

Design and Comparative Evaluation of Visualization Onboarding Methods

Christina Stoiber
St. Poelten UAS, Austria
christia.stoiber@fhstp.ac.at

Holger Stitz
datavisyn GmbH, Austria
holger.stitz@datavisyn.io

Conny Walchshofer
JKU Linz, Austria
conny.walchshofer@jku.at

Marc Streit
JKU Linz, Austria
marc.streit@jku.at

Florian Grassinger
St. Poelten UAS, Austria
florian.grassinger@fhstp.ac.at

Wolfgang Aigner
St. Poelten UAS, Austria
wolfgang.aigner@fhstp.ac.at

ABSTRACT

Comprehending and exploring large and complex data is becoming increasingly important for a diverse population of users in a wide range of application domains. Visualization has proven to be well-suited in supporting this endeavor by tapping into the power of human visual perception. However, non-experts in the field of visual analysis often have difficulties in correctly reading and interpreting information from novel visualization idioms. Visualization onboarding can support novices in learning how to use new digital technologies. Therefore, we developed an interactive step-by-step guide and applied the method to four visualization techniques—a bar chart, a horizon graph, a change matrix, and a parallel coordinates plot. Results using Amazon Mechanical Turk workers show that there is a need for onboarding, especially for more complex visualization techniques. We further investigated the perception and rating of a scrollytelling and a video tutorial for the most unfamiliar visualization—the parallel coordinates plot. A comparison between the three onboarding methods indicates that participants appreciated the easy-to-understand examples, the precise wording of the onboarding messages in a step-by-step manner, and the introduction of interaction concepts by highlighting the most relevant information over all onboarding methods. The video tutorial supported the introduction of unknown interaction techniques best.

CCS CONCEPTS

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

KEYWORDS

Visualization literacy, user onboarding, learning, visual analytics

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1 INTRODUCTION

Visualization is a tool that has become indispensable not only in the context of science and business, but also in everyday life, such as data stories in newspapers, in books, or on the Internet. The amount of data and the associated complexity often exceed the capabilities of traditional business charts, such as bar charts, line charts, or pie charts. As a consequence, more advanced visual representations are needed to capture large and complex datasets.

Visual mapping is the process of assigning data variables to visual channels, which results in either a static or an interactive visual representation. This process is the central component of virtually all known conceptual models of visualization, such as the model by Card et al. [9] or van Wijk [49]. Understanding the process of visual mapping is a key component for correctly decoding both the visual representation and the underlying data. Furthermore, data analysis, filtering, and rendering steps of the visualization process influence the appearance of a visualization and need to be used and selected precisely. Especially for novice users, however, this can be difficult and may lead to wrong conclusions as well as erroneous insights into the data. Visualization onboarding methods aim to support end users in comprehending data visualizations and taking full advantage of the tools at hand [46]. So far, there has been little discussion about the design of onboarding methods for visualization types and visual analytics tools. A few onboarding methods exist in the literature using different strategies and educational theories, such as learning by doing [25], learning by analogy [41], scaffolding [4], or top-down and bottom-up teaching methods as well as active and passive learning types [48]. Nonetheless, much more research is needed to identify effective designs of onboarding methods and to understand users' behavior while using onboarding methods.

Therefore, we extended the current literature by assessing the need and active usage of visualization onboarding for four different visualization types (bar chart, horizon graph, change matrix, and parallel coordinates). We use textual instructions, divided into the three sections of *Reading the Chart*, *Interacting with the Chart*, and *Using the Chart*, combined with in-place annotations to onboard users to a visualization. Qualitative feedback on interaction behavior with the onboarding method was captured and assessed using Amazon Mechanical Turk (MTurk) workers. Based on the most unfamiliar and most complex visualization type, the parallel coordinates plot, we investigated differences in the perception and

rating of three onboarding methods by analyzing feedback on a step-by-step guide, a scrollytelling tutorial, and a video tutorial with a voice-over. Thus, we further developed our onboarding methods by designing the scrollytelling tutorial and the video tutorial with voice-over for a parallel coordinates plot. In a second phase of the evaluation with MTurk workers, we investigated differences in the perception and rating of the three different onboarding methods.

