of support for the input AOI and labels AOI).

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