User-adaptive Support for Processing Magazine Style Narrative Visualizations: Identifying User Characteristics that Matter

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ABSTRACT
In this paper we present results from an exploratory user study to uncover which user characteristics (e.g., perceptual speed, verbal working memory, etc.) play a role in how users process textual documents with embedded visualizations (i.e., *Magazine Style Narrative Visualizations*). We present our findings as a step toward developing user-adaptive support, and provide suggestions on how our results can be leveraged for creating a set of meaningful interventions for future evaluation.

Author Keywords
User study; Narrative visualization; Individual differences; User characteristics; User-adaptation; Personalization.

INTRODUCTION
As digital information continues to accumulate in our lives, information visualizations have become an increasingly relevant tool for discovering trends and shaping stories from this overabundance of data (e.g., Infographics [26], Timelines [6]). However, visualizations are typically designed and evaluated following a one size-fits-all approach, meaning they do not take into account the potential needs of individual users. There is mounting evidence that user characteristics such as cognitive abilities, personality traits, and learning abilities, can significantly influence user experience during information visualization tasks (e.g., [25,33,38,41]). These findings have prompted researchers to investigate user-adaptive information visualizations, i.e., visualizations that aim to recognize and adapt to each user's specific needs. Whereas existing work has been mostly limited to tasks involving just visualizations, the aim of our research is to broaden this work to include scenarios where users interact with visualizations embedded in narrative text, known as *Magazine Style Narrative Visualization* [35], or MSNV for short (e.g., Figure 1).

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Research has shown that text and graphical modalities are well suited information channels to combine (e.g., [44]). Moreover, the *multimedia principle* states that "users learn more deeply from words and pictures than from words alone." [29]. However, an established problem arising from combined modalities is the *split-attention effect*. Split-attention occurs when users are required to split their attention between two information sources (e.g., text and visualization), which can increase cognitive load and can negatively impact learning [2]. This problem is exacerbated in MSNVs where often there is more than one visual task specified through the narrative text. Multiple visual tasks in MSNVs are captured by *references*, namely segments of text that specifies a visual task in on an accompanying visualization. An example of a reference is shown in Figure 1, it includes the sentence *"An overwhelming majority of chaplains who responded to these questions say that inmates' requests for religious texts (82%) and for meetings with spiritual leaders of their faith (71%) are usually approved."* plus the two bars outlined in orange. Typically, references are used to support arguments or statements being made in the document text by providing added details or interpretations to an accompanying visualization. As a user reads through a MSNV, they will often encounter a variety of references in the text, each soliciting attention to different aspects of the accompanying visualization. Since visualizations cannot be designed to favor the performance of any particular reference (because favoring one task may hinder the others) it has been proposed by Carenini et al. [8] to address this problem by providing *user-adaptive* support: highlighting interventions would be provided to relevant aspects of the visualization depending on what part of the text the user is reading and depending on the *user's characteristics* that may impact MSNV processing.

In this paper we present a first step toward understanding how to provide this adaptive support, by focusing specifically on identifying which user characteristics impact MSNV processing and thus warrant personalization. We conducted an exploratory user study to evaluate a set of 9 different user characteristics that could potentially influence MSNV performance. These include characteristics that were previously found to impact visualization processing (e.g., perceptual speed, spatial memory), plus some that are related to text processing (e.g., reading proficiency, verbal

IQ). Results from our user study identified five user characteristics that could be suitable targets for providing adaptive support. In the remainder of the paper we discuss related work, followed by a description of the user study. We then report results, and wrap up with the conclusion.

