Inconspicuous Guides: A Qualitative Study to Understand the Degree of Intrusiveness in Visualization Onboarding

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Keywords: Visualization Onboarding, Learning, Accepted Annoyance, Visualization Literacy, Intrusiveness.

Abstract: Current visualizations are becoming more and more complex. Visualization onboarding is a possibility to assist users in understanding such visualizations. Nevertheless, previous research indicates that users tend to ignore this kind of assistance, even if it is evident that they need help to interact with the system efficiently. This investigation aims to collect prototypes of visualization onboarding systems taking into account the degree of intrusiveness through a user inquiry using sketching and a questionnaire. We conducted a study with 65 participants. We asked them to what extent intrusion on the part of the system (e.g., compulsory tutorials, automatic pop-up messages) would be acceptable. In addition, we asked them to create solutions to this problem. Most found less intrusive visualization onboarding forms (e.g., tooltips, optional and concise tutorials) helpful. Compulsory visualization onboarding forms were considered less helpful. Participants also suggested chatbots or ML algorithms as convenient solutions for visualization onboarding.

1 INTRODUCTION

The increasing size and complexity of modern datasets often surpass the capabilities of traditional visualizations like bar charts, line graphs, and pie charts to effectively represent the underlying data. As data becomes more complex, these methods frequently fail to capture its full depth. While advanced visualization techniques can address this, many users struggle to interpret them, which leads to misinterpretations (Börner et al., 2016; Galesic and Garcia-Retamero, 2010). This can result in frustration and reluctance to use these otherwise powerful tools.

Despite the availability of visualization onboarding systems (Stoiber et al., 2022d; Stoiber, 2023; Dhanoa et al., 2022) designed to guide users in interpreting and navigating these complex visualizations, users tend to ignore them (Pohl et al., 2023). Instead, they often rely on a "trial-and-error" approach, attempting to figure out the visual encoding and the system's functionality on their own (Mahmud et al., 2020; Andrade et al., 2009). This behavior increases the risk of users drawing incorrect conclusions from the data, as they may not fully understand the visual mappings or the capabilities of the system (Pohl et al., 2023; Börner et al., 2016; Galesic and Garcia-Retamero, 2010). Moreover, unlike traditional software, where errors typically trigger clear feedback or error messages, visualization systems often do not provide such indicators when users misinterpret information. This makes it difficult for users to recognize when they have made a mistake (Lee et al., 2016; Rezaie et al., 2024).

Thus, it is crucial to understand how to motivate users to engage with visualization onboarding systems. The challenge lies in finding the "sweet spot" between effectively onboarding users (nudging) and avoiding annoyance. Research in the area of help systems has shown that this is a difficult balance to strike (Mahmud et al., 2020; Andrade et al., 2009). If the assistance is too unobtrusive, users may not notice it; if, however, it is too intrusive, users may find it annoying and deactivate it completely. The case of Microsoft's Clippy is a prime example of how a well-intentioned but poorly executed help system can lead to widespread user frustration and a general aversion to such systems (Chundury et al., 2023; Yalçın, 2016).

To contribute to the challenge of finding the right degree of intrusiveness in visualization onboarding

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Pohl, M., Potzmann, B., Stoiber, C. and Aigner, W.
Inconspicuous Guides: A Qualitative Study to Understand the Degree of Intrusiveness in Visualization Onboarding.
DOI: 10.5220/0013135900003912

In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 1: GRAPP, HUCAPP and IVAPP*, pages 706-717
ISBN: 978-989-758-728-3; ISSN: 2184-4321

systems, we conducted a user inquiry using sketching (Roberts et al., 2015) with 65 Computer Science master students at a university. Their feedback was instrumental in generating innovative design ideas for visualization onboarding solutions in complex visualization systems that consider the degree of intrusiveness. Furthermore, we developed a questionnaire to collect their opinions and attitudes toward visualization onboarding.

Our investigation focuses on three key research questions:

RQ1. What kind of **attitudes** do participants have regarding the intrusiveness of visualization onboarding?

