Abstract and Concrete Materials: What to use for Visualization Onboarding for a Treemap Visualization?

Christina Stoiber
christina.stoiber@fhstp.ac.at
St. Pölten University of Applied Sciences, Austria

Florian Grassinger
florian.grassinger@fhstp.ac.at
St. Pölten University of Applied Sciences, Austria

Wolfgang Aigner
wolfgang.aigner@fhstp.ac.at
St. Pölten University of Applied Sciences, Austria

ABSTRACT

Visual exploration of large and complex data is becoming increasingly important in different domains. However, non-experts in the field of visual data analysis often have problems with correctly reading and interpreting information from visualization idioms that are new to them. To make new forms of visualizations understandable and interpretable for a broad range of audiences, visualization onboarding methods can support users. However, it is unclear whether concrete or abstract materials yield better results to foster learning. In order to answer this question, we conducted a within-subject study with 40 students to compare abstract and concrete onboarding messages for a treemap visualization. The results show that (1) concrete onboarding messages are more helpful than abstract, whereas the length of the abstract messages is ranked higher; (2) abstract onboarding messages lead to more valuable descriptions; and (3) either concrete or abstract onboarding messages can lead to high valuable insights.

CCS CONCEPTS

• **Human-centered computing → Visualization design and evaluation methods**.

KEYWORDS

visualization onboarding, visualization literacy, learning materials

ACM Reference Format:
Christina Stoiber, Florian Grassinger, and Wolfgang Aigner. 2022. Abstract and Concrete Materials: What to use for Visualization Onboarding for a Treemap Visualization?. In *15th International Symposium on Visual Information Communication and Interaction (VINCI'22), August 16–18, 2022, Chur, Switzerland*. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3554944.3554949

1 INTRODUCTION

Visualization has become more important and more widespread; not only in the context of science and business, but also in everyday contexts such as data stories in newspapers, in books, on the Internet, or personal data (e.g., sleep tracking, nutrition, sports, etc.). Just right now, the complexity and social relevance of the COVID-19 pandemic has put data visualization at the center of worldwide attention [30]. Since the outbreak, data visualization researchers and experts have been providing various data visualizations for public education. The general public got in touch with diverse data visualizations presenting medical data such as reproduction number, COVID-19 cases, hospitalization, etc. As a matter of fact, the size and complexity of today's datasets overwhelm traditional business charts such as bar charts, line charts, or pie charts. Therefore, more advanced visual representations are necessary to capture more complex data structures and larger amounts of data.

Visualization onboarding supports users in reading, interpreting, and extracting information from visual representations of data [35, 36]. In our previous work [36], we elaborated on the need for visualization onboarding for four different visualization types based on a step-by-step guide, as well as further developed onboarding methods: a scrollytelling and a video tutorial with voice-over. We phrased onboarding instructions referring to the data set used in the visualization, by providing examples and insights. Further onboarding methods exist, which use a concrete approach to support users [20, 27, 37] by referring to the data used in the visualization or using easy to understand data sets.

In the literature [8, 17], there are discussions about concrete vs abstract examples to teach new concepts. According to [17], concrete examples would hinder learners from transferring and generalizing new concepts. However, more recent studies provide counter-evidence. De Bock et al. [8], for instance, show a more successful knowledge transfer by using concrete examples. Similarly, when introducing new visualizations, it is recommended to use an easy and understandable data set that can be assumed to be well-known by the general public [10, 19, 21].

To fill this research gap, we aim to investigate abstract and concrete onboarding instructions to assess which is more appropriate for users, who are not highly familiar with a particular visualization technique. Therefore, we conducted a within-subject study with 40 students. We collected different data, which we describe in the following in more detail. The paper has the following contributions:

- We present abstract and concrete onboarding instructions for a treemap visualization for two different data sets: Biden's tax overhaul [9, 24] and The Austrian federal budget of 2022 [23] (see Section 3.1). In our previous study [36] the need of onboarding concepts was visible, especially, for more complex visualization techniques. Therefore, we decided to generate onboarding messages for a treemap visualization.
- Furthermore, we present the results of the comparative study with 40 students. First, we show the results of a 7-point Likert scale towards the quality of the onboarding instruction per condition — abstract and concrete.

VINCI'22, August 16–18, 2022, Chur, Switzerland

ACM ISBN 978-1-4503-9806-0/22/08.
https://doi.org/10.1145/3554944.3554949

- Additionally, we present the categorization schema (Section 4.1) we used to assess the quality and the value of the descriptions and insights the participants had to provide. We show the results of this analysis in Section 4. Besides, we present the results of a sentiment analysis of the subjective feedback in Section 4.5.
- We derived design implications for the phrasing of onboarding instructions, which we list in Section 5.1.

2 RELATED WORK

Opinions on the used data set tend to differ when it comes to explaining visualization systems and the underlying data. On the one hand, literature calls for abstract explanations to be more generalizable and transferable to a novel context [17]. On the other hand, more recent scientific work provides counter-evidence. De Bock et al. [8], for instance, show a more successful knowledge transfer by using concrete examples. Similarly, when introducing new visualizations, it is recommended to use an easy and understandable data set that can be assumed to be well-known by the general public [10, 19, 21]. In the following sections, we discuss the related literature using concrete vs abstract material for teaching in general, as well as for teaching visualizations. Furthermore, we present studies in the field of visualization onboarding.

