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Who benefits from Visualization Adaptations? Towards a better Understanding of the Influence of Visualization Literacy

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Abstract

The ability to read, understand, and comprehend visual information representations is subsumed under the term visualization literacy (VL). One possibility to improve the use of information visualizations is to introduce adaptations. However, it is yet unclear whether people with different VL benefit from adaptations to the same degree. We conducted an online experiment (n = 42) to investigate whether the effect of an adaptation (here: De-Emphasis) of visualizations (bar charts, scatter plots) on performance (accuracy, time) and user experiences depends on users' VL level. Using linear mixed models for the analyses, we found a positive impact of the De-Emphasis adaptation across all conditions, as well as an interaction effect of adaptation and VL on the task completion time for bar charts. This work contributes to a better understanding of the intertwined relationship of VL and visual adaptations and motivates future research.

Keywords: User Study; Visualization Adaptation; Visualization Literacy; Visualization Competence; Information Visualization; Online Survey; User Experience

Index Terms: Human-centered computing—Visualization—Visualization design and evaluation methods

1 Introduction

Visual representations of information pervade our everyday life and are already present at an early age in school and later during adulthood, on news websites, or on personal mobile devices. The number of visualization types and the diversity of users is increasing continuously. Therefore, it is likely to see a wide variance in skill level across users as well as for different types of visualizations. Some users may be left behind and experience difficulties in understanding visualizations in general or have deficiencies in reading certain types of visual data representations. The competence and the cognitive process related to the ability to read, understand, and comprehend visualizations have been summarized and conceptualized under the term visualization literacy (VL) [7] or data visualization literacy [6]. As the VL level can differ between users and even visualization types for each user, one cannot take it for granted that specific visualization instances can be equally well understood by every person.

One possibility to support users is to adapt a given visualization to the specific characteristics of the current user, thus tailoring the presentation to their needs. This in turn enhances the probability of conveying the information successfully. There exist several aspects that can be adapted, such as changing visual channels [15], using metaphors [43], as well as altering the layout or even completely changing the visualization type [44]. How adaptations of visualizations affect the performance and user experience is likely to be based on the VL level of the individual user. The aptitude-treatment interaction [29] describes the effect that the same instructional strategy (i.e., treatment, in this case the adaptation) can be more or less effective for individuals depending on their specific abilities. Further, the expertise reversal effect [18] describes that instructional support exerts a positive effect on individuals with low level of prior knowledge, whereas the effect on experts can be detrimental. Hence, an adaptation can be beneficial for users if it matches the aptitude of the individual or detrimental in case of a low match.

In order to design the most conducive individualized visualization adaptations, it will be important to gain a better understanding whether the effect of specific visual techniques is dependent on individual VL level. Therefore, we conducted an experiment with 42 participants to investigate the differential effect of visualization adaptations on performance and user experience in dependence of individual VL levels. We used basic visualization types of bar charts and scatter plots and a simple highlighting and De-Emphasis [9] approach as an adaptation. In the following, we will present the design and results of our experiment[1] on the effect of 2D visualization adaptation with regard to VL level.

2 Background & Related Work

This work touches the areas of adaptive information visualization as well as user characteristics, particularly visualization literacy.

2.1 Adaptive & Responsive Information Visualizations

Information visualizations can take on different forms, ranging from basic visualizations (e.g., bar charts, scatter plots) [33], to more complex ones (e.g., parallel coordinate plots, tree maps), or specialized visualization types (e.g., Sankey charts) [32]. In the presence of the growing population that interacts with an increasing number of visualization types, it becomes ever more challenging to create them in such a way that every person can equally read, interpret, and understand a given information visualization. Dynamic adaptations are used to account for the individual differences and needs of users and thus aim to provide each individual with their ideal set of adaptations. Responsive visualizations [11, 25, 26] are a special type of adaptive data visualizations which are capable *"to adapt themselves automatically to external contextual requirements"* [17]. Such a requirement could be the size of a device or the display resolution [11, 25], data

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[1] Study material and data are provided in the supplemental material.