RQ2. What **suggestions** do participants have concerning the intrusiveness of visualization onboarding?

RQ3. What kind of **onboarding prototypes** do they **construct** to avoid intrusiveness? How do they combine different features of onboarding?

By addressing these questions, this paper contributes to the ongoing discourse on designing effective visualization onboarding systems and their role in enhancing user interaction with complex data visualizations. In detail, the main contributions of the paper are the following: (1) Discussion of related work in the field of help systems, visualization onboarding, and guidance as related fields (in Section 2); (2) Presentation of the results of an investigation with 65 participants aiming to find a feasible visualization onboarding concept that is accepted by users in terms of intrusiveness (Section 3). (3) Additionally, we present examples of the participants' resulting sketches (see Section 3.4.3).

2 RELATED WORK

Within the landscape of Human-Computer Interaction (HCI), research has intensively examined the challenges users face while seeking help with complex, feature-rich software (Kiani et al., 2019). Visualization onboarding (Stoiber, 2023; Dhanoa et al., 2022) and guidance (Pérez-Messina et al., 2022; Ceneda et al., 2017, 2019a; Sperrle et al., 2021) are integrated as part of user assistance (Stoiber et al., 2022a) in visual analytics (VA), helping users during different phases of analysis by providing structured introductions and support for interpreting data (Stoiber et al., 2022d, 2023a, 2021). Guidance provides support for users as they solve analytical tasks (Pérez-Messina et al., 2022). In the context of data visualization and VA, a recommendation system, also known as a recommender system, refers to any system that proposes content to a user based on a calculated correlation between the content and the user's interests (Pazzani and Billsus, 2007; Zhou et al., 2023). Recommender systems for VA can suggest relevant visualizations, data filters, or analysis methods to users (Resnick and Varian, 1997). Some recommender systems already use AI-based approaches (e.g., some forms of content-based filtering). The widespread adoption of ChatGPT indicates a possible additional area of research. The first attempts for software tasks (Khurana et al., 2024) and programming-related tasks (Xu et al., 2022) have been made. To the best of our knowledge, extensive research in the context of visualization onboarding, guidance, or help systems has not yet been conducted in this area.

The synergy between these areas lies in their collective goal to empower users to effectively engage with complex systems, particularly in VA. In the following, we discuss related work in the field of (1) help systems, (2) visualization onboarding, and (3) guidance in VA.

2.1 Help Systems

The design of help systems has been discussed at some length in the scientific literature. Grayling (2002), for example, provides an overview of approaches on how to design help systems. According to him, research indicates that users tend to ignore help systems and prefer trial and error. He suggests possible solutions to this problem, e.g., tooltips or embedded help panels. In general, he states that help should be context-specific, useful, obvious to invoke, non-intrusive, and easily available. Vouligny and Robert (2005) describe an approach for help systems based on situated action theory. They also point out that users are often sceptical of help systems. Technical documentations often provide descriptions of a system's functionalities, but they are not tailored to assist users in their tasks and are, therefore, rarely used. The authors also discuss the issue of intrusive help systems. They argue that these systems are often annoying because they rely on simplistic assumptions about the users' intentions. Silveira et al. (2001) propose a semiotic engineering approach. The emphasis of this approach is on identifying the intents of the users and the design of appropriate help messages. The authors developed a taxonomy of users' utterances expressing specific needs for help (e.g., Where is . . . ?, What's this? What happened?). Our research indicates that similar to research on help systems, users enjoy finding out about the features of the systems themselves and prefer unobtrusive and context-sensitive forms of assistance.

2.2 Visualization Onboarding

Visualization onboarding methods (Stoiber et al., 2022d; Stoiber, 2023; Stoiber et al., 2023a; Dhanoa et al., 2022) aim to support end users in comprehending data visualizations and taking full advantage of the tools at hand. There are different types of help-seeking behaviors: help initiated by the user (pull) vs. the system (push) (Horvitz, 1999; Kiani et al., 2019). Visualization onboarding can be external (Stoiber et al., 2022c), separate from the tool, or in-situ (Stoiber et al., 2023a), i.e., integrated within it. In-situ systems use either the "pull" or "push" approach for providing help (Horvitz, 1999; Kiani et al., 2019).