2.1 Concrete vs abstract materials

A longstanding debate concerns the use of concrete versus abstract instructional materials, particularly in domains such as mathematics and science [12]. Concrete materials are widely used including physical, virtual, and pictorial objects [6]. Concrete materials can provide a practical context and activate real-world knowledge [29]. A second advantage is that concrete material can enhance memory and understanding by inducing physical or imagined action [13]. Brown et al. [5] also found out that concrete materials enable learners to construct their own knowledge about abstract concepts. Transfer in a new concrete domain is also enhanced more by concrete exemplification than by abstract exemplification [8]. However, studies report on disadvantages such as the distraction of learners from the relevant information [17], or constrained transfer of knowledge [32]. In contrast, abstract material eliminates extraneous perceptual details and can increase generalizability to various contexts [34]. Learners can focus on the structure and representational aspects, rather than the surface features [38]. In general, one weakness of abstract learning material is that learners manipulate meaningless symbols without conceptual understanding [22]. To summarize, the mentioned research outlines no clear direction on the usage of concrete or abstract learning materials.

2.2 Visualization Onboarding

Educational Community: Little is known about the effectiveness of concrete vs abstract materials for visualization onboarding instructions. The educational community has studied how students interpret and generate data visualizations [3] and how to teach bar charts in early grades [1] using a tablet app, called "C'est la vis", supporting elementary school pupils to learn how to interpret bar charts based on the concreteness fading approach [12]. Concreteness fading is a pedagogical method where new concepts are presented with concrete examples at first, before progressively abstracting them. In recent literature, Wang et al. [39] present a set of cheat sheets to support visualization literacy around visualization techniques inspired by infographics and data comics, which are well-established onboarding methods in domains such as machine learning. The cheat sheets use a combination of abstract and concrete instructions. For explaining the anatomy, construction, as well as the introduction to the visualization technique a concrete data set (nutrition values like calories, calcium, water, etc.) is used.

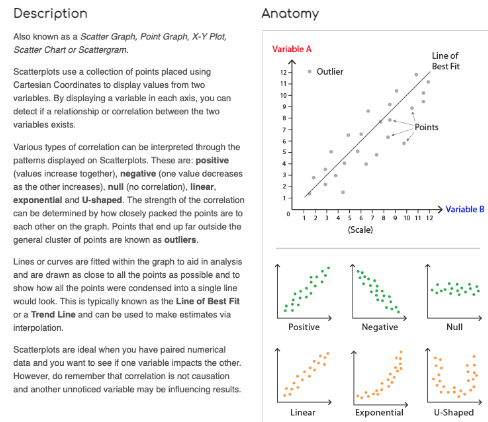

Figure 1: Scatterplot - abstract explanation [26]

Scientific community: Furthermore, Kwon and Lee [20] followed the "Experiential Learning Model" [18]. The knowledge is constructed via concrete experience and reflection on the experience. They used the well-known car data set [14]. Approaches by [27, 37] use concrete onboarding as well by using concrete data sets to explain a certain visualization technique and to facilitate learning. For example, Ruchikachorn and Mueller [27] explored the learning-by-analog concept by demonstrating an unfamiliar visualization method by linking it to another more familiar one. The authors found out that the learning by analogy concept is useful as participants in their study could understand the unfamiliar visualization methods fully or at least significantly better after they observed or interacted with the transitions from the familiar counterpart. Additionally, Tanahashi et al. [37] investigated top-down and bottom-up teaching methods as well as active or passive learning types. The bottom-up teaching method ("textbook approach") [42] focuses on small, detailed pieces of information which students then combine to get a better understanding. Besides, a top-down teaching method is given when a broad overview first helps to understand the abstract, high-level parts of an idea/topic which then provide context for understanding its components in detail [37]. Furthermore, a distinction can be made between active and passive learning types. Passive learning means that students only receive the information without participatory dialog. In contrast, active learning describes an active participation [37]. Their analysis indicates that top-down exercises were more effective than bottom-up and active learning types with top-down tasks the most effective ones.

Visualization Tools & Visualization Platforms: Besides scientific literature, onboarding concepts are integrated in commercial visualization tools as well, which focus on the explanation of features using abstract instructions. For example, Advizor [33] makes use of highly abstract textual descriptions to explain the visual mapping for visualization techniques, e.g., *"A Scatterplot shows the interaction of two fields. They may be continuous (numbers) or categorical (names), although two continuous fields work best. Size and color of data points can be used to show additional dimensions"*. In contrast, IBM Cognos Analytics [2], uses step-by-step tours with tooltips and overlays for onboarding new users. The tour includes the creation of visualizations using a concrete data set — donations per year in Mio $.