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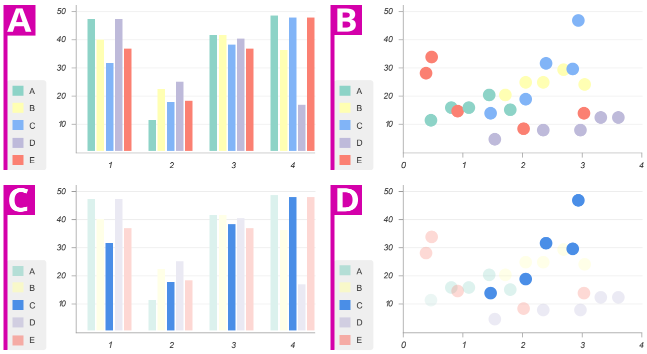

Figure 1: Schematic presentation of the used visualizations. **(A)** and **(C)** show a *Bar Chart*, while **(B)** and **(D)** depict a *Scatter Plot*. **(A)** and **(B)** show visualizations which are not adapted. On the other hand, **(C)** and **(D)** show adapted visualizations using De-Emphasis.

density, layout, and interaction-related aspects [4, 16, 26]. Adaptive visualization can also be based on explicitly provided or inferred user actions, characteristics, or other parameters [2]. One way to facilitate the reading and interpretation of the depicted data is to, e.g., change visual marks or channels to alter the visual encoding [31] or a combination thereof. Exemplary types of visual techniques that can be used for adaptations are highlighting [39], De-Emphasis [9], the introduction of additional visual overlay elements [2, 20, 38], or simplifying [22, 42] as well as hiding whole visualizations [22].

2.2 User Characteristics & Visualization Literacy

There exists a growing body of related work that identifies internal and external user characteristics or properties [2] that can be used to trigger different adaptations. These are, e.g., user context properties (e.g., education, aim) [13], cognitive load [42], personal traits (e.g., locus of control, cognitive style) [9, 22, 38], working and spatial memory [21, 39], or areas of interest measured through gaze [10, 22, 23, 37]. The human ability to understand and comprehend visual stimuli can be described as visual literacy, the *"ability to understand, interpret and evaluate visual messages"* [8] and consists of various dimensions for visual thinking, learning, and communication [1, 40]. Further visual competencies, like visual production, perception, interpretation, and reception [30] can also be seen as parts of this literacy. In the case of reading information visualizations, an extended skill set is required, which is defined as visualization literacy (VL) or data visualization literacy (DVL) [6] and can be described as *"the ability to confidently use a given data visualization to translate questions specified in the data domain into visual queries in the visual domain, as well as interpreting visual patterns in the visual domain as properties in the data domain"* [7]. In order to base adaptation on VL, it is vital to have a reliable and easily administered way of assessing this construct. Existing approaches for VL measurement include the VLAT [27], the DVL framework [6], and the assessment of VL based on Item Response Theory for line charts, bar charts, or scatter plots by Boy et al. [7].

Overall, the level of prior knowledge and competencies affect how well a task can be accomplished and how difficult and strenuous processing of the task will be perceived as by the users. Therefore, assistance and support in form of adaptations offered to the user are likely to have different effect on individuals with either high or low level of competence. More precisely, additional support may not be beneficial in every case, but rather depends on the level of user expertise. It is observable that instructional support can have a detrimental effect on experts and a positive effect on users with low level of prior knowledge, which is further described by the expertise reversal effect [18, 19]. Adaptations are likely to be most beneficial if they match the users' individual competence level (i.e., VL level) thus achieving an ideal aptitude-treatment interaction [29].

Therefore, we conjecture that by taking the individual VL level into account it may be possible to provide adaptations that are better suited to the user's requirements.

3 Study Goals & Hypotheses

Our goal is to shed light on the interaction of VL and visualization techniques, which could be facilitated for adaptation in the future, on the users' performance and user experience. Therefore, we conducted a study in which we manipulated the presentation state (de-emphasized and non de-emphasized; hereafter referred to as *Adapted* and *Non-Adapted*) of two Visualization Types (*Bar Chart* and *Scatter Plot*) in a randomized 2x2 factorial within-subject design. For this study, we generated three hypotheses:

H1 **(Main effect of VL on task performance)** We expect participants with higher VL to perform better than those with lower VL scores.