So far, most visualization onboarding systems can be categorized as external learning environments (Stoiber et al., 2022c), detached from the core visual analytics tools. For example, Firat et al. (2020) developed an interactive pedagogical treemap application for training. Additionally, Peng et al. (2022) present results of a study to evaluate six parallel coordinate literacy modules based on Bloom's taxonomy (Bloom et al., 1956) using videos, tests, and tasks. Both examples provide a platform to enhance students' visualization literacy.

The few papers where in-situ visualization onboarding is observed explain the features of the visualization tool by exploring both push and pull onboarding assistance, with the main focus on the "pull" help-seeking behavior. Yalçın (2016) presented HelpIn, a system designed for the Keshif visualization tool that demonstrates some aspects of "push" and "pull" models, providing contextual in-situ help (Chundury et al., 2023) without disrupting user tasks. They utilize the "push" model through notifications to suggest relevant help topics on the fly. The notifications are designed in such a way that users are not disrupted in their exploration tasks. Similarly, IBM Cognos (Analytics, 2022) and Advizor (Solutions, 2022) employ step-by-step tours with tooltips, overlays, and textual descriptions, respectively, thus aligning with the "pull" model (Horvitz, 1999). However, these examples primarily focus on feature explanation.

Stoiber et al. developed four visualization onboarding methods for visualization tools: a step-by-step guide, scrollytelling, video tutorials, and in-situ scrollytelling (Stoiber et al., 2022d; Stoiber, 2023). They conducted studies with MTurk workers and students to assess the impact of these methods on user performance and experience. They also examined different instruction styles (concrete vs. abstract) in a separate study (Stoiber et al., 2022b). Building on their findings (Stoiber et al., 2022d, 2021, 2022c,b), they recently proposed nine design actions for effective visualization onboarding, emphasizing in-situ methods and considering factors like user engagement and accepted annoyance (Stoiber et al., 2023a).

Furthermore, the literature reveals a variety of visualization onboarding concepts focusing on exploring different teaching methods and learning types in the broader context of visualization literacy. Tanahashi et al. (2016) contrast top-down and bottom-up approaches, while Kwon and Lee (2016) highlight the effectiveness of active learning strategies in understanding complex visualizations like parallel coordinate plots. Ruchikachorn and Mueller (2015) emphasize the power of learning by analogy in grasping unfamiliar visualization methods.

In summary, the current landscape of visualization onboarding systems predominantly consists of external learning environments with limited examples of in-situ integration. Moreover, the subtle balance between providing sufficient assistance and causing annoyance – a critical aspect of the push model – remains an underexplored area.

2.3 Guidance in Visual Analytics

The concept of guidance was initially introduced by Schulz et al., serving as an umbrella term encompassing various aspects such as "recommender systems", "user support", and "assistance" within Visual Analytics (VA) (Schulz et al., 2013). Ceneda et al. further refined this definition, describing guidance as a computer-aided method designed to actively bridge a user's knowledge gap during interactive visual analytics sessions (Ceneda et al., 2017).

Their work also discusses the importance of unobtrusiveness in guidance in VA, emphasizing the need for guidance methods that do not hinder the analytical process (Ceneda et al., 2017). They propose a model of guidance that gradually narrows the gap hindering the effective continuation of data analysis, highlighting the significance of unobtrusive guidance (Ceneda et al., 2019a).

Several factors influence the optimal timing for guidance and help-seeking behavior. Firstly, the complexity of the analytical task and, secondly, the user's skill level play a crucial role in determining the timing for guidance (Pérez-Messina et al., 2022). In this regard, Ceneda et al. also explored the issue of the proper timing of guidance by using facial recognition software and a machine learning model trained to detect when to guide according to changes in the user's facial expressions (Ceneda et al., 2021).

