Understanding the Effectiveness of Adaptive Guidance for Narrative Visualization: A Gaze-Based Analysis

Oswald Barral†, Sébastien Lallé†, Cristina Conati
Department of Computer Science
University of British Columbia, Vancouver, Canada
{obarral, lalles, conati}@cs.ubc.ca

ABSTRACT

We study the effectiveness of adaptive guidance at helping users process textual documents with embedded visualizations, known as narrative visualizations. We do so by leveraging eye tracking to analyze in depth the effect that adaptations meant to guide the user's gaze to relevant parts of the visualizations has on users with different levels of visualization literacy. Results indicate that the adaptations succeed in guiding attention to salient components of the narrative visualizations, especially by generating more transitions between key components of the visualization (i.e., datapoints, labels and legend). We also show that the adaptation helps users with lower levels of visualization literacy to better map datapoints to the legend, which leads in part to improved comprehension of the visualization. These findings shed light on how adaptive guidance helps users with different levels of visualization literacy, informing the design of personalized narrative visualizations.

CCS CONCEPTS

• H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous

KEYWORDS

Narrative visualization, Adaptive visualization, Guidance, Visualization literacy, Eye-tracking

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†Authors with equal contribution.

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Figure 1. Sample narrative visualization studied in this paper, extracted from a real-world document.

1 Introduction

There is extensive evidence that even well-known and well-designed visualizations can be difficult to understand for some users. This has generated increasing research on how to provide personalized support to visualization processing, ranging from recommending alternative visualizations based on recorded user's preferences [11, 23] to adapting the amount of information included in a visualization [42], and guiding users' attention within the visualization. This latter approach has been especially researched to help users process visualizations embedded in narrative text (see Figure 1), a widespread form of *narrative visualization* [32]. This type of visualization can be challenging due to the need to split attention between the two information sources, a phenomenon known as the split-attention effect, which can increase cognitive load and reading time [1].

Steinberger et al. [34] investigated how to guide user attention in narrative visualizations by displaying upfront a set of lines linking words in the text to the corresponding information in the visualization, leading to reduced visual search time. However, providing all the links upfront does not scale to visualizations that contain a large amount of links between the text and the visualization, as it may overly clutter the visualization. Zhi et al. [41] proposed an alternative approach that avoids cluttering by allowing the users to willingly trigger the guidance mechanism, when they like. Parts of the text that refer to datapoints in the visualization are underlined, and the user can click on each of these parts to have the relevant elements of an accompanying visualization highlighted. This approach, however, did not result

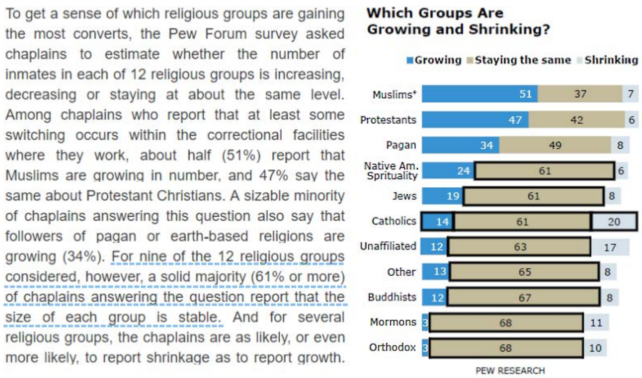

Figure 2. Sample narrative visualization with the adaptive highlighting mechanism from Lallé et al. [21] (fully described in section 3).

in improved comprehension, possibly because users did not use the self-triggered guidance in an effective manner. In recent work [20] we attempted to overcome these issues by proposing a novel gaze-driven adaptive mechanism that dynamically highlights the relevant parts of the visualization when users read the corresponding part in the text, as captured via eye-tracking (see Figure 2). We found that such adaptive guidance leads to improved comprehension of the narrative visualizations, but only for users with low levels of visualization literacy (*vis literacy* from now on: the ability to use common data visualizations in an efficient and confident manner [4]).

Eye-tracking is also commonly used to evaluate how users process information visualizations, e.g., [5, 19, 28, 38, 39], as it can reveal the underlying attentional behaviors of users. In particular, previous work has showed that eye-tracking can reveal how vis literacy influences gaze behaviors during processing of non-adaptive visualizations, showing for instance that low vis literacy users focus less on important regions of the visualizations compared to high literacy users [19, 24]. Eye-tracking has also been used to drive adaptation in real time based on users' gaze behaviors in maps, but without successfully improving user performance [9]. However, previous work has not yet investigated in depth how users' attentional gaze behaviors are modified by effective adaptive visualizations, as a way to explain how and why such adaptation improves user performance.

In this paper, we leverage eye-tracking to evaluate how the gaze-driven adaptive guidance we presented in Lallé et al. [20] supports processing of narrative visualizations, depending on the user's levels of vis literacy. Specifically, we address the following research questions:

- ***RQ1*:** How does adaptive guidance in narrative visualizations influence users' gaze behaviors, compared to no guidance?
- ***RQ2:*** What are the changes in gaze behaviors of users with low vis literacy that can explain their better comprehension when provided with adaptative guidance?

In exploring these research questions, we present two main contributions. First, we uncover the underlying eye movement changes that are induced by the target adaptive guidance. As discussed, while previous work provided such guidance in narrative visualizations [20, 34, 41], it is still unknown how exactly users benefit from them, and how they process them. We fill this gap by showing that these adaptations lead to increased integration of the key elements of the visualization (labels, legend, datapoints), as shown by an increased amount of transitions between them. Furthermore, the adaptations lead to more processing of the relevant datapoints and of the legend of the visualization.