RELATED WORK

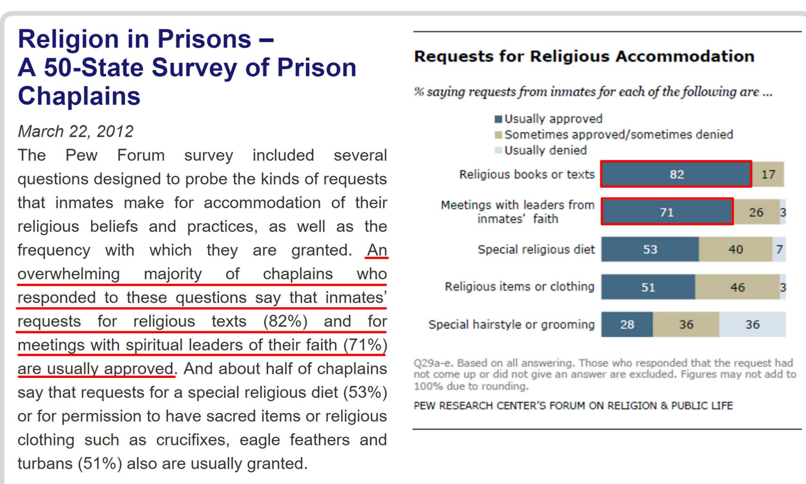
A growing amount of work has linked several user characteristics to performance and preference with various information visualizations. For instance, the cognitive ability *perceptual speed* has been shown to correlate negatively with time on task [9,10,41], and can also influence visualization suitability [1,12]. Users with high *visual working memory* were found to have a stronger preference for radar charts [38], and were shown to prefer deviation charts over maps [24]. Findings for other cognitive traits include: *disembedding* on task accuracy [41], *verbal working memory* on response time [9,10], and *spatial memory* on performance [12,41] and usability [24]. *Locus of control*, a personality trait, has also been shown to play a significant role in determining which type of visualization a user performs best with [20,33,43].

There are several works that have demonstrated the value of employing user-adaptive strategies in visualization systems. For instance, Gotz & Wen [17] reported a significant reduction in task time and task error-rate, by recommending an appropriate visualization to users based on patterns detected in the sequence of actions they performed while carrying out search and comparison tasks. Grawemeyer [18] also reported improved task performance with a series of database queries, by tracking users' evolving knowledge of the task domain and recommending visual representations accordingly. Nazemi et al. [32] improved the performance of searching bibliographic entries, by tracking users' interactions and adapting the size, color, and order of the entries shown across several visualizations. Carenini et al. [9] evaluated several forms of dynamic highlighting to guide attention to relevant datapoints within grouped bar charts, and they reported a significant improvement in task performance when compared to using no interventions. Outside of visualization, work has been done on providing user-adaptive support to text reading/comprehension. For instance, Lobodoa et al. [27] examined the feasibility of using eye tracking to infer word relevance during reading tasks, so that the informational needs of users could be assessed unobtrusively. Some work in intelligent user interfaces has looked at automatic generation of text and graphical presentations [19], but to the best of our knowledge, no one has focused on designing user-adaptive support to help users process them.

USER STUDY

Study Procedure

56 subjects (32 female) ranging in age from 19 to 69, participated in the study. 60% of participants were university students, and the others were from a variety of backgrounds (e.g., retail manager, restaurant server, retired). The experiment was a within-subjects repeated measures design, lasting at most 115 minutes. Participants were given the task of reading over a MSNV, and would signal they were done by clicking 'next'. They were then presented with a set of questions designed to elicit their opinion and to test their comprehension of relevant concepts discussed in the document. Participants were required to carry out this task for 15 different MSNVs (described in the next subsection). Users were not given a time-limit to read the MSNVs, but we told them that speed and accuracy would be factors in determining their performance. Standard tests were used to assess user characteristics (see Table 1). To reduce fatigue, we split up the user characteristic tests so that some were done at home the night before the experiment, and the rest were



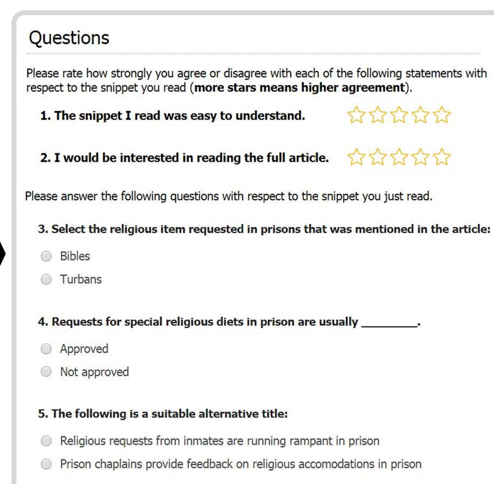


Figure 1. One of 15 MSNVs administered in the user study.
***Note: Orange highlighting is shown to illustrate the concept of a *reference*. Highlighting was <u>not</u> provided to users in the study.**

Figure 2. Comprehension questions presented to users after reading each MSNV.

administered in the lab before and after the set of 15 MSNV tasks[1]. Each participant was compensated $45 for the study. We further incentivized users by offering a $50 bonus to the top three participants with the best performance, so that users would be more inclined to put in effort with the tasks.