Summary. The takeaways of this body of research show that successful visualization onboarding systems should provide assistance that is contextually relevant, minimally intrusive, and adaptable to individual user preferences and skill levels (Grayling, 2002; Silveira et al., 2001; Stoiber et al., 2023a; Ceneda et al., 2019b). The degree of intrusiveness accepted by the user of visualization onboarding systems is still an open question, particularly when it comes to the utilization of pull or push models (Chundury et al., 2023), which set the stage for further investigations. Therefore, we conducted a study to find ideas and concepts of visualization onboarding that consider nudging and intrusiveness (see Section 1). We present our investigation in the following, discussing the study design, participants, and derived results in detail.

3 INVESTIGATION

3.1 Study Design & Procedure

Study Design. We conducted the study with a dual objective: to understand participants' subjective experiences with visualization onboarding systems, and to gather innovative ideas for designing effective onboarding solutions for complex visualization systems (see research questions section 1).

We designed a **questionnaire** and a **user inquiry using sketching** with our study participants to answer our research questions. We wanted to understand which visualization onboarding solutions (e.g., tutorials, pop-ups, tooltips) the participants favored, found effective, or disliked and what their attitudes concerning the trade-off between helpfulness and intrusiveness were. From previous research, we know that systems might be helpful but intrusive when they offer unsolicited help messages indicating features that have been overlooked by users. We also included questions on how the participants thought programs might detect when users need assistance and how users can realize their need for help. The questionnaire consisted of the following questions:

- What kind of onboarding system would you personally be most willing to use?
- What kind of systems might be helpful but unusable or intrusive?
- What level of annoyance is necessary?
- How could users realize that they need help?
- How could programs detect that the users need help?

A practical component of the study, the sketching sessions, involved participants sketching prototypes for onboarding solutions tailored to a complex visualization system featuring various visualization types and filtering options. This task was intended to reveal the range of approaches participants considered effective for encouraging the use of onboarding systems. The goal of developing the prototype was to determine whether they could devise concrete solutions for the visualization onboarding process they appreciated, and what kind of nudging they suggested. Possible existing approaches to this problem were not discussed with the participants so as not to influence them in the development of creative solutions.

Procedure. The participants were given a document consisting of the following parts: 1. a short description of the investigation, 2. an informed consent form, 3. a questionnaire, and 4. a brief description of the task of developing the prototype. Before starting to work, one of the co-authors met the participants and gave them an introduction of about one hour regarding the goals of the investigation and the study process. The participants had eight weeks to complete both tasks. They filled in the questionnaires individually but were allowed to develop the prototypes in pairs because we assumed that if they could discuss their solution with a colleague, they would reflect on it more and create more creative solutions. Nine pairs of participants cooperated to develop the prototype. The other 47 participants developed the prototypes on their own. Participants were required to create a prototype consisting of a textual description and drafts of screenshots.

3.2 Participants

As detailed in Table 1, we recruited 65 students (average age $\approx$ 25.7 years) from an international master's program in computer science at Vienna University of Technology, conducting the study within a lecture setting (16 female, 49 male, the students came from several different European countries). Upon examining their self-reported skills, it became clear that most participants had a strong foundation in visualization design, with about half also indicating experience in UX design. In contrast, very few had experience in designing help or support systems. The participants were master's students in data science; many already worked part-time as computer scientists in that

Table 1: **Distribution of proficiency and education levels.** This table presents the 65 participants' self-reported proficiency in three areas: visualization design, UX design, and help/support system design.

Proficiency	Viz Design	Help Design	UX Design	Education	n
Beginner	13	56	31	Bachelor's	57
Intermediate	30	7	28	Master's	5
Advanced	21	1	4	PhD	1
Expert	0	0	1	Undergraduate	1

area. These students were not only potential users but also future developers of systems administrating large datasets. As such, they had already developed their first ideas about designing such systems during their studies. They might be called semi-experts, and their ideas about motivating users to study IT systems representing large datasets in detail are undoubtedly relevant.