Second, we reveal how this adaptive mechanism affects users differently depending on their levels of vis literacy. As said above, our previous work [20] found that users with low vis literacy were the ones who benefited the most from the adaptive mechanism, but it was still unknown why. We show that receiving the adaptations leads these users to transition more often between the relevant datapoints and the legend in the visualization, indicating improved information processing of these key elements. This constitutes the first analysis that investigates the relationship between users' individual differences and their gaze behaviors when processing visualizations with and without dynamic adaptations. Based on these findings, we discuss how to further improve the adaptive guidance via personalization to the user's vis literacy.

2 Related Work

2.1 Guidance in Multimodal Documents

Previous research has studied how to guide the user attention to relevant parts of multimodal instructional material consisting of text and accompanying diagrams or pictures (but not visualizations), by means of visual cues, i.e., visual prompts that guide user attention (see [40] for an overview). In particular, color coding matching parts of the text and the graphics, and visual links connecting these parts, were found to increase comprehension [14, 27]. These cues were provided either upfront [27], or at the user request when clicking on a specific paragraph referring to the graphics [14].

There has been a recent interest in studying cuing for supporting the processing of visualizations embedded in narrative text, often called *magazine-style narrative visualizations*, or *MSNV* for short [32]. MSNV is a widespread form of visualization frequently used to convey story out of data in the press, textbooks, scientific documents, etc. Cuing in MSNVs is meant to guide the user attention to *relevant datapoints* in the visualization, i.e., datapoints that are described (or *referred to*) in the narrative text. One approach for delivering these cues is by displaying them upfront in the MSNV, as done in Steinberger et al. [34] who drawn colored lines over the document to link words in the text to the corresponding datapoints in the visualization. A preliminary evaluation showed that the cues can reduce task time in simple search tasks. However, providing all cues upfront is hard to scale to MSNVs with a large number of *references* between the text and the visualization, as it is often the case in real-world documents (e.g., Pew Research documents on public policy can include up to

30 references [16]), because the many cues can visually clutter the document and create overlaps. Other work allowed the users to display the cues themselves. Specifically, Zhi et al. [41] highlighted relevant datapoints in the visualization when the users select a reference in the text, and vice versa. While they found that users extensively use such on-demand cues, it did not result in improved reading comprehension, possibly because users did not use the on-demand cues in an effective manner, or because not all users can effectively process them. Metoyer et al. [21] proposed a similar approach for sports narratives with visualizations, albeit with no evaluation.

As an alternative to cues displayed upfront or on-demand, in recent work [20] we leveraged eye-tracking to guide the user attention in an adaptive way, based on user reading behaviors captured by an eye-tracker (see Figure 2). We found that the gaze-driven adaptive guidance significantly improved comprehension performance of some users, depending on their levels of vis literacy. Specifically, low vis literacy users achieved significantly higher comprehension when reading MSNVs with the adaptive guidance, compared to non-adaptive MSNVs, whereas there was no such difference for high vis literacy users. In fact, low vis literacy users even outperformed high vis literacy users thanks to the adaptive guidance. These findings are intriguing as they indicate that gaze-driven guidance can improve the performance of some users, however, the reasons and underlying processing behaviors that led to this increase in performance are still unknown. As said in the introduction, we leverage in this paper eye-tracking to gain a more fine-grained understanding of how the gaze-driven adaptation we proposed in [20] impacts MSNV processing, in particular for low vis literacy users who do benefit from the guidance. Such analysis is also important to understand why users with higher vis literacy do not benefit from the adaptation, by examining whether they exhibit suboptimal gaze behaviors when processing the adaptation compared to low vis literacy users.

2.2 Eye-Tracking for Adaptive Visualizations

Recent work has used eye-tracking to drive adaptive guidance in stand-alone (non-narrative) visualizations, although they found no evidence that these adaptations can improve the user performance. Specifically, Göbel et al. [9] used eye-tracking to deliver adaptive support in maps by dynamically placing the legend of the map next to where the user is looking, and highlighting in the legend the symbols that lie in the area of gaze location. Although they found that users could process the adaptive legend faster than the non-adaptive one, this did not translate into improved user performance in map reading tasks. Silva et al. [33] used eye-tracking to recommend relevant patterns in line charts showing time-series signal, based on where the user look at in the visualization system. A preliminary analysis revealed that users extensively look at the recommended patterns, however, this work did not include a control group to formally evaluate the effects of the adaptation. Unlike these works, we leverage eye-tracking to perform an in-depth evaluation of gaze-driven adaptation that has been shown to improve the performance of some users, in order to elicit what are the gaze patterns that may explain this improvement. We also extend the type of visualizations studied in [9, 33] by focusing on narrative visualizations, and further examine how vis literacy affects processing of the gaze-driven guidance.

2.3 Eye-Tracking and Individual Differences

There is extensive evidence that user performance in non-adaptive visualization tasks is impacted by individual differences, such as cognitive abilities, personality traits and expertise (see [6, 26] for an overview). To understand these differences in performance, researchers have leveraged eye-tracking to investigate if and how individual differences influence processing of stand-alone visualizations. Most of this research has focused on comparing eye-tracking patterns of experts and novices in different visualization tasks, namely map reading [25], visual information search [17] and processing of scientific charts [12, 35]. A few studies have investigated how cognitive abilities and skills influence gaze patterns in low-level analytic tasks with bar and radar charts [37, 39], in decision making tasks with maps and deviation charts [19], and in tasks involving to understand medical information with bar charts and line charts [24]. Results showed in particular that eye-tracking can unveil suboptimal gaze behaviors exhibited by low vis literacy users, such as performing few visual comparison among visualizations [19] and not focusing on important regions of the visualizations [24]. Another work examined whether vis literacy influences processing of visual cues displayed upfront in visualizations, but found no such influence [15]. Cognitive styles were also linked to how users visually process a visualization-based bibliographic retrieval system [36]. So far, no work has looked into the relationship among adaptive guidance, gaze behaviors and individual differences in visualization tasks, as we do in this paper.