H2 **(Interaction effect of VL and Adaptation on task performance)** Higher performance is expected with *Adapted* than with *Non-Adapted* visualizations, which difference should be more distinct for participants with lower VL.

H3 **(Interaction effect of VL and Adaptation on user experience)** We expect that user experience for *Adapted* visualizations is rated more positively by participants with lower VL compared to participants with higher VL.

All study materials, i.e., the complete questionnaire, the created visualizations, the tasks, as well as the collected study data and its analysis can be found in the supplementary material.

3.1 Participants

Our online experiment had a completion rate of 38.4 %, which resulted in a total of 43 submitted and completed data sets. One data set was excluded as the subject did not comply with the instructions. Promotion was done via mailing lists in our local university and over two survey websites[2]. All participants had a chance to win one of three 15€ Amazon vouchers. As requested by the data security board of our local university we only recorded age groups. Most of the 42 participants (19 female, 23 male) were in the age groups of 20 to 23 (9 out of 42), 24 to 27 (18 out of 42), and 28 to 31 (9 out of 42), the remaining were older than 31 (6 out of 42). All participants reported an academic background. Further three indicated to have a red-green weakness.

3.2 Task Design

Question Design We created questions based on the low-level analysis task taxonomy of Amar et al. [3]. Concretely, we decided to use the low-level tasks of *Filter*, *Determine Range*, and *Compute Derived Value* and combined two of those for every question (see Tab. A1 in Appendix). We created five task groups, which were repeated in each condition. Each question in a task group was based on the same structure wherein only specific values of the respective data attributes were altered (e.g., country names, year). We created a total of 20 questions (5 task groups x 2 visualization types x 2 adaptation styles).

Design of Visualization Condition We constrained our study to two Visualization Types (*Bar Chart* and *Scatter Plot*). We used the De-Emphasis approach presented by Carenini et al. [9] in the *Adapted* condition (see Fig. A1 in Appendix), as it creates a simple pop-out effect [31] thus highlighting important data points. 20 visualizations were created (see Fig. 1) using features presented in Tableau[3], ten for each Visualization Type (five *Adapted* and five *Non-Adapted*). Each of the *Adapted* visualizations were handcrafted based on their corresponding question. All 20 visualizations were

[2] `https://surveyswap.io/` and `https://www.surveycircle.com`
[3] `https://www.tableau.com/`

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based on the same data set generated from gapminder[4]. In all visualizations, groups of e.g., years, were visually separated by the use of different colours. Grid lines were included in the visualizations in order to make it easier to read values from the axes (see Fig. 1).

3.3 Data Collection & Measurement

Visualization Literacy Assessment We used the VL assessment of Boy et al. [7] to record the individual VL level of each participant. For the assessment, participants were redirected to the online version of the test[5]. The test measured VL scores separately for *Bar Chart* and *Scatter Plot*.

Task Performance The task performance was operationalized as the *task completion time* (*TCT*) and *task accuracy* (*TA*). Each data point greater than $M + 2 * SD$ was defined as an outlier and was subsequently replaced by the exact value of this formula, as proposed by Field et al. [12]. A total of 4.4 % values were classified as outliers and replaced. We used multiple-choice tests with up to seven options for the tasks, whereof only one answer option was correct. Scoring for the *TA* was mapped to 1 if the answer was correct and to 0 if the answer was incorrect.

User Experience To measure *user experience*, we used three scales from the User Experience Questionnaire Plus (UEQ+)[6] [24, 34, 35]: Dependability, Usefulness, and Intuitive Use. Each scale contains four questions on a seven-point likert scale. Additionally, we asked the participants to state whether they preferred the *Adapted* or *Non-Adapted* version of both Visualization Types.