Study tasks

As we mentioned in the introduction, salient processing points in a MSNV are solicited by *references*, namely segments of text that specify a visual task on an accompanying visualization. The 15 MSNVs we used for the study tasks were derived from an existing dataset of magazine style documents by Kong et al. where the *references* in each document were identified via a rigorous coding process indicating which data points in each visualization correspond to each reference sentence [23]. All documents in the dataset were extracted from real-world sources including *Pew Research*, *The Guardian*, and *The Economist*. The 15 MSNVs in our study were self-contained excerpts from longer articles, selected to include one visualization each, and one body of narrative text ranging between 42 and 228 words (avg. = 91), and 1 to 7 *references*[2] (avg. = 2.6). Number of words and references were varied to account for the potential influence that these factors of complexity might have on MSNV processing. All the visualizations we selected were an assortment of bar charts (e.g., simple, stacked, grouped [31]).We focused on one class of visualizations to keep the complexity of study manageable, and we chose bar-graphs because they are one of the most popular and effective visualizations.

The aim of our study is to evaluate the impact of user characteristics on users' experience with MSNVs, where experience comprises of both task performance and subjective measures. These measures were assessed for each MSNV via a set of questions (see Figure 2) shown to the user after they read each document. Two *subjective* questions measured, respectively, perceived ease-of-understanding and interest (see top two questions in Figure 2), based on work by Waddell et al. [42]. The remaining questions measured task performance in terms of document comprehension, based on the work by Dyson & Haselgrove [13]. They included:

- One *title question* which asks to select a suitable alternative title for the MSNV (see question 5, bottom of Figure 2), and provides a simple way to ensure that the user had a grasp of the general document narrative.
- One or two (depending on document length) *recognition questions* asking to recall specific information from the MSNV: either a *named entity* discussed in the text (e.g., question 3 in Figure 2), or the *magnitude/directionality* of two named entities (e.g., question 4 in Figure 2).

User Characteristics Explored in the Study

The nine user characteristics we investigated in the study are shown in Table 1. The first seven characteristics consist of cognitive abilities and traits that we selected because previous research has shown that they play a significant role in user experience with visualizations (e.g., [9,10,12,24,38,41]). In addition, we included two user characteristics relating to reading abilities, to account for the fact that the MSNVs each contain a body of narrative text. All of the user characteristics were measured with standard tests in psychology (refer to Table 1 for citations).

Characteristic	Definition + Test Source
NEED FOR COGNITION	Extent to which individuals are inclined towards effortful cognitive activities [7].
BAR CHART LITERACY	Ability to use a bar chart to translate questions specified in the data domain into visual queries in the visual domain, as well as interpret visual patterns in the visual domain as properties in the data domain [5].
VISUAL WORKING MEMORY	Part of the working memory responsible for temporary storage and manipulation of visual and spatial information [16,28].
SPATIAL MEMORY	Ability to remember the configuration, location, and orientation of figural material [14].
VERBAL WORKING MEMORY	Part of the working memory responsible for temporary maintenance and manipulation of verbal information [3,40].
PERCEPTUAL SPEED	Speed in scanning/comparing figures or symbols, or carrying out other very simple tasks involving visual perception [14].
DISEMBEDDING	Ability to hold a given visual percept or configuration in mind so as to disembed it from other well defined perceptual material [14].
READING PROFICIENCY	Vocabulary size and reading comprehension ability in English [30].
VERBAL IQ	Overall verbal intellectual abilities that measures acquired knowledge, verbal reasoning, and attention to verbal materials [4,36].

Table 1. User characteristics measured in the study.

RESULTS

To assess the impact of the tested user characteristics on MSNV processing, we looked at 4 dependent measures:

- *MSNV Speed:* time in seconds that users spent looking at the document (M = 57.2, SD = 32.9).
- *MSNV Accuracy:* combined score of the objective comprehension questions (M = 0.69, SD = 0.30).
- *MSNV Ease-of-Understanding:* subjective rating on a 5-point Likert Scale (M = 3.9, SD = 1.0).
- *MSNV Interest:* subjective rating on a 5-point Likert Scale (M = 3.3, SD = 1.3).

To account for possible redundancies, we carried out a preliminary check for correlations within the user characteristics as well as within the dependent measures

[1] In the future, we plan to predict user characteristics in real-time by using classifiers based on eye tracking data, as done in [11,39].

[2] We also varied the *type* of references included in the documents, e.g., references that identify specific datapoints in the visualization; and references that emphasize comparisons among groups of datapoints.