While the above works were all focused on non-narrative visualizations, in Toker et al. [38] we studied how gaze behaviors is affected by individual differences in MSNVs, still with no guidance. We identified that low levels of several cognitive abilities generate longer suboptimal processing behaviors that result in longer reading time, such as spending longer time processing non-relevant datapoints. Here, we extend this previous work by showing that vis literacy also influences gaze behaviors when receiving adaptive guidance, and we provide insights into how these behaviors explain the performance of the users depending on their levels of vis literacy.

3 Dataset Used in this Paper

The eye-tracking dataset used in this paper to evaluate adaptive MSNVs was previously collected in two separate user studies we conducted, together conforming a between-subject design. In the first study (fully reported in Toker et al. [38]), participants read a set of MSNVs with no adaptive guidance (*control group*), while in the second study (fully reported in Lallé et al. [20]), participants read the same MNSVs with adaptive guidance (*adaptive group*). The two studies used the exact same task and procedure, as summarized next.

3.1 Adaptive Guidance in MSNVs

Both the control study and the adaptive study used the same set of 14 bar-chart-based MSNVs that we derived from an existing dataset of MSNVs extracted from real-world sources [38]. Each MSNV in the dataset consisted of "snippets" of larger source documents whereby each snippet included a self-contained excerpt of the original text and one accompanying bar chart (see Figures 1-3). We focused solely on bar charts to keep the complexity of the study manageable, and because bar chart is one of the most ubiquitous visualizations in the real world [22]. The 14 MSNVs were selected to include a balanced variety of bar chart types (simple, stacked, grouped), document length, and number of referenced datapoints. The selection process is fully described in Toker et al. [38].

For the adaptive group, we proposed in [20] gaze-driven adaptive guidance meant to drive the user's attention to the relevant data in the visualization side of the MSNV when it is the most relevant, i.e., when the user is attending to that piece of information in the text. To this end, we devised an eye-tracking mechanism that dynamically highlights the bars in the MSNV visualization corresponding to the reference sentence that the user is reading. These highlights are displayed by thickening the border of the bars in black, for instance in Figure 3, the two bars at the bottom are highlighted with such thick border when the user reads the underlined sentence in the text, as this sentence directly describes these two bars. As the user reads though the text, highlights corresponding to each newly read reference sentence are cumulatively added to the previously highlighted bars. To help the user distinguish the most recent highlighting from the previous ones, previous black outlines are desaturated so that they become grey, as shown in Figure 3 with the two bars on the top left. This mechanism has been carefully designed, pilot tested and evaluated, as reported in the related work and in Lallé et al. [20].

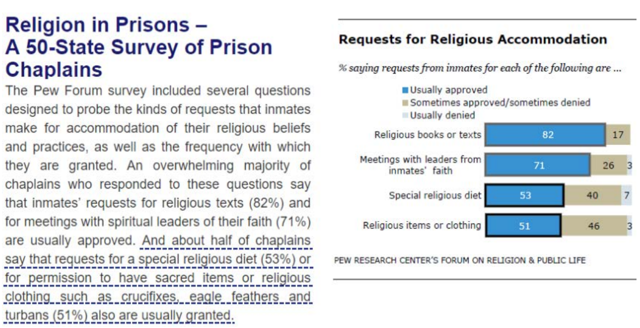

Figure 3. Adaptive guidance implemented on the MSNVs. When the user reads a sentence that refers to specific bars in the visualization (blue underline), the bars are dynamically highlighted with a thick black border.

3.2 Procedure for Data Collection

The control study included 56 subjects (32 female), with age from 19 to 69 (M=28, SD=11), while the adaptive study included 63 participants (34 female), with age from 18 to 59 (M=25, SD=8). In both studies, about 60% of participants were university students. First, the *Bar Chart Visualization Literacy Test* was administered to collect the levels of vis literacy of the participants [4]. Then, participants underwent an eye-tracking calibration procedure with a Tobii T-120 high-end remote eye-tracker embedded in a display of 1280 x 1024 pixels, with sampling rate of 120 Hertz. Participants were instructed to read each of the 14 MSNVs on the computer screen. After reading each MSNV, they were presented with a set of comprehension questions meant to evaluate their understanding of the MSNV they just read. The MSNV order was fully randomized, and there was no time limit to read the MSNVs, nor any sort of training, to mimic how users read MSNVs in their daily life. In both the control and adaptive studies, the users took on average about 20 minutes to read through all 14 MSNVs and answer the comprehension questions.

4 Eye-Tracking Experiment

In this section, we describe the eye-tracking experiment we performed to address our research questions, starting with the description of the gaze metrics we leverage for analysis.

4.1 Areas of Interest and Gaze Metrics

In order to analyze the differences in gaze behaviors with and without the adaptive guidance, we define a set of Areas of Interest (AOIs) over the key regions of the MSNVs. We focus on these AOIs because in [38] we showed that they can reveal users' suboptimal gaze patterns within non-adaptive MSNVs. Here we aim to understand whether the adaptive guidance modifies how users attend to them. AOIs are shown in Figure 4, and described next.

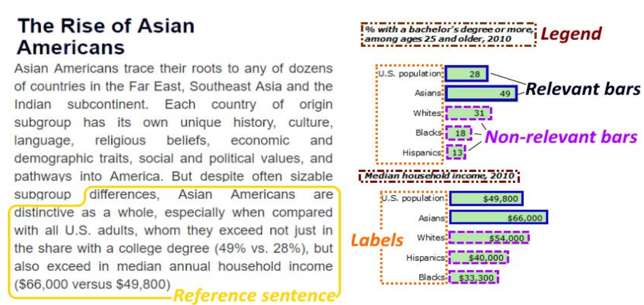

Figure 4. Areas of Interest (AOIs) defined in the MSNVs.