3.4 Setup & Procedure

The study was conducted as an online experiment implemented in LimeSurvey[7]. It consisted of the following parts: (1) A demographic questionnaire; (2) VL assessment [7] for *Bar Chart*, followed by *Scatter Plot*; (3) the *Non-Adapted* tasks; (4) the *Adapted* tasks; lastly, (5) a post-study questionnaire focused on user preferences and procedures. To reduce a potential carry-over and anchoring effects, we decided to present tasks on *Non-Adapted* visualization (3) before the *Adapted* visualizations (4), while the order of the five tasks within each adaptation block (3 and 4) was randomized. Participants were asked to report their VL assessment [7] score obtained on their return to the online experiment site. After each Adaptation condition in (3) and (4) the participants were asked to answer the *user experience* questionnaire [35]. The total duration of the experiment averaged to approximately 50 min ($M = 50.26$ min, $SD = 14.57$ min) while around 12 min ($M = 12.24$ min, $SD = 4.47$ min) were needed for the *Bar Chart* and for the *Scatter Plot* VL assessment each.

4 Data Analysis & Results

We will describe the main data analyses and findings. Additional analyses focusing on the collected VL scores (see Sec. A and Fig. A2 in Appendix) and tables (see Tab. A2 to A5 in Appendix) are provided with the supplemental material.

4.1 Data Analysis Methods

We used JASP[8] for the data analyses. We performed the following statistical tests on both Visualization Types independently. We applied multilevel modeling [12, 14, 36, 41] in order to account for the repeated measures and VL score interaction. We constructed a linear mixed model for *task completion time* and a generalized linear mixed model (GLMM) [5] for the dichotomous variable *TA*. In order to test main and interaction effects of the fixed effect factors (VL and Adaptation), we used the likelihood test ratio method to compare the crossed random effect models. In order to account for the violation of independence of the repeated measurements as well as the measurements of the task groups that are expected to be more similar within one task group, we included the factors participants, task groups (see Tab. A1 in Appendix), and their interaction as random effects into the model (for *TCT* and *TA*). In the model for *user experience* values, the interaction term was dropped as this parsimonious model provided a better fit.

4.2 Results

Task Completion Time For the *task completion time* (*TCT*), we used a linear mixed model (see Fig. 2) without random slopes as it showed the best model fit. For *Bar Chart*, we found a relationship between the VL ($\chi^2(1) = 4.009, p < .05$), Adaptation ($\chi^2(1) = 20.432, p < .001$), and their interaction ($\chi^2(1) = 8.882, p < .01$) on the *TCT* across the participants and task groups (see Tab. A2 in Appendix). This shows that the *TCT* can be significantly predicted by the VL ($b = -7.046, t = -2.052, p < .05$), by the Adaptation ($b = -4.43, t = -4.583, p < .001$), and the interaction of both ($b = 4.689, t = 2.998, p < .01$) (see Tab. A4 in Appendix). In contrast, for *Scatter Plot*, we found only a relationship between VL ($\chi^2(1) = 6.365, p < .05$) and Adaptation ($\chi^2(1) = 40.867, p < .001$) on the *TCT*, but no interaction effect (see Tab. A3 in Appendix). This in turn shows that the *TCT* can be significantly predicted by the VL ($b = -8.032, t = -2.623, p < .5$) and the Adaptation ($b = -5.368, t = -6.571, p < .001$) (see Tab. A5 in Appendix).

Task Accuracy For the *task accuracy* (*TA*), we used a generalized linear mixed model (see Fig. 2) of the binomial family (logit link[9]) and a random slope for Adaptation. For *Bar Chart*, we did not find any relationship between the fixed effects and the *TA* (see Tab. A2 in Appendix). For *Scatter Plot*, we found a relationship between the Adaptation ($\chi^2(1) = 12.774, p < .001$) and the *TA* (see Tab. A3 in Appendix). This in turn shows that the *TA* can be significantly predicted by the Adaptation ($b = 0.641, t = 4.126, p < .001$) (see Tab. A5 in Appendix).