2 RELATED WORK

We base the design of the onboarding user interfaces and instructional materials on insights and lessons learned from empirical research, as well as on the analysis of contextually relevant visualization platforms and websites [19, 39, 47].

A comparative study conducted by Kwon et al. [25] shows that participants who use an interactive guide or a video tutorial outperform participants who use a static tutorial or none at all. Moreover, using a direct interaction with the visualization (also known as active learning) [48] or a *learning-by-doing* approach [25] positively influences the visualization comprehension. We additionally investigated popular visualization platforms and websites to understand non-scientific explanation approaches for different visualization types. *The graphic continuum* [47] provides an overview and helps in choosing the appropriate design or visualization type. Furthermore, the visualization library *Data Viz Catalogue* [39] seeks to help users understand the encoding and building blocks of different visualization types. A decision tree provided by *From Data to Viz* [19] helps to find an appropriate visualization type based on the input data. The catalogue offers definitions, variations, and the use of each visualization type in addition to potential issues that may arise during use and interpretation. However, it quickly became apparent that the exclusively textual descriptions and used datasets on these platforms are very abstract—which is particularly problematic for novice users. Furthermore, all these instructions are provided externally and decoupled of the particular visualization.

Opinions on the dataset to be used for onboarding tend to differ sharply when it comes to explaining visualization systems and the underlying data. On the one hand, literature proclaims abstract data to be more generalizable and transferable to a novel context [23]. On the other hand, more recent scientific work provides counterevidence. De Bock et al. [13], 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 dataset that can be assumed to be well-known to the general public [15, 24, 27] or to be domain-specific [45] and well-known to the end user.

3 VISUALIZATION ONBOARDING METHOD

Previous studies [21, 22] examined how people create, update, and explain their visualizations using only tangible building blocks. So far, there are no studies available exploring how persons explain a certain visualization type. To better understand the explanation strategies, we conducted preliminary interviews with 13 participants ($m = 8$, $f = 5$; Age: $M = 30.23$, $SD = 3.32$). The participants indicated that they had moderate to high experience with visualizations and a background in computer science, accounting, and HCI. The systematic analysis outlined that the participants started

by explaining the dataset and attributes before continuing with the visual encoding, e.g., “The first thing I would say is that the diagram explains how many hours of sunshine the city of Innsbruck had in previous years.” (translated from German to English).

Based on these insights of the analysis of empirical studies, online platforms, and the interviews, we derived the following four key design requirements: (i) explain visual encoding and give examples on insights a user can generate (based on the interviews), (ii) use concrete examples [1, 13], (iii) follow an active learning approach [48] and make use of an interactive guide, and (iv) video [25] as onboarding methods.

In the following section, we provide descriptions of our onboarding methods, describe their main components, provide rationales based on related literature, and elaborate on our design decisions.

3.1 Interactive Step-by-Step Guide

For the first approach, the visualization onboarding interface is divided into four sections, as illustrated in Figure 1. We start with an introductory part **A** that serves as a brief overview to explain the attributes within the dataset. We added navigation elements **B** to enable viewing all steps at a glance or exploring the instructions one after the other. To explain how to read, use, and interact with the chart, we provide interactive numbered textual descriptions **C** which enable the respective in-place annotations in the chart. Finally, **D** represents our interactive visualization.

Introduction A: Due to the importance of title elements and legends [5], we integrated an introductory sentence on top of our onboarding method to describe the basic idea of the visualization type and provide general information about the data.

Navigation B: The current or selected step is highlighted in the respective sections (reading, interacting, using) as well as in the visualization itself, while the other steps are greyed out. The user can click on the numbered textual description within the step-by-step guide or use the *Next* and *Previous* buttons on the top right (see Figure 1 **B**). As an alternative for those who do not need a step-by-step explanation on how to read, interact with, and use the chart, we provide a *Show All* toggle element to hide and show all hints at a glance.