Furthermore, the *Data Visualisation Catalogue* [26] seeks to support users to understand the encoding and building blocks of different visualization types using abstract instructions and data, see Figure 1 for a Scatterplot. Furthermore, *From Data to Viz* [15] aims to find an appropriate visualization type based on the input data using a decision tree. The catalog offers definitions, variations, and the use of each visualization type in addition to potential issues that may arise during use and interpretation. All the definitions and explanations are abstract, though. Therefore, we developed two sets of onboarding instructions and conducted a comparative evaluation to assess which onboarding instructions are more appropriate. The concrete instructions refer to the data; and the abstract instructions are phrased without referring to the data set. In Section 3.1, the onboarding instructions are presented in detail.

3 EVALUATION

This study aims to compare abstract and concrete onboarding instructions in a within-subject study design setting using Google Forms. We were generally interested in assessing the usefulness and understandability of the abstract and concrete visualization onboarding instructions for a treemap visualization. As data visualizations are aiming to support users in gaining valuable insights of the data [7], participants had to identify and describe insights. As visualization onboarding can support users in interpreting data visualizations, especially, when they are not that experienced in visual data analysis we invited students in the first and third semester of the study program Media Technology. We also carried out a pilot study with two experts in usability and visualization to ensure the suitability and correctness of the onboarding instructions.

3.1 Visualization Onboarding Instructions

In the following section, we describe the design, general layout of the prototypes, the onboarding messages and implementation.

Design and Architecture: We created four prototypes, collected here: https://treemaps.netlify.app/. All of the prototypes show on the left side the treemap visualization and on the right side the onboarding messages (see Figure 2). In the visualization area the current data set - either Biden's tax overhaul [9, 24] or the Austrian federal budget of 2022 [23] - is shown as a hierarchical treemap. We used similar data sets to provide comparability between conditions. Each cluster of tiles has a specific color which is unique to each category. Hovering over a rectangle reveals detailed information about the current entity, which includes the name, a short description (if available) and the exact value. Above each category the total values are displayed as well as the category name. The messages are tailored to the respective data set. We distinguish between **concrete** and **abstract** onboarding messages, while the former try to include concrete facts from the visualizations, e.g. values or insights — *"The size of each rectangle represents the spendings in US-Dollars (e.g., the Housing rectangle, representing $213 billion, is approx. twice as large as the Clean drinking rectangle, representing $111 billion.)"* The later try to provide a more generic description of the treemap which doesn't include any concrete values from the visualization, e.g., *"The size of each rectangle represents a quantitative value associated with each element in the hierarchy."* In general, the onboarding messages are grouped into *Reading the chart* - explaining the general encoding (e.g. size, color) -, *Interacting with the chart* - explaining the possible interactions with the visualization - and *Analyzing the chart* - trying to guide the reader towards further insights (e.g. making comparisons). The structure is based on our previous work [36]. In Figure 2, exemplary, the abstract onboarding prototype for Biden's tax overhaul plans can be seen.

Implementation: We used HTML, CSS and JavaScript as our main languages in order to create the four prototype websites. For bootstrapping the applications and creating the basic setup we used Vite JS [41] — a powerful frontend build tool. For the visualization the common and well known library D3.js [4] was used. The treemap itself was created with d3 and only one additional library was used for enhancing the user experience. The library is called *d3-v6-tip* (https://www.npmjs.com/package/d3-v6-tip) and is used in order to generate the tooltips for the treemap.

3.2 Hypotheses

We developed our hypotheses based on the existing literature and open questions of other conducted studies [35, 36].

- **H-Quality:** We expect participants to rate the concrete onboarding instruction as more *understandable*, *helpful*, and *complete* compared to the abstract ones. Additionally, the participants also assess the *length of instructions as short enough.*
- **H-ExperienceLevel**: We expect that the experience level of the participant has an effect on the statements.
- **H-Value:** We expect participants to *generate more valuable insights and descriptions after reading the concrete onboarding instructions than reading the abstract instructions.* We believe that referring to the data shown in the visualization and giving concrete examples improves insight generation.
- **H-Preference:** We expect *concrete onboarding is subjectively preferred over abstract onboarding*. This means participants are more likely to read the instructions and feel more confident in interpreting and reading the visualization.

3.3 Study Design & Data Collection

This study used a within-subject design with students. We collected the following data during the study: (1) *demographic information* such as gender, age, color blindness, and assess their level of experience with data visualizations in general and with the treemap visualization. (2) Task 2: descriptions of the treemap in participants own word; (3) Task 3: at least three insights; (4) rating based on