(Pearson correlation). For both groups, no correlations were high enough to justify removal. We then ran one path analysis model[3] on each of the 4 dependent measures of user experience using the *lavaan* software package in R [34]. Each path model included the set of 9 user characteristics as covariates, as well as 5 factors to account for document complexity (e.g., number of words in the text, amount of references, number of datapoints in the visualization). We adjusted for multiple comparison error using a Bonferroni correction of $m = 4$ [15]. In terms of model fit, all four path models yielded a Tucker-Lewis Index (TLI) = 1.0, which is the best fit possible, and is well above the minimum acceptable threshold of 0.9 [21]. Due to space limitations, we report only the statistically significant findings for which there are obvious implications for adaptive support.

Main Effect of User Characteristic	MSNV Speed	MSNV Accuracy	MSNV Understanding	MSNV Interest
Disembedding	$p = .002$, $\beta = -0.12$	-	-	-
Verbal WM	$p < .0001$, $\beta = -0.22$	-	-	-
Reading Proficiency	$p < .0001$, $\beta = -0.15$	-	-	-
Need for Cognition	$p < .0001$, $\beta = 0.12$	-	$p < .0001$, $\beta = 0.21$	$p < .0001$, $\beta = 0.14$
Spatial Memory	$p < .0001$, $\beta = 0.19$	-	$p < .0001$, $\beta = 0.13$	-
Bar Chart Literacy	$p < .0001$, $\beta = 0.20$	-	-	-

Table 2. Significant results from our path model analyses. Beta values reported indicate size and directionality of standardized regression coefficient.

We found main effects for six user characteristics on MSNV Speed, but no main effects on MSNV Accuracy (see Table 2), which indicates that all users were similarly accurate though some of them likely needed more time to achieve comparable accuracy. If we look at the results in more detail, the main effects can be clustered into three rather different groups.

The first group includes user characteristics (*Disembedding*, *Verbal WM*, and *Reading Proficiency*) that display a *negative directionality* with MSNV Speed (i.e., users with **low** abilities spend more time looking at the MSNV). This is not surprising, as *Disembedding* relates to visualization processing, and *Verbal WM* and *Reading Proficiency* relate to text processing, and having low abilities for these characteristics are plausible causes of slower performance.

The second group of main effects includes user characteristics (*Need for Cognition* and *Spatial Memory*) that have *positive directionality* with MSNV Speed (i.e., users with **high** abilities are the ones spending more time looking at the MSNVs). This would seem counterintuitive, if we had not also found that for these same two characteristics there are main effects on the subjective measures of MSNV Understanding and/or Interest (see last two columns of Table 2), indicating that these users with **high** abilities are also rating the documents more favorably. What appears to be happening for this group of users, is that longer time on task does not translate into higher accuracy, but it does improve their overall experience, and this could be beneficial depending on the goals of the system or user.

The third group only includes only *Bar Chart Literacy*, for which we also found *positive directionality* with MSNV Speed, but no results with the subjective measures. A possible explanation is that these users linger on the document because they are more inclined to explore extra details in the visualizations (i.e., bar charts), but this unfortunately does not generate any improvement in either accuracy or user experience.

Discussion

Although our results are quite preliminary, the first two groups of main effects can viably inform some adaptation strategies. We have identified characteristics where users with *low abilities* were taking longer to achieve comparable accuracy as their counterparts. Such users could be supported in completing the task faster by providing interventions to facilitate visualization processing for users with low *Disembedding*, or facilitating text processing for users with low *Verbal WM* or *Reading Proficiency*. In the second group of main effects, we have identified characteristics (*Need for Cognition* and *Spatial Memory*) where users with *high abilities* were spending more time on task, with no improvement in objective accuracy, but with higher subjective ratings of document understanding and document interest. For these characteristics, it may make sense to focus on engaging users with low abilities to spend more meaningful time with the MSNVs, which may consequently improve their attitude towards the documents.

CONCLUSION

In this paper, we conducted an exploratory user study to investigate which user characteristics play a role in user experience with Magazine Style Narrative Visualizations (MSNVs). Results from our analysis identified several significant main effects of user characteristics that can inform possible strategies for adaptation. As a next step, we plan to analyze eye tracking data that we collected in our study, which can support and further clarify our results in an objective way. For instance, we expect that users with low *Reading Proficiency* spend more time processing the text in the MSNVs compared to their counterparts. Using gaze analysis methodology described in [37], we can verify if our expectation is true, plus we can further evaluate where within the text users are having difficulty (e.g., possibly while they are processing the *references*).

[3] Path analysis is a more sophisticated model that will facilitate mediation analysis for future work, but at this stage is equivalent to using multiple regression analysis [22].

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