Step-by-Step Messages C: Based on the explanatory sequences of our interview participants, the step-by-step guide incorporates textual descriptions on how to read, interact with, and use the chart. The first section contains information, e.g., about the visualizations’ shape, axes, or color coding. The second section *Interacting with the Chart* emphasizes the applied interaction techniques, e.g., indicating how to re-order axes or filter attribute values. For the section *Using the Chart*, we provide three examples that make use of the low-level typology (identification, comparison, and summarization task) by Brehmer and Munzner [32]. The design is organized in numbered textual descriptions with highlighted attributes in combination with in-place annotations [50] (numbers and symbols) to indicate the connection between the highlighted text elements and the visual encoding. Inspired by different annotation designs by Lu [30], we use circular visual markers with numbers that relate to the selected step. To understand the visual encoding, we make use of *data*, *guides*, and *marks* from the Vega grammar [43] by highlighting the respective attributes in the onboarding message. Hence, in

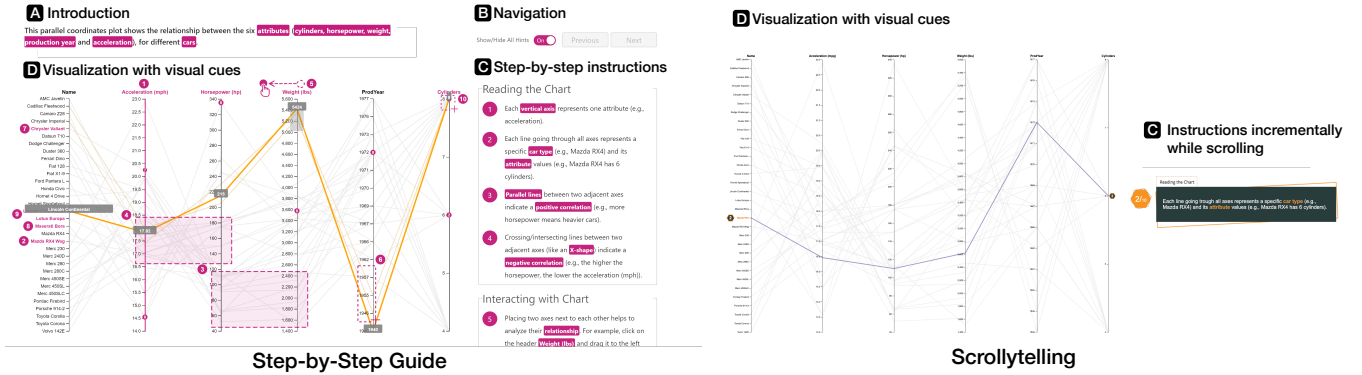




Figure 1: Two onboarding approaches are demonstrated using the example of a parallel coordinates plot—(left) a step-by-step guide and (right) a scrollytelling tutorial. They are based on textual descriptions and in-place annotations and consist of four parts: a brief textual introduction providing contextual information about the visualization **A, navigational elements **B** to go through the step-by-step instructions **C**, and the visualization itself **D**. We divide the textual descriptions into *Reading the Chart*, for explaining the visual encoding, *Interacting with the Chart*, for explaining the interaction concept, and *Using the Chart*, for providing exemplary insights. (The prototypes can be accessed here: <https://onboarding-methods.netlify.app/>)**

each step, we accentuate words that are related to visual properties of the visualization, an encoding, a data transformation, a pattern, or a finding. Moreover, as seen in step 3 in Figure 1 **C**, we use rectangular elements to demonstrate how patterns (e.g., positive or negative correlations) can be read in parallel coordinates plots. In addition, for the interaction concepts, we introduce small icons, e.g. for brushing  and reordering axes . Subsequently, by connecting the text-based instructions to the respective visualization, the interactive legend serves as direct linking.