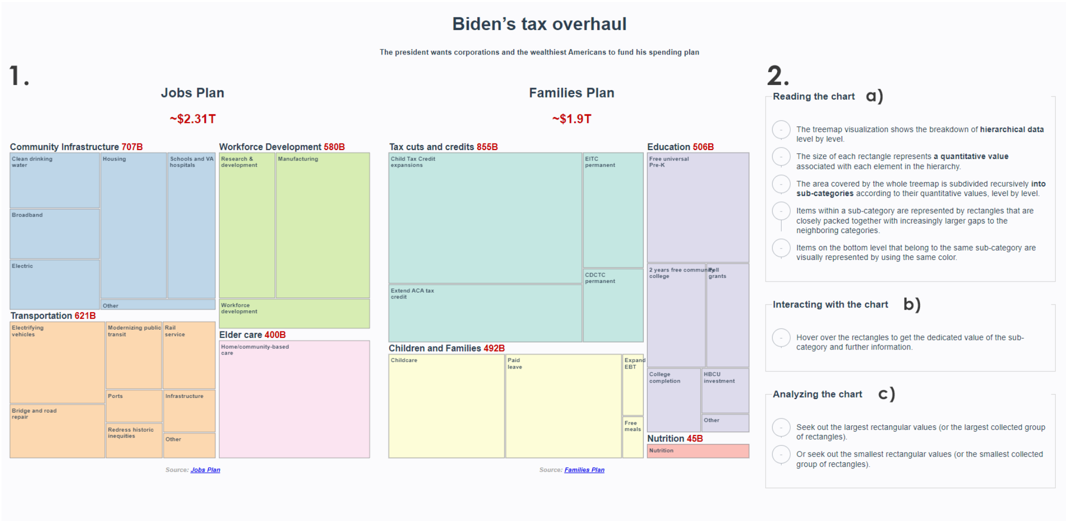

Figure 2: The visualization area (1) with the treemap visualization — Biden's tax overhaul [9, 24]. The onboarding area (2) contains abstract onboarding messages split into three thematic sections: *Reading the chart* (2.a) provides instructions on how to read the treemap. In *Interacting with the chart* (2.b) the reader learns about the interaction possibilities and in *Analyzing the chart* (2.c) examples and insights are provided. Prototypes: https://treemaps.netlify.app/

a 7-point Likert scale of four statements to assess the quality of the onboarding instructions; and (5) answers to open questions to gather more comments, suggestions and remarks regarding the onboarding instructions.

There were two independent variables: onboarding instruction type (concrete or abstract) and data set (Biden's tax overhaul plan (B) or Austrian federal budget payments (A)). The dependent variables were question scores (4) to four statements regarding the textual instructions. We used a Google Forms to set up the online questionnaire. Students had to enroll to the test with their student ID. Then, we randomly assigned students to the concrete and abstract onboarding (counterbalancing) and also randomly assigned them to the two different data sets. We used the university internal Moodle platform to create groups per condition and publish the link to the study.

3.4 Participants

There were 40 students (Abstract A: 18, B: 22; Concrete A: 22, B:18) (Gender: m = 18, f = 20, prefer not to say = 2) conducting the study between 2022/01/25 to 2022/02/01. The students were from the bachelor study program Media Technologies of the first and third semester. The participants were between 18 and 27 years old. Two of the participants have stated that they have a red-green/blue-purple color blindness. The survey started with a question about the level of experience with data visualization in general (Figure 3) as well as the level of experience with the treemap visualization (Figure 3) by using a 7-point Likert scale. In general, the participants rated their level of experience "little" (3 and 4 (Mdn) on the likert scale).

3.5 Procedure

At first the participants had to add some information regarding demographic information. As the next step, they continued with Task 2 (description) and Task 3 (insights). Additionally, they had to fill out a questionnaire to assess the quality of the onboarding instructions based on a 7-point Likert scale. We presented four statements they had to assess: **(S1)** The textual instructions were easy to understand. **(S2)** The textual instructions were short enough. **(S3)** The textual instructions were helpful to understand the treemap visualization. **(S4)** All relevant aspects to understand the treemap were described.

We also integrated two open questions to gather more comments, suggestions and remarks regarding the onboarding instructions. As it is a within-subject design, the participants then started with assessing the second condition with another onboarding type and data set with the same tasks and questions.

4 RESULTS

All 40 participants completed the study. We had to exclude the answers of one participant of task 2 and task 3 as the participant was not working on the tasks. We downloaded the data from Google Forms and included all the data in one analysis spreadsheet. The analysis table can be found in the supplemental material. We used R to analyze the data as well as produce the plots for the paper.

4.1 Categorization of descriptions and insights

For the data analysis of task 2 and task 3 we defined categories. For task 2 (descriptions) we assessed the quality of the answers of all participants along a scale of 1 – 3. Whereas, 1 means trivial description, 2 intermediate description, and 3 highly understandable explanation of the treemap visualization. Furthermore, we also coded if the descriptions contain the following information with Yes and No: description of *color* and *size* of rectangles of the treemap, *interaction*, and example based on a distinct value. Insights characteristics (task 3) were inspired by the paper by Saraiya et

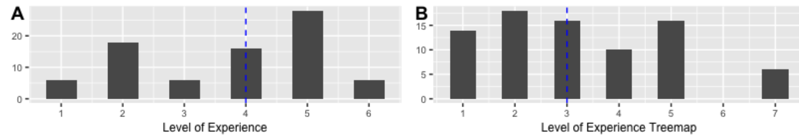

Figure 3: (A) Level of experience for data visualizations and for the (B) treemap visualization on a 7-point Likert scale, where 1 means no experience at all and 7 highly experienced. The blue dashed line shows the 4 (experienced) as the median (Mdn) for data visualization in general, and 3 (little experienced) as the median (Mdn) for the treemap visualization.

al. [28]. We define an insight as an individual observation about the data by the participant. The following quantifiable characteristics of each insight were then to be encoded:

- **Observation:** The actual finding about the data. We counted distinct data observations by each participant. As the participant had to find at least three insights the number of observations do not vary much.
- **Value of Insight:** The value, importance, or significance of the insight. Simple observations such as "Most money has been spent on public pension schemes." are assessed as trivial, whereas observations comparing two different subcategories "The presidents biggest spending section would be the child tax credit expansions in which he aims to extend the child tax credit expansion and to make the child tax credit expansion fully refundable." earned 2 points. And insights that included domain knowledge/experience or created new hypotheses earn 3 points.
- **Correctness of Insight:** Some insights were incorrect observations that result from misinterpretation of the visualization. This is coded by the coders with Yes/No per insight.
- **Task Difficulty Taxonomy**: We also categorized the insights along the Task Difficulty taxonomy by Friel et al. [11] including (1) reading the data (identify one value, or biggest or smallest rectangle in the sub-category of the treemap), (2) reading between the data (make comparisons between different sub-categories in the treemap), and (3) reading beyond the data (own interpretation).

Three coders (two authors of the paper and one external) separately categorized the answers of task 2 and task 3 alone. In an online meeting, we discussed the samples we did not agree on and came to a conclusion.

4.2 Quality

The quality of the onboarding instructions **(H-Quality)** was assessed by participants along a 7-point Likert Scale. Figure 4 shows the boxplots of the four statement per condition and data set. Table 1 gives an overview of the mean and standard deviation for a 7-point Likert scale [1-7 strongly disagree to strongly agree].

Table 1: Mean and SD per condition and data set

Statement	Ranking			
	Abstract A	**Concrete A**	**Abstract B**	**Concrete B**
S1 (understandable)	6.17 (SD 0.62)	5.68 (SD 1.48)	5.55 (SD 1.22)	6.11 (SD 0.68)
S2 (helpful)	5.83 (SD 1.47)	5.05 (SD 1.33)	6.18 (SD 1.05)	5.00 (SD 1.53)
S3 (length)	6.11 (SD 0.9)	6.23 (SD 1.02)	5.82 (SD 1.14)	6.33 (SD 1.08)
S4 (complete)	6.33 (SD 0.77)	6.09 (SD 1.06)	5.95 (SD 1.36)	6.33 (SD 0.77)

A Friedman test was conducted to determine whether statement scores (Likert data) differ between onboarding instruction types and one of the four statements as well as the data set. The results show significant differences of the type of onboarding on the statement 2 (length of onboarding messages) (p-value = 0.0002607) as well as statement 3 (helpfulness) (p-value = 0.04123). Participants rated the length of the concrete onboarding instructions with 5 (Mdn) for both Data sets (see Figure 4). For the abstract onboarding conditions for data set A participants rated the statement **S2** as 6 (Mdn) and for the data set B with 6.5 (Mdn), which is higher than for the concrete one. Additionally, the statement **(S3)** regarding helpfulness to better understanding was ranked better in the concrete onboarding condition as in the abstract one. Therefore, the concrete onboarding instructions are more *helpful* as the abstract onboarding instructions for both data sets.

4.3 Experience Level

The aim was to see if there is a difference between the level of experience **(H-ExperienceLevel)** and the score of each of the four statements. Based on the analysis of the visual exploration of the experience levels (see Figures 3), we decided to use three categories *not experienced*, *moderately experienced*, and *very experienced*. We assigned the scores 1 to 3 in the category *not experienced*, 4 and 5 in *moderately experienced*, and the 6 and 7 in *very experienced*. A Kruskal Wallis test revealed no significant effect on the four statements either on the experience level in general or on the level of experience.

4.4 Value

Results Analysis of Description (Task 2): As the concrete onboarding provides distinct examples and refers to the used data set we expected participants to generate more valuable descriptions and insights in contrast to participants reading the abstract onboarding instructions (**H-Value**). Based on the categorization of the descriptions along the categories we described in Section 4.1 we can report on the following results. The bar chart in Figure 5 shows that participants reading the abstract onboarding instructions submitted more high-qualitative descriptions (11) than in the concrete condition (5). Slightly more intermediate descriptions could be found in the concrete condition (14) than in the abstract one (10). The most descriptions were categorized as trivial and high-level in both conditions. Then, we analyzed the descriptions in more detail towards the content. Based on our own onboarding instructions, we derived categories (size, color, interaction) and analyzed if they are also part of the participants descriptions. In general, 53.75% of the participants explained the color of the categories in the treemap,

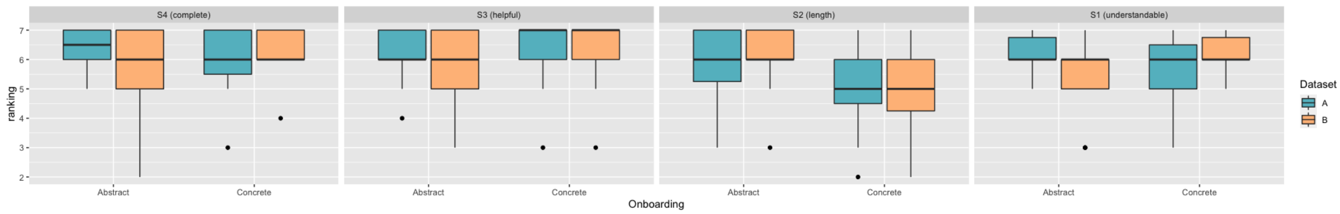

Figure 4: Boxplots showing the results of the four statements per condition and data set

73.75% the size of the rectangles, 41.25% the interaction concept (hovering), and 21.25% used distinct examples and values.