User Experience Ratings For all three *user experience* scales, we used a linear mixed model (see Fig. 2) without random slopes as they showed the best model fit. For *Bar Chart*, we found a relationship between the Adaptation and the Dependability ($\chi^2(1) = 12.65, p < .001$), Usefulness ($\chi^2(1) = 5.429, p < .05$), and Intuitive Use ($\chi^2(1) = 6.16, p < .05$) but no effects of VL and no interaction effect (see Tab. A2 in Appendix). This in turn shows that the Adaptation can significantly predict the Dependability rating ($b = 0.535, t = 3.842, p < .001$), Usefulness rating ($b = 0.399, t = 2.407, p < .05$), and Intuitive Use rating ($b = .362, t = 2.576, p < .05$) (see Tab. A4 in Appendix). The same holds true for *Scatter Plot*, where we found a relationship between the Adaptation and the Dependability ($\chi^2(1) = 16.254, p < .001$), Usefulness ($\chi^2(1) = 7.579, p < .01$), and Intuitive Use ($\chi^2(1) = 14.832, p < .001$) (see Tab. A3 in Appendix) showing that the Adaptation can significantly predict the Dependability rating ($b = 0.378, t = 4.455, p < .001$), Usefulness rating ($b = 0.298, t = 2.882, p < 0.01$), and Intuitive Use rating ($b = 0.393, t = 4.218, p < .001$) (see Tab. A5 in Appendix). We found no effects for VL and no interaction effects.

Our data showed that the participants (P) slightly preferred the *Adapted* visualizations over the *Non-Adapted* ones, for both the *Bar Chart* (55% of all participants) and the *Scatter Plot* (62%). This was further supported by participants' comments, indicating that the De-Emphasis approach helped them to focus on the given task (48%). Some participants reported a beneficial effect of the color

[4] `www.gapminder.org` and `https://public.tableau.com/en-us/gallery/how-has-world-changed-1962`

[5] The online version is no longer accessible but code is still available here: `https://github.com/INRIA/Visualization-Literacy-101`

[6] English version: `http://ueqplus.ueq-research.org/`

[7] `https://www.limesurvey.org/`

[8] `https://jasp-stats.org/`

[9] In the logit model the log odds of the outcome is modeled as a linear combination of the predictor variables.

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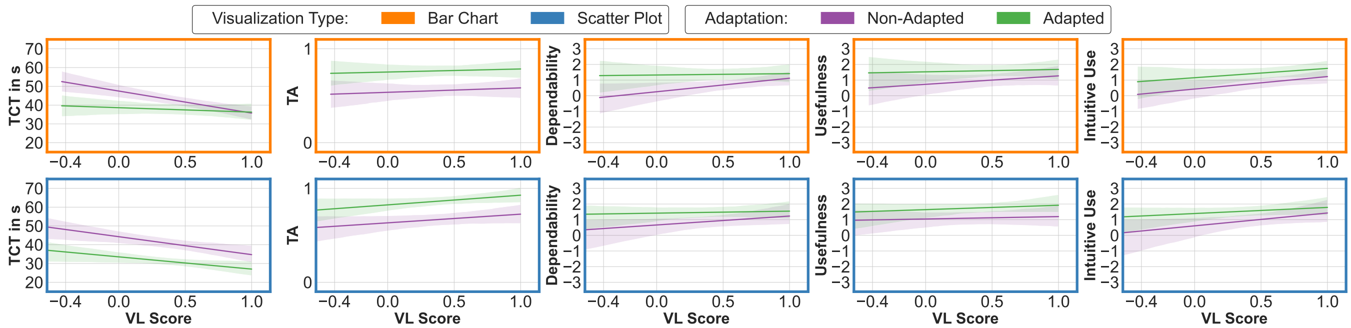

Figure 2: The linear regression of all dependent variables (*task completion time* as *TCT* and *task accuracy* as *TA*) over the VL. ***Bar Chart*** and ***Scatter Plot*** are presented in different plots, while ***Adapted*** and ***Non-Adapted*** are presented as different lines. The shadow behind the lines shows the confidence interval of 95%.