- **Reference sentences (Ref)** contain the combined area of all the sentences that directly refer to the visualization of the MSNV. For instance, in Figure 4, there is one reference sentence, constituting the AOI with plain yellow border. We expect to capture more transitions from this AOI to the visualization side, given that the adaptive guidance was designed to guide the attention of users towards the visualization when they read a reference sentence.
- **Relevant (R-Bar) and Non-Relevant Bars (NR-Bar)** contain the combined area of all the bars in the visualization that are described (R-Bar) or not (NR-Bar) by any of the

references. We expect users to focus more on the R-Bar when provided with adaptive guidance, since the guidance specifically highlights these bars, and expect the inverse for NR-Bar that would not be highlighted.

- **Legend** and **Labels** contain respectively the legend and the combined area of all the labels in the visualization. These are key elements to integrate the information conveyed by the bars, and we expect them to be accessed more from the R-Bar, which are highlighted by the adaptive guidance, and less from the NR-Bar.

In order to evaluate how users process the MSNV, we leverage gaze metrics meant to capture how users allocate their attention to each of the AOIs, as well as how they integrate these AOIs by transitioning between them.

Attention metrics. We compute the *number of fixations* and the *average fixation duration* within each AOI. These two measures are complementary in understanding how users processed the target AOI. In particular, the total number of fixations gives a sense of attention allocation to that AOI [13, 29]. The average fixation duration gives a sense of how users process the AOI, in particular, longer fixations on average can indicate more cognitive processing dedicated to that AOI [30] or that the AOI is more engaging to the users [8, 29].

Transition metrics. We investigate the shift in attentional focus between the different regions of the visualization by computing, for each AOI, the *number of transitions* to every other AOIs. Such transitions have been used in particular to understand the processing strategies of users, i.e., how users integrate different components of a visual interface [10, 29, 31]. In our case, transitions are important to evaluate not only to what extend users process certain AOIs, but also how they sequentially access these areas to integrate the different parts of the visualization.

In total, we generated 6 gaze metrics for each of the 5 AOIs, resulting in 30 gaze metrics.

4.2 Statistical Analysis

To ensure accurate analysis, we retain only users that have high eye-tracking data quality (> 80% of valid data samples as reported by the eye-tracker). For the adaptive group we furthermore remove users who triggered less than 75% of the adaptive guidance due to tracking issues (replicating the procedure described in Lallé et al. [20]). This results in a total of 98 valid participants (52 control, 46 adaptive). These participants are then divided into three bins based on a 3-way-median split of their vis literacy scores: low (N=31, 18 control), medium (N=34, 16 control), high (N=33, 18 control), following the same approach as in Lallé et al. [20].

We evaluate differences in the users' attention allocation with and without adaptations using Mixed-Effect Models, as they can handle more than one random effect at once (i.e., within-subject and within-document correlation, as each user performed several tasks, and each of the 14 MSNVs were presented to every user). Specifically, we fit one model for each the 30 above-defined *gaze metrics*, by selecting each of them one at a time as the dependent variable, with *group* (adaptive, control) as the independent variable, *vis literacy* (low, medium, high) as the fixed effect, and *Participant-ID* and *MSNV-ID* as random effects (i.e., repeated measures). For *average fixation duration*, we fit a Linear Mixed Model (LMM) using the lmerTest package in R [18], as *average fixation duration* follows a near normal distribution. For the *number of fixations* and *number of transitions* between AOIs, we fit Generalized Mixed-Models (GLMM) for the negative binomial family using the *glmer.nb* function in the lme4 package in R [2], which is suitable for discrete count distribution. We account for multiple comparisons within each AOI-family (gaze metrics within the same AOI) and report results significant after applying the Benjamini–Hochberg procedure to control for the false discovery rate (FDR) [3].

5 Results

We first discuss results pertaining to RQ1, namely the main effect of groups found in the statistical analysis that capture changes in gaze behaviors among the adaptive and control group (Section 5.1, Table 1). Next, we examine RQ2 by discussing the effects of group that are qualified by an interaction with vis literacy, and discuss their potential implications in terms of improved comprehension for users with low vis literacy (Section 5.2, Table 2).

5.1 Effect of Adaptive Guidance on Gaze Behavior (RQ1)

Table 1 reports the significant[1] main effects of group that were found on several of the gaze metrics that we evaluated showing that the adaptive guidance influences the user's processing behaviors in several ways. In fact, all of the main effects found follow the same direction, indicating that users in the adaptive group present higher values than users in the control group. These main effects are shown in Figure 5 and discussed next.

Table 1. Gaze metrics for which a significant Main Effect of group was found.

AOI	Gaze Metric	Main Effect of Group
R-Bar	*Number of fixations*	More in adaptive $x^2_{(1)} = 6.83$, $p = .0089$, r = .26
	Transitions to Label	More in adaptive $x^2_{(1)} = 6.43$, $p = .0011$, r = .26
Label	*Transitions to* Legend	More in adaptive $x^2_{(1)} = 9.44$, $p = .0021$, r = .31
Legend	*Transitions to* R-Bar	More in adaptive $x^2_{(1)} = 9.70$, $p = .0018$, r = .31
	Avg fixation duration	Longer in adaptive $x^2_{(1)} = 5.58$, $p = .0181$, r = .24

[1] We report in this paper statistical significance at $p < .05$ after FDR correction, as well as effect sizes as high for r > .5, medium for r > .3, and small otherwise.