Split up in the abstract and concrete condition we can report the following: 53.49% explained the color, 51.72% the size, 57.58% the interaction in the abstract condition, and 47.06% used distinct values in their explanation. Whereas, in the concrete condition 46.51% of the participants stressed the color of the rectangles, 48.28% the size, 57.58% the interaction possibility of the treemap visualization, and 52% distinct values. Together these results indicate no difference between the individual explanation in the concrete or abstract onboarding instruction. Interestingly, 21.52% of the participants used distinct values for their explanations overall. Split up in the conditions the usage of distinct values to explain the treemap is nearly balanced (Abstract 47.06% and Concrete 52.94%).

Analyzing the data on a participant level, we found some interesting insights. Participant 23 does not relate to the data in the abstract condition: *"You can see rectangles divided in categories, which are then also divided in sub-categories within themselves."*. In the concrete condition the participant indicates to the data — the first sentence is *"The treemap is about Biden's tax overhaul, which is divided in 2 categories, jobs plan and families plan."* Furthermore, participants 13, 20, 31, 32, 37 used a concrete example in the concrete condition to explain the treemap, but not in the abstract condition: *"The jobs plan is divided into Community Infrastructure, Workforce Development, Transportation and Elder care with a budget of 2,3 trillion dollars."* (P31). Participant 20 added the USD in the instructions but not an exact value. In contrast, participants 27, 30, 32 used examples in the abstract condition but not in the concrete one.

Results Analysis of Insights (Task 3): In general, participants in both conditions submitted trivial observations which give a high-level view on the data, see Figure 5. The used data set and resulting treemap is not that complex. Therefore, the results are not surprising. However, based on the categorization of the *value of the insight* we see no difference in abstract and concrete condition, illustrated in Figure 5. In the concrete condition (28) eight more intermediate observations could be found than in the abstract one (20). Participant 27 wrote: *Over a half of the money from Austrian Federal Ministry of Finance goes the into Work, Social Affairs, Health and Family sector, whereas the most money in that category went into Public Pension Schemes.* Slightly more high valuable insight could be found in the concrete condition (12 to 9). Participants integrated their prior knowledge and generated insights which we ranked as high-valuable insight. For example, *"As you can see is Austria planing to invest most of the budget into Work, Social Affairs, Health and Family. Which shows how important the government thinks it is to spent money for their people."* (P38).

Furthermore, we categorized the insights along the task difficulty level by Friel et al.[11]: reading the data, reading between the data, and reading beyond the data. We couldn't find any difference between the two conditions. In general, more insights are ranked as "reading the data". In the concrete condition more insights are categorized as reading between the data (26 to 17). All the insights of the participants were correct.

4.5 Subjective feedback

Table 2: Results of sentiment analysis

Sentiment Analysis	#Comments	Positive	%	Negative	%	Neutral	%
Concrete B	8	4	50.00	3	37.50	1	12.50
Concrete A	8	4	50.00	3	37.50	1	12.50
Abstract B	10	4	40.00	4	40.00	2	20.00
Abstract A	7	3	42.86	2	28.57	2	28.57
Sum	**33**	15	45.45	12	38.71	6	18.18
Concrete			50.00		37.50		12.50
Abstract			41.18		35.29		23.53

As part of the study, we also evaluated comments on visualization and onboarding to assess the preferences **(H-Preference)**. We were able to extract 32 comments that were considered usable and related to the onboarding instructions. The exact breakdown can be seen in Table 2. We performed a sentiment analysis using OpenAI API https://openai.com/api/ – while also reviewed each comment ourselves. The comments are categorized as positive, neutral and negative. More details about the parameters used and the analysis setup can be found in the supplemental material.

Positive comments: The results of the analysis (see Table 2) did not show a clear difference between abstract and concrete onboarding **(H-Preference)**. 50.00% of the comments from the concrete onboarding are rated positive and 41.18% of the abstract onboarding. Participants highlighted that the abstract onboarding concept in general *"[...] was good, and I think that a person, who is not familiar with this type would easily understand it with those instructions."*–(P32 | Abstract A); and another subject commented: *"I like the division of the instructions with headings like "Reading the chart" and think it's a very good idea to include instructions when it comes to visualizations in general. I think they can be very helpful, especially if you don't know how to read graphs. It also makes the chart look less intimidating or overwhelming if that makes any sense."* –