3.3 Data Analysis

We conducted a qualitative and exploratory investigation to get an overview of the issues relevant to the research question. We chose a qualitative content analysis approach (Schreier, 2012) to examine the participants' responses to the questionnaire and the prototypes and ideas they generated. We were able to break down the data into manageable, discrete pieces of information by identifying recurring patterns and themes, especially the kinds of visualization onboarding solutions that the participants mentioned. Through iterative rounds of refinement, we developed a nuanced understanding of the participants' perspectives and experiences as well as their preferences and expectations. Two co-authors met repeatedly to discuss the data analysis, compare the results, and resolve diverging interpretations.

We developed a set of codes distinguishing between different features of visualization onboarding systems. There are "push features" (e.g., pop-up fields, compulsory tutorials), "pull features" (e.g., optional tutorials, documentation), and features in between that can be designed either as "push" or as "pull feature." Tooltips, for example, can be interpreted as a "pull feature", but when they are opened because a user moves the mouse unintentionally over the feature, it can be seen as "push feature". Chatbots or intelligent recommender systems can be designed both ways. They either give advice only when the user activates them, or they are always active.

The codes were partly based on previous research (Stoiber et al., 2022d) and partly derived from the analyzed material. The following set of codes was used for the analysis (see also Figure 1): ML/chatbots, tooltips, video, tutorial, example, gamification, help button, interactive walkthrough, pop-up, together, doc/full search, test, compulsory tutorial, forum. Participants mainly suggested using either machine learning or chatbots (code ML/chatbots), but the code encompasses any kind of AI-based support. Some participants suggested offering practical examples (sometimes with solutions) to assist users. Gamification was considered to motivate users more to use visualization onboarding than simple tutorials. An interactive walkthrough is supposed to be an interactive form of tutorial. Pop-ups are always generated by the system and are therefore "push features". Doc/Full search is meant to be documentation with full-text search capabilities. Tests are entry tests to assess users' knowledge. A forum was sometimes suggested so users could exchange experiences and help each other. Some participants explicitly mentioned that a specific subset of these features should be combined to create an appropriate visualization onboarding system (code: together).

3.4 Results

In this section, we present the results of this investigation, divided into the questionnaire and prototype results based on the sketching sections.

3.4.1 Results of the Questionnaire

The goal of the questionnaire was to clarify the personal opinions of the participants concerning nudging and acceptable annoyance in onboarding systems.

Nudging Preferences. The first question pertained to the participants' personal preferences concerning the nudging behavior of visualization onboarding systems. Participants primarily chose in-situ tooltips as the preferred form of nudging (36 participants out of 65). Tooltips are a very subtle and unobtrusive form of nudging, which makes them seem very attractive. Participants also appreciated onboarding systems that include AI/ML elements (21 out of 65). Tutorials (14 out of 65) and learning by concrete and practical examples (13 out of 65) were mentioned as unobtrusive concepts. Eight participants explicitly said they preferred to explore independently and use assistance only when completely stuck.

Perceptions of Intrusiveness vs. Helpfulness. We also asked participants about visualization onboarding features that might be intrusive but still helpful. The answers to this question were more general. 22 participants mentioned compulsory tutorials as helpful but intrusive, and 31 said that pop-ups were helpful. Participants said visualization onboarding should not be nudging users constantly (e.g., by pop-ups that appear frequently and are difficult to eliminate). Visualization onboarding should be manageable in length. Additionally, it should not present unnecessary or unwanted information.

Degree of Intrusiveness. In a third question, we asked about the necessary level of annoyance or intrusiveness that would be acceptable for the participants. In this case, the answers were sometimes very general and provided no clear indication of specific features that would or would not be acceptable. Those participants who gave more precise answers said that short and concise tutorials at the beginning would be acceptable (9 participants). Another possibility was to use AI-based recommendations (9 participants) and, surprisingly, pop-up messages (8 participants). In this context, AI-based recommendation summarizes any visualization onboarding system that uses machine learning, for example, to track and react to user behaviors or AI concepts such as "virtual" assistants to answer questions similar to ChatGPT. Participants also mentioned that the amount of intrusiveness depends on the users' previous experience (10 participants) and the complexity of the tool (5 participants).