(38%), e.g., *"different colors [helped] to better differentiate [data points]"* (P1). Participants also acknowledged the beneficial effects of the adaptations by reducing the overwhelming amount of information (24%). Specifically, one participant labeled *"graphs where too much data was presented simultaneously"* (P41) as frustrating. Some participants also highlighted that the tasks were challenging (17%). One participant experienced *"understanding the question and searching for the applicable bars/dots"* (P34) as frustrating.

4.3 Hypotheses Results

(H1) We found a significant effect of VL on the *task completion time* (*TCT*) where higher levels of VL were associated with lower *TCT* for *Bar Chart* and *Scatter Plot* (see Fig. 2). However, for the performance indicator *task accuracy* (*TA*), we did not find a significant effect of VL. Therefore, **H1** was only partly confirmed as only time was affected by VL level but not accuracy.

(H2) We found that Adaptation had a positive effect on both, the task performance and the *user experience* (see Fig. 2). In general, participants working with *Adapted* visualizations had a lower *TCT*. Further, we only found a significant positive effect of adaptations on the *TA* for *Scatter Plot*. We saw an interaction effect on the *TCT* for *Bar Chart* (see Fig. 2), indicating that participants with lower VL might benefit more from the presented adaptations than participants with higher VL. However, we did not find any interaction effects for *TA*. Hence, **H2** was only partly confirmed.

(H3) Participants working with *Adapted* visualizations reported higher ratings in the three scales of *user experience* for both Visualization Types (see Fig. 2). However, we did not find any interaction effect of VL and Adaptation for any *user experience* ratings, which shows that a simple visualization technique (i.e., De-Emphasis), appears to be beneficial for all participants with regard to *user experience*. Further, we did not find any detrimental effect of Adaptation for higher levels of VL. Therefore, we reject **H3**.

5 Discussion

We found support for the notion that the effect of Adaptation varies for different levels of VL, in form of an interaction effect of Adaptation and VL on *TCT* for *Bar Charts*. However, we did not find any other interactions. We conjecture that the visualization technique De-Emphasis, which reduces the amount of information presented to the users, has a positive effect for users across different VL, explaining the results with regard to hypotheses **H2** and **H3**. On the other hand, it is conceivable that adaptation strategies that present additional visual elements with the aim to support the understanding of the visualization may be of hindrance for more experienced users. Examples of such adaptation strategies are provision of tooltips, additional visual elements such as arrows, or textural hints. As external information and internal knowledge from the long-term memory needs to be integrated, the additional information that may be redundant for experts employs additional strain on the working memory of experts, thus increasing cognitive load instead of reducing it and consequently diminishing experts' performance [18]. Meanwhile the additional information may facilitate the understanding of more complex visualizations for inexperienced users, i.e., with lower VL.

We could see differences for both Visualization Types in the participants' familiarity rating, task performance, and *user experience*. It is conceivable that the De-Emphasis approach is more effective on bar charts, since bars make up a larger portion of the diagram than the points in a scatter plot. These results show that the quality and the layout of visual marks influence the effectiveness of a given adaptation. Other visualization types use different features (e.g., lines) and can additionally be less common, like parallel coordinate plots or tree maps, which may result in different effects of adaptations.

The overall VL level within our sample seemed to be above average (see Sec. A in Appendix). One reason for this could be the academic background of the participants in our sample [28]. Since visualizations play a vital role in academic teaching and thinking, it is likely that academics are more accustomed to and practiced at dealing with information visualizations resulting in high levels of VL. Therefore, we can only draw conclusions about the interplay of VL and adaptation for a limited range of VL scores, which in turn affected hypotheses **H2** and **H3**. Additionally, we think that the quality of the VL assessment should be improved by exploring benefits of aggregated (e.g., VLAT [27]) or separate assessments for different visualization types (e.g., VL assessment [7]), as well as generating reference group baseline VL scores. Lastly, as we found an effect of VL on *TCT*, which can be partly explained by the type of VL assessment (e.g., Item Response Theory for Boy et al. [7]), we believe that new types of test could even map other user performance and experience properties besides the *TCT*.