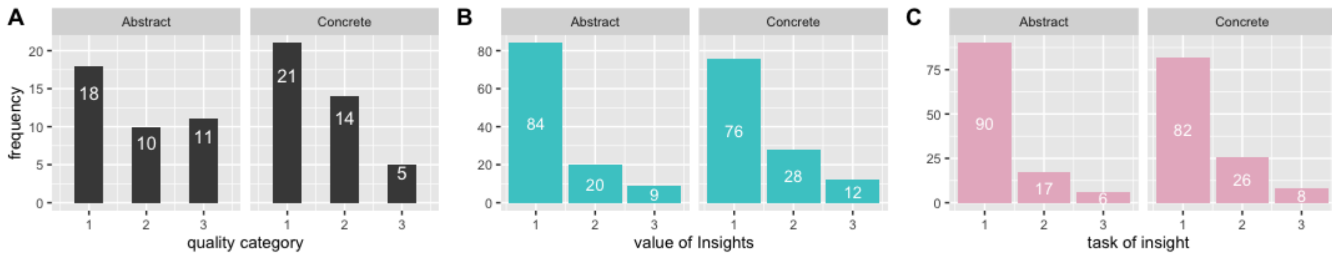

Figure 5: Quality of Descriptions (Task 2), where 1 means trivial descriptions, high-level instructions, 2 intermediate, and 3 highly understandable descriptions. (A) Value of Insights (Task 3), where 1 means trivial observation; 2 intermediate value of insight, and 3 insight that confirm or create a hypothesis, own interpretation or integration of domain knowledge. (B) Categorization along Task Taxonomy by Friel et al. [11] where 1 is reading the data, 2 is reading between the data, and 3 is reading beyond the data.

(P3 | Abstract B); However, if we look at the comments in detail participants stated: *"...I preferred this concrete one to the abstract one. Because there were examples included in the instructions... My understanding was definitely supported more in this prototype..."* – (P3 | Concrete A); *"The analyzing the chart section was more helpful then in the other example because it provided two actual examples."* – (P6 | Concrete A); The only noteworthy aspect here is the change of mind of a user who preferred the abstract onboarding: *"In retrospect, I find this treemap much clearer and I also like the description better. I first thought the examples in "Analyzing the chart" would be helpful in the other treemap, but I honestly didn't miss them here."* – (P39 | Abstract A).

Negative comments: 37.50% of the feedback in the concrete onboarding condition and 35.29% of the abstract condition was categorized as negative in the sentiment analysis.

Participants stated the following in the concrete onboarding condition: *"In my opinion the descriptions are a bit too long. Especially the second paragraph includes information I would not have needed to understand the visualization. Nevertheless, the information concerning the items is good, because it easier to understand."* – (P2 | Concrete A); Participants commented on the length (P24 | Concrete B) and level of detail of the onboarding message (P3 | Concrete A), as well as perceived the onboarding messages as "bloaded and frustrating to read" (P11 | Concrete A).

Furthermore, in the abstract condition, P31 (Abstract A) mentioned that *"The messages are in my opinion too concrete and could use a more casual language."* while P23 (Abstract A) stated *"I had to concentrate a lot to read them, maybe shorter and more general sentences would be easier."* which should be the case in abstract onboarding anyway. Maybe this can be seen as possible future improvement for abstract onboarding messages. Contrary some are seeking for more information in the abstract condition:*"It is not entirely obvious how these rectangles are divided up in terms of size. A more detailed description would be appropriate here."* – (P8 | Abstract B); *"More Information about reading the chart correctly."* – (P22 | Abstract B);

Subjects commented negatively to the section *Analyzing the chart* of the onboarding instruction. *"I don't fully understand the purpose of the last set of messages (Analyzing the chart)."* (P6 | Abstract B). While P5 (Abstract B) phrased the following: *"...I would also argue that analyzing and reading the chart are more or less the same thing in this context."* Besides, one participant didn't like the phrasing of the sentence: Seek out the largest rectangular values (or the largest collected group of rectangles). The subject indicated that it ' *'sounds more like a command rather then a how to analyze."* (P5 | Abstract B).

Neutral comments: Some of this suggestive neutral feedback's include suggestions toward the structure and design of the onboarding messages: *"Maybe adding subheadings to the paragraphs in the "reading the chart" section could help the reader find relevant information faster."* – (P11 | Concrete A); *"I would highlight the most important parts of the text before, for example by making some words bold."* – (P33 | Concrete B, Abstract A). Additionally, P3 (Abstract B) suggested: *"I'd maybe simplify the instructions a bit more or use examples if it's intended for users without much experience when it comes to understanding visualizations."*. Additionally P15 (Abstract B) made the suggestion that *"In the instructions it should also say that rectangles can be stretched in different dimensions and still represent the same value"*. Overall the neutral feedback's can be seen as suggestions for improvement or additional features.

Summary: Overall, based on the sentiment analysis there is no clear trend identifiable toward concrete or abstract onboarding instructions. However, concrete and abstract onboarding instructions are often described as simple, easy to understand and helpful. Participants highlighted the helpfulness of the examples in the section "Analyzing the chart" especially in the concrete condition. Contrary, abstract onboarding is seen as simpler and shorter, although the specific examples are often missing, and the messages could be phrased more easily.

5 DISCUSSION

This section summarizes our findings, design implications for onboarding instructions, as well as limitations and future work.