Detection of Help-Seeking Behavior. We also asked the participants how users could find out that they needed help. 35 out of 65 participants said that users notice that they need help when they cannot finish their task, are confused, and show specific interaction patterns (e.g., doing the same actions repeatedly without result). 15 participants answered that users should know they need help when receiving repeated error messages from the system. Only 10 participants mentioned that users should know they need help because of a general understanding of visualizations or a test before using the visualization. The last question was about the system's ability to detect whether users needed help. Almost all participants (64 out of 65) said the visualization system should monitor the users' activities and detect inappropriate behavior.

Lessons Learned. The study revealed a preference for subtle in-situ nudging techniques in visualization onboarding (RQ1), with a general skepticism towards more intrusive methods. The participants showed an interest in AI-based assistance but also had high expectations for system capabilities in detecting and responding to user needs. The participants said they found intrusive features acceptable for inexperienced users and complex visualizations (RQ2).

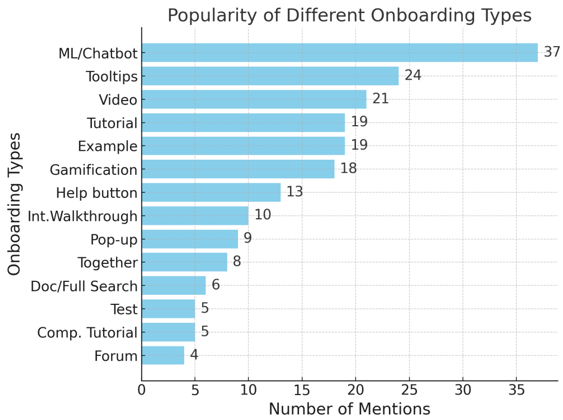

Figure 1: Distribution of mentioned onboarding types (prototypes).

3.4.2 Results Prototype

Participants were asked to generate ideas or very small prototypes for visualization onboarding considering nudging and intrusiveness (see Figure 1). Participants were generally very reluctant to force users to seek assistance. They tried very hard to find solutions that could, on the one hand, motivate users to learn about the visualization but that, on the other hand, did not interfere too much with the users' workflow.

Interestingly, the participants most frequently mentioned any kind of features supported by artificial intelligence (code ML/Chatbots) in a very broad sense (37 out of 65 participants). Sometimes, we got the impression that the participants had unrealistic ideas about the capabilities of AI. Some suggested a kind of personal assistant who unobtrusively looked over their shoulder and reminded them cautiously and restrainedly about possible better solutions. Most had at least some sort of chatbot in mind that would answer questions. Additionally, it should be mentioned that these AI-based features were usually not the main component of the small prototype that the participants suggested. Rather, they were additional features accompanying other onboarding methods.

Another very frequently mentioned feature was tooltips (34 out of 65 participants) (see Fig. 1). In contrast to pop-ups, tooltips are unobtrusive and only appear upon mouse-over. Tooltips are a borderline case as far as the activity of the system is concerned. They are relatively unobtrusive but can appear without the user asking for help. In addition, the information offered by tooltips is usually very short. It was often mentioned throughout the investigation that help texts should be short and concise and offer necessary information only. Tooltips meet these requirements, which makes them very popular. Other features that were also mentioned quite often were videos (21 out of 65), the use of concrete and practical examples (19 out of 65), optional tutorials (19 out of 65), and gamification (18 out of 65). Gamification was seen as a possibility to motivate users to use the visualization onboarding system by giving them rewards or by using features that increase enjoyment and a positive mood so that it was not seen as a burden. Short initial tutorials, especially for inexperienced users, were seen as an acceptable possibility for visualization onboarding. Some participants also mentioned MS Word's spell-check as a good example of an unobtrusive way of showing users how to correct errors.