6 Conclusion

In this work, we investigated the effect of visualization strategies, i.e., De-Emphasis, on bar charts and scatter plots with regard to the user characteristic visualization literacy (VL). Our findings suggest that taking individual VL levels into account may be a promising way to create adaptations tailored to the individual needs. Further research is required to substantiate the effect for other types of visualizations and adaptations. We hope that our work can be used as a stepping stone in future research on adaptive visualizations based on VL.

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References

[1] J. Aanstoos. Visual literacy: An overview. 2004. doi: 10.1109/AIPR.2003.1284270

[2] J. W. Ahn and P. Brusilovsky. Adaptive visualization for exploratory information retrieval. 2013. doi: 10.1016/j.ipm.2013.01.007

[3] R. Amar, J. Eagan, and J. Stasko. Low-level components of analytic activity in information visualization. 2005. doi: 10.1109/INFVIS.2005.1532136

[4] K. Andrews and A. Smrdel. Responsive Data Visualisation. 2017. doi: 10.2312/eurp.20171182

[5] R. H. Baayen, D. J. Davidson, and D. M. Bates. Mixed-effects modeling with crossed random effects for subjects and items. 2008. doi: 10.1016/j.jml.2007.12.005

[6] K. Börner, A. Bueckle, and M. Ginda. Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. 2019. doi: 10.1073/pnas.1807180116

[7] J. Boy, R. A. Rensink, E. Bertini, and J. D. Fekete. A principled way of assessing visualization literacy. 2014. doi: 10.1109/TVCG.2014.2346984

[8] V. J. Bristor and S. V. Drake. Linking the Language Arts and Content Areas through Visual Technology. 1994.

[9] G. Carenini, C. Conati, E. Hoque, B. Steichen, D. Toker, and J. Enns. Highlighting interventions and user differences: Informing adaptive information visualization support. 2014. doi: 10.1145/2556288.2557141

[10] C. Conati, G. Carenini, D. Toker, and S. Lallé. Towards user-adaptive information visualization. 2015.

[11] R. Dachselt, P. Isenberg, and B. Lee. Mobile Data Visualization (Dagstuhl Seminar 19292). 2019. doi: 10.4230/DagRep.9.7.78

[12] A. Field, J. Miles, and Z. Field. *Discovering statistics using R*. 2012. doi: 10.5860/choice.50-2114

[13] M. Golemati, C. Halatsis, C. Vassilakis, A. Katifori, and G. Lepouras. A context-based adaptive visualization environment. 2006. doi: 10.1109/IV.2006.5

[14] S. Greenland. Principles of multilevel modelling. 2000. doi: 10.1093/ije/29.1.158

[15] J. Heer and M. Bostock. Crowdsourcing graphical perception: Using mechanical Turk to assess visualization design. 2010. doi: 10.1145/1753326.1753357

[16] J. Hoffswell, W. Li, and Z. Liu. Techniques for Flexible Responsive Visualization Design. 2020. doi: 10.1145/3313831.3376777

[17] T. Horak, P. Berger, H. Schumann, R. Dachselt, and C. Tominski. Responsive Matrix Cells: A Focus+Context Approach for Exploring and Editing Multivariate Graphs. 2021. doi: 10.1109/TVCG.2020.3030371

[18] S. Kalyuga. Expertise reversal effect and its implications for learner-tailored instruction. 2007. doi: 10.1007/s10648-007-9054-3

[19] S. Kalyuga, P. Ayres, P. Chandler, and J. Sweller. The expertise reversal effect. 2003. doi: 10.1207/S15326985EP3801_4

[20] N. Kong and M. Agrawala. Graphical overlays: Using layered elements to aid chart reading. 2012. doi: 10.1109/TVCG.2012.229

[21] S. Lallé and C. Conati. The role of user differences in customization: A case study in personalization for infovis-based content. 2019. doi: 10.1145/3301275.3302283

[22] S. Lallé, C. Conati, and G. Carenini. Impact of individual differences on user experience with a visualization Interface for Public Engagement. 2017. doi: 10.1145/3099023.3099055