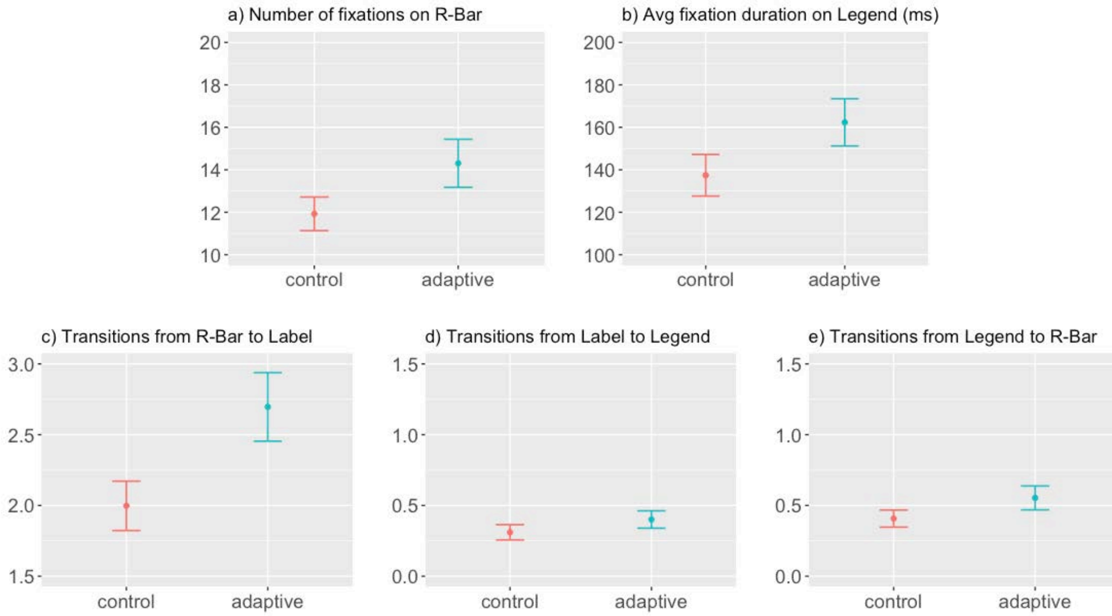

Figure 5. Gaze metrics for which a main effect of group was found. Error bars show 95% confidence intervals.

Number of fixations on R-Bar. Figure 5 (a) shows that users in the adaptive group fixate on average 20% more on the relevant bars that users in the control group. This indicates that the adaptive highlights helped the users in the adaptive group focusing their attention on the relevant bars, which was the main purpose of the adaptations (Section 3.1). Noteworthy, previous analysis on the same dataset did not report significant difference in overall MSNV processing time among groups [20]. This indicates that this additional processing of the relevant bars comes at no expense of the overall information processing time.

Transitions from R-Bar to Label, from Label to Legend, and **from Legend to R-Bar.** These main effects reveal several interesting findings:

- Users in the adaptive group transition on average 35% more often from the relevant bars to the labels (Figure 5, c), most likely to understand to what label(s) the highlighted bars are mapped to.
- Users in the adaptive group transition on average 29% more often from the labels to the legend (Figure 5, d), and 36% more often from the legend to the relevant bars (Figure 5, e), indicating that the adaptive guidance may be prompting users to integrate better the key components of the bar charts.

These findings indicate that users are overall proactive in processing the bar charts once their attention is directed to the relevant bars, which is very encouraging in terms of the effectiveness of the adaptive guidance. In particular, the adaptive guidance seems to encourage users to integrate the relevant bars with their labels and the legend, which is a key aspect of understanding the information conveyed by the bar charts.

Average fixation duration on the Legend. Figure 5 (b) shows that users in the adaptive group presented on average 18% longer fixations on the legend than users in the control group. Longer fixations can indicate higher engagement in processing the target AOI [13, 29], here the legend. This is consistent with the rest of the main effects described above, as users transition more to the legend, and thus may pay closer attention to the legend in order to better understand the meaning of the highlighted bars and their labels.

5.2 Effects of Adaptive Guidance and Vis Literacy on Gaze Behaviors (RQ2)

We found two interaction effects of group with vis literacy on gaze metrics, namely the number of transitions from relevant bars to legend, and number of fixations on the legend. We investigate these interaction effects with post-hoc, pairwise contrast comparisons using the *emmeans* package in R[2]. Table 2 reports results significant after applying the Benjamini–Hochberg FDR procedure [3] to account for multiple comparisons, and we discuss them next.

Number of transitions from R-Bar to Legend. The pairwise comparisons show that users with low levels of vis literacy perform significantly more of these transitions in the adaptive group compared to the control group, representing an increase of 181% of these transitions on average (left side of Figure 6). There is no such statistical difference for users with higher levels of vis literacy (middle and right side of Figure 6). This finding is interesting because our previous work on the same dataset [20] showed that low vis literacy users performed significantly better in the adaptive group compared to the control group, in terms of comprehension of the information conveyed by the MSNV. Here,

Table 2. Gaze metrics for which a significant interaction effect of group and vis literacy was found.

AOI	Gaze Metric	Group x Vis Literacy	Significant Pairwise Contrasts
R-Bar	*Transitions to* Legend	$x^2_{(1)} = 15.18$, $p = .0005$, r = .39	More in adaptive for low vis literacy z = 4.27, $p < .0000$, r =.43 In control, less for low than for medium z = -2.9, $p = .01$, r = .29
Legend	*Number of fixations*	$x^2_{(1)} = 11.28$, $p = .003$, r = .34	*No significant results after FDR correction*

our finding indicates that the adaptive guidance prompted specific gaze behaviors in low vis literacy users, related to integrating the relevant bars and the legend, which possibly further helped these users making sense of the MSNV. This is consistent with our findings discussed in the previous section (5.1), that the adaptive guidance overall induces similar transitions in the opposite direction, i.e., from the legend to the relevant bars. Here, our results suggest that low vis literacy users go one step further in the integration of the legend and the relevant bars by transitioning back and forth between these two AOIs.