Compulsory tutorials (5 out of 65), (ability) tests at the beginning (5 out of 65), extensive documentation with full-text search capabilities (6 out of 65), and pop-ups (9 out of 65) were features of visualization onboarding systems that were hardly mentioned at all. Compulsory tutorials and pop-ups in particular generated very negative comments among the participants. Communication in a user forum or interactive walkthroughs was not seen as attractive, either. Some users intended to use several features combined (code: together).

Lessons Learned. Summarizing the results of the qualitative content analysis on the prototypes for visualization onboarding showed that tooltips, AI features, and interactive methods such as videos and practical examples (tutorials) were favored, as shown in Figure 1. Conversely, features perceived as forcing information onto the user, such as compulsory tutorials and repetitive pop-ups, were regarded unfavorably (RQ3). The results from the development of prototypes aligned closely with the questionnaire responses.

3.4.3 Examples of Prototypes

The results of the overall analysis of the prototypes developed by the participants conform to the results of the analysis of the questionnaires. Nevertheless, the prototypes, investigated individually, indicate that the participants came up with a wide variety of solutions.

The four examples, three of which are illustrated in Figure 2, Figure 3, and Figure 4, are discussed in the following and show this nicely. They were chosen for their clarity of presentation and lucid structure.

Example 1: Self-Test. First-time users of the visualization receive a self-test (see Figure 2). The system provides feedback about the user's answers. If they make a mistake, they are offered a demo video. These videos should be short and to the point. While the user is working, the system monitors their activities. When the system detects an error, the user is asked whether they need help. This is intrusive but helps the users to solve their tasks quickly. Another possibility is tooltips (called "hover info buttons" here), which are less intrusive. Extensive documentation should also be available when needed.

Example 2: e-Learning System. This solution offers an onboarding system that is similar to an e-learning system but aims to teach the specific information that users need at the time they need it (see Figure 3). The system tries to engage users by motivating them to solve examples on their own. A sidebar is added to the existing visualization on the left-hand side of the screen. This sidebar contains challenges that are ordered according to their difficulty. Each has a clearly defined goal and several steps to reach it. Multiple-choice questions are shown if a user selects a challenge (see Figure 3). Each question contains the next step required to reach the solution. The system explains the correct solution when the user clicks on the wrong solution. In addition, a scoring system can be introduced, adding an element of gamification.

Example 3: Exemplary Workflows and Use Cases. The system proposed by this participant consists of various elements. It starts out with a short test at the beginning to assess the user's level of expertise. This helps to avoid presenting hints and onboarding tools to users who do not need them. The system will also provide information about typical workflows with numbers and explanatory text (see Figure 4). This helps to inform the user on the correct sequence of steps to perform a task. In addition, there will be a concrete use case informing the user about interactive features in particular. If the user does not fulfill the task, feedback is provided about how to solve it successfully. The onboarding system will also contain videos.

Example 4: Chatbot. This prototype is unique because a chatbot forms the main element of the onboarding system. In contrast, most other prototypes only use chatbots or AI-based features as assistive features. This chatbot is supposed to accomplish several different tasks. It answers questions about how to complete specific tasks. In addition, it provides information about the data (e.g., the mean values of the