3.2 Scrollytelling Tutorial

Scrollytelling [2] is an effective and powerful narrative format to package and transmit complex information [40, 44]. The content and organization (visual cues and assignment to one of the three sections) are the same as in the step-by-step guide, but the visual presentation of this method differs. Based on the principles of construction by Nolan et al. [33], text elements can be displayed incrementally by scrolling up and down the screen [40, pp. 95]. Our prototype shows **D** the interactive visualization with visual cues (annotations) on the left, an **A** introductory sentence, and **C** ten instruction steps on the right side of the user interface, see Figure 1.

3.3 Video Tutorial

Videos are commonly used in the context of onboarding and help systems [3, 18, 25, 26, 34, 36, 41]. Our video tutorial is based on a guided introduction to parallel coordinates plots and relies on passive instructions, as interaction with the visualization is not supported. Similar to the explanation and structure of the step-by-step guide, we show each *mark* and interaction element. Moreover, we use a voice-over to describe each step of the explanation. To enable auditory impaired people to understand the explanations, we support textual description with subtitles.

3.4 Implementation

The prototypes are implemented using web technologies such as JavaScript, HTML, and CSS. We rely on React [37] as the basic front-end framework to provide a responsive user interface and a fast application and both Vega-Lite [42] and the Vega-Lite wrapper for React [38] to render the charts. For the parallel coordinates plots, we integrated a modified version of the parcoords library [10]. Due to the limitations of interactive features in Vega/Vega-Lite, we enrich the parallel coordinates and other visualizations with in-place annotation using D3.js [11].

4 EVALUATION

Our study aimed to investigate (1) for which visualization type (bar chart, horizon graph, change matrix, and parallel coordinates plot) an onboarding is needed by assessing interactions (e.g., click events) with the step-by-step onboarding method and qualitative feedback (see Section 4.1). (2) We investigated differences in the perception and rating of three onboarding methods (interactive step-by-step guide, scrollytelling, and video tutorial) based on parallel coordinates, described in Section 4.2.

4.1 Visualization Types

Experiments with MTurk workers were conducted in 2019-2020 to investigate whether and how participants use and reflect on a step-by-step guide as an onboarding method for four visualization types (bar chart, horizon graph, change matrix, and parallel coordinates plot). We chose these four visualization types as we did not intend to exclusively evaluate onboarding for one single visualization type but rather compare different visualization types with diverging levels of familiarity and complexity [6–8, 16, 17, 35].

Methods & Participants: We conducted the experiments using LimeSurvey [29] and MTurk for deployment. We asked the participants about their level of experience per visualization type. In line with previous work [7], the bar chart shows the highest average level of experience (71.68%), followed by the horizon graph

(34.04%), the parallel coordinates plot (27.19%), and the change matrix (18.81%). As the quantitative data of answer correctness and response time no longer provided in-depth information about the usage of visualization onboarding, we concentrate on the qualitative aspects of the study. To qualitatively capture the needs for visualization onboarding, we employed 58 workers ($m = 28$, $f = 19$, prefer not to say=1; Age: $M = 39.91$, $SD = 9.56$) from the crowdsourcing platform. We used the Hotjar behavior analytics software [20] to record and analyze mouse movements and click events. We relied on easy-to-understand time series datasets: weather [14], car data [12], and Olympic medal allocations [28].

Results from Observations and Feedback: Based on observations from the behavioral mouse tracking tool and the qualitative feedback on the step-by-step guide, we identified that for business charts such as the bar chart, the change matrix, and the horizon graph, onboarding was not needed as the charts were “easy to understand” (Bc2, Bc5, Bc36, Hg13, Hg43, M45) and “straightforward” (Bc22). Hence, hardly any mouse movements were recorded. Moreover, participants appreciated the “calming color scheme” (P35) and the coloring of text elements (Bc41, Hg43, Hg45, M26), which is in line with our consideration of using specifications of Vega-Lite (visual properties) for emphasizing relevant information. For the more complex visualization type (parallel coordinates plot), however, more mouse movement and click events were registered within **B** our interactive visualization and **D** step-by-step guide pane. This can be traced back to brushing and re-ordering axes in **B** as well as selecting the respective text elements in **D** to get familiar with them. Besides, participants claimed that the step-by-step guide leads to a cluttered view (St25, St38), which means that alternative onboarding methods have to be considered.