[23] S. Lallé, D. Toker, C. Conati, and G. Carenini. Prediction of users' learning curves for adaptation while using an information visualization. 2015. doi: 10.1145/2678025.2701376

[24] B. Laugwitz, T. Held, and M. Schrepp. Construction and evaluation of a user experience questionnaire. 2008. doi: 10.1007/978-3-540-89350-9_6

[25] B. Lee, M. Brehmer, P. Isenberg, E. K. Choe, R. Langner, and R. Dachselt. Data visualization on mobile devices. 2018. doi: 10.1145/3170427.3170631

[26] B. Lee, R. Dachselt, P. Isenberg, and E. K. Choe. Mobile Data Visualization. 2021. doi: 10.1201/9781003090823

[27] S. Lee, S. H. Kim, and B. C. Kwon. VLAT: Development of a Visualization Literacy Assessment Test. 2017. doi: 10.1109/TVCG.2016.2598920

[28] A. Maltese, D. Svetina, and J. Harsh. Research and Teaching: Data Visualization Literacy: Investigating Data Interpretation Along the Novice-Expert Continuum. 2015. doi: 10.2505/4/jcst15_045_01_84

[29] D. B. McLeod, L. J. Cronbach, and R. E. Snow. Aptitudes and Instructional Methods: A Handbook for Research on Interactions. 1978. doi: 10.2307/748778

[30] M. G. Müller. Visual competence: A new paradigm for studying visuals in the social sciences? 2008. doi: 10.1080/14725860802276248

[31] T. Munzner. *Visualization Analysis and Design*. 2014. doi: 10.1201/b17511

[32] T. Poetzsch, P. Germanakos, and L. Huestegge. Toward a Taxonomy for Adaptive Data Visualization in Analytics Applications. 2020. doi: 10.3389/frai.2020.00009

[33] B. Saket, A. Endert, and C. Demiralp. Task-Based Effectiveness of Basic Visualizations. 2019. doi: 10.1109/TVCG.2018.2829750

[34] M. Schrepp, A. Hinderks, and J. Thomaschewski. Design and Evaluation of a Short Version of the User Experience Questionnaire (UEQ-S). 2017. doi: 10.9781/ijimai.2017.09.001

[35] J. Schrepp, Martin; Thomaschewski. Eine modulare Erweiterung des User Experience Questionnaire. 2019. doi: 10.18420/muc2019-up-0108

[36] H. Singmann and D. Kellen. An introduction to mixed models for experimental psychology. 2019. doi: 10.4324/9780429318405-2

[37] B. Steichen, G. Carenini, and C. Conati. User-adaptive information visualization - Using eye gaze data to infer visualization tasks and user cognitive abilities. 2013. doi: 10.1145/2449396.2449439

[38] B. Steichen and B. Fu. Towards Adaptive Information Visualization - A Study of Information Visualization Aids and the Role of User Cognitive Style. 2019. doi: 10.3389/frai.2019.00022

[39] D. Toker, C. Conati, and G. Carenini. User-adaptive support for processing Magazine Style Narrative Visualizations: Identifying user characteristics that matter. 2018. doi: 10.1145/3172944.3173009

[40] J. Trumbo. Visual literacy and science communication. 1999. doi: 10.1177/1075547099020004004

[41] B. Winter. Linear models and linear mixed effects models in R with linguistic applications. Technical report, 2013.

[42] A. Yelizarov and D. Gamayunov. Adaptive visualization interface that manages user's cognitive load based on interaction characteristics. 2014. doi: 10.1145/2636240.2636844

[43] C. Ziemkiewicz and R. Kosara. The shaping of information by visual metaphors. 2008. doi: 10.1109/TVCG.2008.171

[44] C. Ziemkiewicz, A. Ottley, R. J. Crouser, A. R. Yauilla, S. L. Su, W. Ribarsky, and R. Chang. How visualization layout relates to locus of control and other personality factors. 2013. doi: 10.1109/TVCG.2012.180