The pairwise comparisons showed in addition that users low in vis literacy within the control group performed significantly less of these transitions compared to users with medium levels of vis literacy, representing 77% less transitions on average (left side of dashed red line in Figure 6). This result indicates that the adaptive guidance helps low vis literacy users catching up with users with higher levels of vis literacy in terms of transitions from relevant bars to legend.

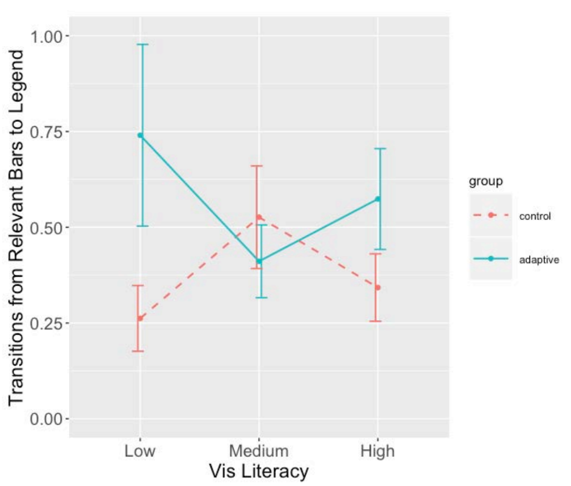

Figure 6. Interaction effect of vis literacy with group on *Transitions* from Relevant Bars to Legend. Error bars show 95% confidence intervals.

[2] https://CRAN.R-project.org/package=emmeans

Number of fixations on the Legend. The pairwise comparisons suggest that low vis literacy users may fixate more on the legend in the adaptive group compared to the control group, representing a 75% increase (z = 2.42, $p = .015$, r = .24). This would be consistent with the results discussed above that users with low vis literacy transition more to the legend, leading to more fixations on the legend. However, as reported in Table 2, none of the pairwise comparisons for the number of fixations on the Legend survived the FDR procedure. Therefore, we do not discuss this effect further as it is unclear whether this finding is meaningful or is a false positive (Type I error) due to multiple comparisons.

6 Discussion

We first discuss how our results inform the design of adaptive guidance in narrative visualizations, via personalization to the user's levels of vis literacy (Section 6.1). We then discuss the implications that the presented eye-gaze analysis holds for evaluating adaptive visualizations (Section 6.2).

6.1 Implications for Personalization

Our results show that providing adaptive guidance encourages several gaze behaviors, which can be leveraged to refine the adaptation mechanism via personalization to the user's levels of vis literacy.

Users with low vis literacy: These are the users who were found to significantly improve their comprehension of the MSNVs when receiving adaptive guidance, and our analysis identified gaze behaviors that can explain their improved performance. We found that, when provided with adaptive guidance, these users fixated more on the relevant bars, transitioned more between the relevant regions of the bar chart, and were more engaged in processing the legend (Section 5.1). While all users exhibited these behaviors, it is possible that users with low vis literacy benefited the most from them, because they needed help the most due to their low literacy. Furthermore, users with low vis literacy transitioned more between the legend and the relevant bars when provided with adaptive guidance, suggesting that they better integrate these two elements (Section 5.2). Altogether, these changes in gaze behavior may explain the increase in comprehension performance for these users, as mapping the relevant bars to their labels and to the information encoded in the legend is fundamental to make sense of bar charts. This may prove to be a challenging task for users with low vis literacy, and we provide insights into how the adaptive guidance helps them in doing so.

While our findings indicate that the current guidance is beneficial to low vis literacy users overall, it is still possible that some of the low vis literacy users do not perform the useful gaze behaviors that we have identified. Moving forward, it could be worthwhile to further personalize the guidance to these users, by encouraging them to perform these behaviors when they do not do it spontaneously, as captured by eye-tracking. We could do so by, for instance, highlighting the relevant labels and items in the legend, in addition to the current highlights.

Users with medium and high vis literacy: We found that the gaze behaviors of these users are overall influenced by the adaptive guidance, showing that they do notice and process the highlights to some extent (Section 5.1). Importantly, these behaviors generated by the adaptation pertain to processing the relevant parts of the bar charts, which was the intended goal of the adaptation, meaning that the guidance, at least, does not generate unwarranted behaviors in these users. However, our previous work showed that providing these adaptations to users with medium and high vis literacy do not help them to better understand the visualizations. This shows that the gaze behaviors we found in Section 5.1 are not sufficient to influence the performance of these users. One possible explanation is that these users are already able to quickly identify the relevant information in the bar chart, due to their higher vis literacy, and they do not benefit as much from improved integration of the relevant bars with the labels and legend. Based on these findings, we encourage future work to investigate whether these users might benefit from other forms of adaptive guidance more suited to their needs.

Altogether, our findings show that the effectiveness of adaptive guidance in narrative visualizations could be improved via personalization to the user' levels of vis literacy. In order to deliver such personalized guidance, one possible approach is to automatically infer the user's levels of vis literacy from their gaze behaviors, as done in [7]. This would be especially suitable for narrative visualizations as our results indicate that users exhibit specific gaze behaviors that might accurately reveal their levels of vis literacy.