4.2 Onboarding Methods

In our next validation step, we performed further experiments with MTurk workers to determine differences in the qualitative feedback between onboarding methods (scrollytelling and video tutorial) for the parallel coordinates plot.

Methods & Participants: Similar to the approach described in Section 4.1, we conducted a between-subject design with further 68 MTurk workers ($m = 44$, $f = 23$, prefer not to say=1; Age: $M = 38.11$, $SD = 10.25$), using either a step-by-step guide, a scrollytelling, or a video tutorial by assessing their feedback. As Hotjar builds heatmaps on top of screenshots, we were not able to assess the scrolling behavior and thus did not assess mouse movements for the method comparison. Additionally, we performed a sentiment analysis on the qualitative feedback of the three onboarding methods using the sentiment analyser by MonkeyLearn [31]—a machine learning platform that aims to retrieve and classify text information—while also evaluating each review ourselves.

Results from the Feedback: Overall, results show that 83.8% of the responses can be classified as positive and 16.2% as negative. We omitted the neutral feedback (e.g., “na”, *no comment*) due to the lack of information. Participants decisively appreciated the condensed, structured, and grouped explanation steps of each of the approaches. On closer examination, the highest positive feedback was given for the video tutorial (93.33%), followed by the step-by-step guide (81.25%), and the scrollytelling tutorial (72.73%).

Noteworthy is that participants highlighted learning new features during the video tutorial (V26, V42, V50), e.g., “*The video was helpful and showed me some features that I wasn’t familiar with [...]*” (V50). More specifically, “*[...] I liked knowing that I could move columns next to one another*” (V60), which relates to the re-arrangement of axes. However, the automatically generated voice-over was described as unattractive as it sounded robotic (V3, V65). In contrast, the step-by-step guide did not support the usage and understanding of interactive elements (e.g., filtering and moving axes) or the interpretation of correlations as St34 described: “*I have trouble with correlations, but I don’t think that is the fault of the guide—although examples would be good*” (St34). Regarding the scrollytelling tutorial, users “*[...] enjoy that the images on the left do not appear until I need to see them, which prevents confusion*” (St38). Hence, the display of information on-demand through scrolling and thereby enriching the visualization type with information increased the perceived satisfaction of the participants.

5 INITIAL REFLECTIONS ON VISUALIZATION ONBOARDING

Reflecting on the feedback from our surveys, we summarize the most important insights. We realized that independently of the visualization type and method applied, an easy-to-understand dataset and concrete examples on how to read the chart, support, and increase comprehension are vital. Furthermore, qualitative feedback indicated that the to-the-point descriptions make it easier to absorb information (see Section 4.2). Based on the comments, the competence to learn new interaction techniques can be increased by video tutorials. Likewise, the understanding of introductions is enabled by interactive and linked descriptions of the visualizations **B** and the described steps **D** (as used for the step-by-step guide and the scrollytelling tutorial). Finally, it is important to consider which visualization types (predominantly unknown and new ones) require an introduction to support the user when needed.

6 CONCLUSION

In this paper, we elaborated on the need for visualization onboarding for four different visualization types based on a step-by-step guide. Parallel coordinates plots showed the highest need for onboarding, which is why we additionally investigated the practicability of another two onboarding methods: a scrollytelling and a video tutorial with voice-over. We present the design, implementation, and comparative evaluation using qualitative feedback and mouse tracking of two MTurk studies. Further research is required to determine whether visualization onboarding methods can increase the visualization literacy level of users. Also, it needs to be further investigated whether the presented onboarding concept can be applied to other visualization techniques, such as node-link diagrams, matrices, and more.

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