Concrete onboarding messages are more *helpful* than the abstract onboarding instructions, whereas the length of the abstract messages are preferred over the concrete one We have to reject this hypothesis **(H-Quality)**. The results of the statistical analysis of the statements show that the concrete onboarding messages were ranked more helpful than the abstract one. However, the length of the onboarding messages was ranked better in the abstract condition. We tested the readability (ATOS level [25]) of the onboarding messages. The ATOs Level is a measure of readability designed to guide students to appropriate-level books. ATOS takes into account the most important predictors of text complexity—average sentence length, average word length, and word difficulty level. The results are provided in a grade-level scale that is easy to use and understand. The concrete onboarding messages where ranked as 11.7 (dataset A) (11th grade), 11.2 (dataset B), and the abstract messages 10.8 (end 10th grade). The complexity of readability is nearly balanced between all the conditions. Therefore, this result may be explained by the fact, that we integrated concrete examples in the section "Reading the chart" and this resulted in longer onboarding messages, e.g., "The size of each rectangle represents the outflow of cash and cash equivalents in € Euro (e.g., the public pension scheme rectangle, representing € 12,468.8 million, is approx. twice as large as the Family and youth rectangle, representing € 7,687.1 million.)". Therefore, participants perceived the abstract onboarding messages as less overwhelming and long.

Abstract onboarding messages lead to more valuable descriptions Based on the categorization of the descriptions, participants wrote more valuable descriptions while reading the abstract onboarding instructions than with the concrete one. In general, we expected to have more examples/distinct values in the descriptions. However, the usage of distinct values is nearly balanced between the conditions. Therefore, we have to reject our hypothesis **H-Value** when it comes to task 2 (descriptions).

Both concrete and abstract onboarding messages can lead to highly valuable insights As in Figure 5 illustrated there is no trend visible towards concrete onboarding instructions leading to higher valuable insights. Therefore, we have to reject this hypothesis **(H-Value)** as well. Previous research has shown that concrete and abstract learning material have both strengths and weaknesses [8, 17]. Manually generating concrete onboarding instructions is costly and effortful. They have to be developed for example by the visualization designer because concrete onboarding instructions must be tailored to a specific visualization technique and dataset. In contrast to that, abstract onboarding instructions can be used in different treemap visualizations with different data sets. Based on our results and the fact of generalization of onboarding instructions to other data sets, we suggest using abstract onboarding instructions along the following structure: Reading the chart, Interacting with the chart, and Analyzing the chart, with highlighting of important words. As the subjective feedback emphasized the importance of examples/insights we recommend to integrate those in the "Analyzing" section referring to the used data set.

Further research might explore semi-automatically generation of onboarding instructions for several visualization techniques with the possibility to adjust and customize the automatically generated abstract onboarding messages.

5.1 Phrasing of Onboarding messages

Our results can be used to discuss and inform the phrasing of onboarding instructions. The results of our study reflects the discussion in the field of abstract or concrete materials for teaching [8, 17]. The presented findings do not give a clear answer on the question of if abstract or concrete instructions are more appropriate for onboarding instructions. According to the data, we can infer that concrete and abstract instructions are helpful to understand visualizations better. The instructions should meet the following points:

- **structure the onboarding messages** with headlines (e.g, Reading, Interacting, Analyzing the chart) to highlight important parts and lead the reader through the instructions. Headlines can increase the contrast [40] and guide the reader.
- onboarding instructions should be placed **integrated with** with the visualization to directly link the reading instructions to the visualization itself.
- **highlight important words**, e.g. by making them bold or highlight with color. In a previous study, we introduced ways to highlight important words and therefore lead the user through the onboarding [36].
- **understandable instructions**: easy to understand and short sentences should be considered [31]. For guidelines of writing understandable sentences see [16].

5.2 Limitations

Participants and context: Our results are naturally limited by the audience and context of the study. The participants in our study are students of the first and third semester of the bachelor study program Media Technology, in nearly the same age group, with the nearly same pre-knowledge about visualizations and the used data sets. Some of the participants seemed less engaged with the study. Despite the fact that students could earn 20 extra points for their lecture still some of the subjects did not invest that much effort in their answers. *Study Material:* In previous studies [36], we presented onboarding concepts including an interactive interface design to interact with the onboarding instructions. In this study we focus on the phrasing of onboarding instructions and the question of abstract vs. concrete for a treemap visualization. Further research might explore an adapted version of the onboarding instructions incorporated in an interactive onboarding concept [36] in different domains such as journalism, medicine, or education using different visualization techniques.

6 CONCLUSION

There are discussions about using concrete or abstract material to foster learning. Especially for visualization onboarding, it is an open question whether to use abstract or concrete onboarding messages. The aim of this paper was to evaluate two types of onboarding messages — concrete and abstract — and investigate which are more appropriate to onboard users to a treemap visualization. The study with 40 participants revealed the following results: (1) Concrete onboarding messages are more helpful than abstract, whereas the length of the abstract messages are ranked higher. (2) Abstract onboarding messages lead to more valuable descriptions. (3) Both, concrete and abstract onboarding messages can lead to high valuable insights.

ACKNOWLEDGMENTS

This work was funded by BMK under the ICT of the Future program via the SEVA project (no. 874018), by the Austrian Science Fund as part of the Vis4Schools project (I 5622-N), and by the GFF NÖ as part of the dissertation project VisOn (SC18-008).

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