6.2 Eye-tracking for Evaluating Adaptive Visualizations

Our work shows that eye-tracking can be valuable to understand how and why adaptive guidance may benefit specific groups of users in narrative visualizations. While previous work has mostly leveraged attention maps and fixation time over the adaptive component to perform such evaluation [9, 33], here we show that capturing gaze transitions among different regions of the visualization is important as well to uncover the user's processing strategy. In particular, we found that highlighting one specific part of the MSNV, seems to generate proactive processing of other important related components in the visualization. Thus, one should leverage processing metrics (transitions across AOIs) in addition to attention metrics (fixation within AOIs) to evaluate in depth the effectiveness of adaptive visualizations.

Furthermore, our results suggest that the adaptive guidance promotes a specific gaze strategy to process the bar charts in the MSNVs, namely by transitioning from the relevant bars to the labels, then the legend, and finally looking back at the relevant bars. However, our current analysis does not allow to explicitly surface the sequencing of these transitions. In future work, it could be worthwhile to ascertain whether such strategy is actually happening, by mining and analyzing longer sequences of transitions among AOIs. Such analysis could reveal other strategies that could further inform the design of improved adaptive guidance for narrative visualizations.

7 Conclusion

In this paper we leveraged eye-tracking to evaluate the effectiveness of gaze-driven adaptive guidance in MSNVs, a widespread form of narrative visualizations in real-world sources. The evaluated guidance consists in dynamically highlighting the relevant datapoints (bars in a bar-chart) when a user reads a reference sentence that describes them, as captured by an eye-tracker. Previous work has shown that such adaptive guidance can improve comprehension of the MSNV, however, only for users with low vis literacy. We extend this previous work by revealing the specific gaze behaviors that the adaptive guidance generates in users, depending on their levels of vis literacy. In particular, providing adaptive guidance leads to more fixations overall on the relevant datapoints, longer fixations on the legend, as well as more gaze transitions between the key components of the visualization (datapoints, labels, legend). These results provide encouraging evidence for this type of adaptive guidance, showing that the mechanism is effective not only in guiding the user's attention towards the relevant datapoints, but also in facilitating processing of the relevant information in the MSNV. In addition, we found changes specific to users with low vis literacy, namely an increased amount of transitions from the relevant datapoints to the legend of the visualization. This further explains how the adaptive guidance helped users with low vis literacy better contextualize and integrate the relevant datapoints with the rest of the components in the visualization, leading to improved comprehension. All in all, our evaluation sheds light on the underlying processing behaviors of users in adaptive narrative visualizations, driving the design of future adaptive guidance mechanisms, more personalized to the user's vis literacy.

REFERENCES

[1] P. Ayres and G. Cierniak. 2012. Split-attention effect. Encyclopedia of the Sciences of Learning. Springer, 3172–3175.

[2] D. Bates, M. Mächler, B. Bolker and S. Walker. 2014. Fitting Linear Mixed-Effects Models using lme4. *arXiv:1406.5823*.

[3] Y. Benjamini and Y. Hochberg. 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1), 289–300.

[4] J. Boy, R.A. Rensink, E. Bertini and J.-D. Fekete. 2014. A Principled Way of Assessing Visualization Literacy. *IEEE Transactions on Visualization and Computer Graphics*, 20(12), 1963–1972.

[5] M. Burch, N. Konevtsova, J. Heinrich, M. Hoeferlin and D. Weiskopf. 2011. Evaluation of traditional, orthogonal, and radial tree diagrams by an eye tracking study. *IEEE Transactions on Visualization and Computer Graphics*, 17(12), 2440–2448.

[6] C. Conati, G. Carenini, Dereck Toker and Sébastien Lallé. 2015. Towards User-Adaptive Information Visualization. *Proceedings of the 29th AAAI Conference on Artificial Intelligence*. AAAI Press, Austin, TX, USA, 4100–4106.

[7] C. Conati, S. Lallé, Md.A. Rahman and D. Toker. 2017. Further Results on Predicting Cognitive Abilities for Adaptive Visualizations. *Proceedings of the 26th International Joint Conference on Artificial Intelligence*. AAAI Press, Melbourne, Australia, 1568–1574.

[8] W. Einhäuser, M. Spain and P. Perona. 2008. Objects predict fixations better than early saliency. *Journal of Vision*, 8(14), 18–18.

[9] F. Göbel, P. Kiefer, I. Giannopoulos, A.T. Duchowski and M. Raubal. 2018. Improving Map Reading with Gaze-adaptive Legends. *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications*. ACM, New York, NY, USA, 29:1–29:9.

[10] L.R. Goldberg. 1999. A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. *Personality psychology in Europe*, 7(1), 7–28.

[11] D. Gotz and Z. Wen. 2009. Behavior-driven Visualization Recommendation. *Proceedings of the 14th International Conference on Intelligent User Interfaces*. ACM, Sanibel Island, FL, USA, 315–324.

[12] J.A. Harsh, M. Campillo, C. Murray, C. Myers, J. Nguyen and A.V. Maltese. 2019. “Seeing” Data Like an Expert: An Eye-Tracking Study Using Graphical Data Representations. *CBE—Life Sciences Education*, 18(3), ar32.

[13] K. Holmqvist, M. Nyström, R. Andersson, R. Dewhurst, H. Jarodzka and J. van de Weijer. 2015. *Eye Tracking: A Comprehensive Guide to Methods and Measures*. Oxford University Press.

[14] S. Kalyuga. 2007. Enhancing Instructional Efficiency of Interactive E-learning Environments: A Cognitive Load Perspective. *Educational Psychology Review*, 19(3), 387–399.

[15] H.-K. Kong, W. Zhu, Z. Liu and K. Karahalios. 2019. Understanding Visual Cues in Visualizations Accompanied by Audio Narrations. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Glasgow, UK, 50:1-50:13.

[16] N. Kong, M.A. Hearst and M. Agrawala. 2014. Extracting references between text and charts via crowdsourcing. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Toronto, Canada, 31–40.

[17] B. Kules and R. Capra. 2012. Influence of training and stage of search on gaze behavior in a library catalog faceted search interface. *Journal of the American Society for Information Science and Technology*, 63(1), 114–138.

[18] A. Kuznetsova, P.B. Brockhoff and R.H.B. Christensen. 2017. lmerTest package: tests in linear mixed effects models. *Journal of Statistical Software*, 82(13), 1–26.

[19] S. Lallé, C. Conati and G. Carenini. 2017. Impact of Individual Differences on User Experience with a Visualization Interface for Public Engagement. *Proceedings of the 2nd International Workshop on Human Aspects in Adaptive and Personalized Interactive Environments*. ACM, Bratislava, Slovakia, 247–252.

[20] S. Lallé, D. Toker and C. Conati. 2019. Gaze-Driven Adaptive Interventions for Magazine-Style Narrative Visualizations. *IEEE Transactions on Visualization and Computer Graphics*, to appear, 1–12.

[21] R. Metoyer, Q. Zhi, B. Janczuk and W. Scheirer. 2018. Coupling Story to Visualization: Using Textual Analysis as a Bridge Between Data and Interpretation. *Proceedings of the 23rd International Conference on Intelligent User Interfaces*. ACM, Tokyo, Japan, 503–507.

[22] T. Munzner. 2014. *Visualization analysis and design*. CRC press.

[23] K. Nazemi, W. Retz, J. Kohlhammer and Arjan Kuijper. 2014. User similarity and deviation analysis for adaptive visualizations. Human Interface and the Management of Information. *Information and Knowledge Design and Evaluation*. Springer, 64–75.

[24] Y. Okan, M. Galesic and R. Garcia-Retamero. 2016. How People with Low and High Graph Literacy Process Health Graphs: Evidence from Eye-tracking. *Journal of Behavioral Decision Making*, 29(2–3), 271–294.

[25] K. Ooms, P. De Maeyer and V. Fack. 2014. Study of the attentive behavior of novice and expert map users using eye tracking. *Cartography and Geographic Information Science*, 41(1), 37–54.

[26] A. Ottley. 2016. *Toward personalized visualizations*. Ph.D dissertation, Tufts University.

[27] E. Ozcelik, I. Arslan-Ari and K. Cagiltay. 2010. Why does signaling enhance multimedia learning? Evidence from eye movements. *Computers in Human Behavior*, 26(1), 110–117.

[28] M.D. Plumlee and C. Ware. 2006. Zooming Versus Multiple Window Interfaces: Cognitive Costs of Visual Comparisons. *ACM Transactions on Computer-Human Interaction*, 13(2), 179–209.

[29] A. Poole and L.J. Ball. 2006. Eye Tracking in HCI and Usability Research. *Encyclopedia of Human Computer Interaction*. IGI, 211–219.

[30] K. Rayner. 1998. Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin*, 124(3), 372–422.

[31] D.S. Rudmann, G.W. McConkie and X.S. Zheng. 2003. Eyetracking in Cognitive State Detection for HCI. *Proceedings of the 5th International Conference on Multimodal Interfaces*. ACM, 159–163.

[32] E. Segel and J. Heer. 2010. Narrative Visualization: Telling Stories with Data. *IEEE Transactions on Visualization and Computer Graphics*, 16(6), 1139–1148.

[33] N. Silva, T. Schreck, E. Veas, V. Sabol, E. Eggeling and D.W. Fellner. 2018. Leveraging eye-gaze and time-series features to predict user interests and build a recommendation model for visual analysis. *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications*. ACM, Warsaw, Poland, 13:1-13:9.

[34] M. Steinberger, M. Waldner, M. Streit, A. Lex and D. Schmalstieg. 2011. Context-preserving visual links. *IEEE Transactions on Visualization and Computer Graphics*, 17(12), 2249–2258.

[35] R.H. Tai, J.F. Loehr and F.J. Brigham. 2006. An exploration of the use of eye-gaze tracking to study problem-solving on standardized science assessments. *International journal of research & method in education*, 29(2), 185–208.

[36] R. Tang and Y. Song. 2018. Cognitive styles and eye movement patterns: an empirical investigation into user interactions with interface elements and visualisation objects of a scientific information system. *Information Research*, 23(2).

[37] D. Toker and C. Conati. 2014. Eye tracking to understand user differences in visualization processing with highlighting interventions. *Proceedings of the 22nd International Conference on User Modeling, Adaptation, and Personalization*. Springer, Aalborg, Denmark, 219–230.

[38] D. Toker, C. Conati and G. Carenini. 2019. Gaze analysis of user characteristics in magazine style narrative visualizations. *User Modeling and User-Adapted Interaction*, 29(5), 977–1011.

[39] D. Toker, C. Conati, B. Steichen and Giuseppe Carenini. 2013. Individual User Characteristics and Information Visualization: Connecting the Dots Through Eye Tracking. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Paris, France, 295–304.

[40] T. Van Gog. 2014. The signaling (or cueing) principle in multimedia learning. *The Cambridge handbook of multimedia learning*, 2nd ed. Cambridge University Press, 263–278.

[41] Q. Zhi, A. Ottley and R. Metoyer. 2019. Linking and Layout: Exploring the Integration of Text and Visualization in Storytelling. *Computer Graphics Forum*, 38(3), 675–685.

[42] M.X. Zhou and V. Aggarwal. 2004. An optimization-based approach to dynamic data content selection in intelligent multimedia interfaces. *Proceedings of the 17th Annual Symposium on User Interface Software and Technology*. ACM, Santa Fe, NM, USA, 227–236.