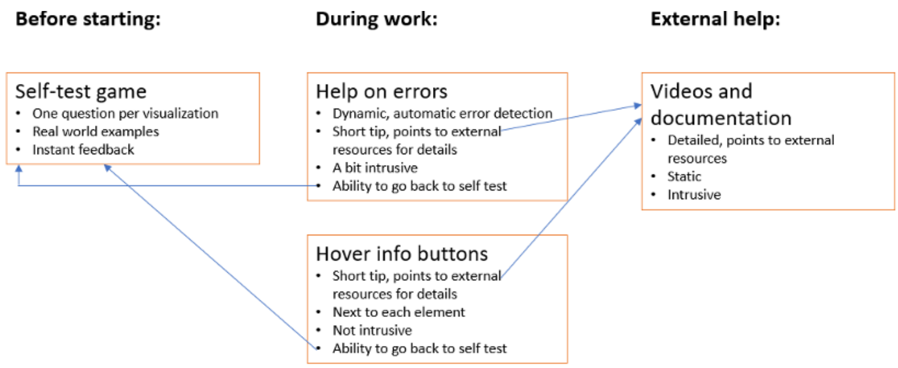

Figure 2: The example of this prototype is highly structured. Several features provide help (self-test game, automatic error detection, videos and documentation, tooltips). These different features are related, and the system can move from one feature to another when needed.

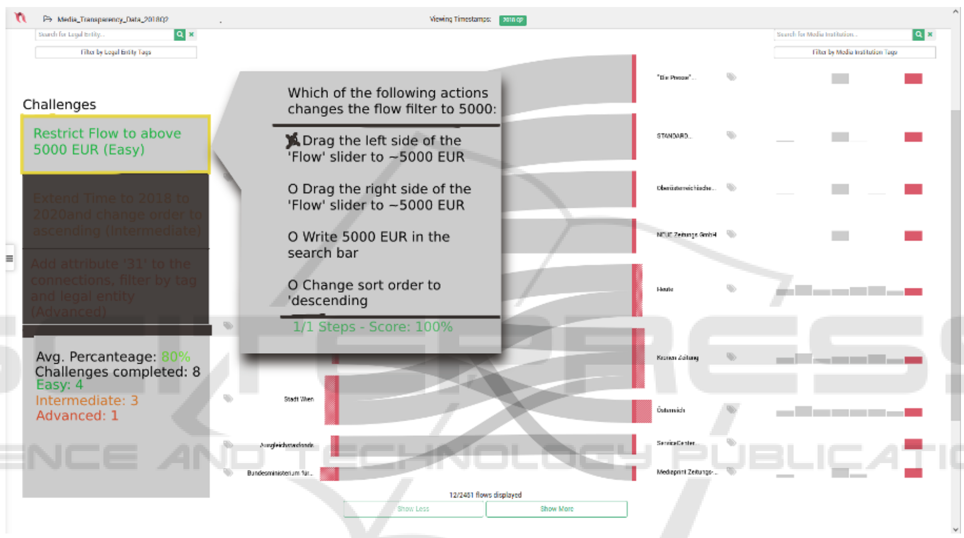

Figure 3: This figure shows a screenshot of example 2. On the left-hand side are the challenges that users have to solve. Right beside it are the multiple-choice questions to be answered by the users.

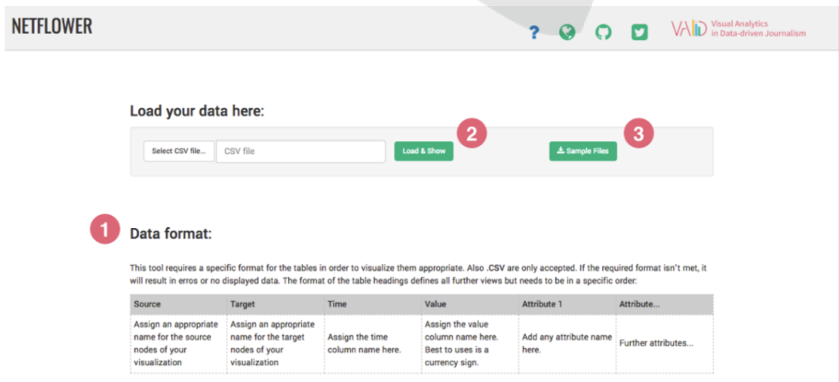

Figure 4: Description of a workflow with numbers and tooltips.

data) and the appropriate interpretation of the data. One of its key features is its ability to become active when it detects a user error (e.g., when the user employs many different tools without finishing the task), providing reassurance that users are always supported. In this case, the user is asked whether they need help. In addition to the chatbot, the system also contains an optional tutorial video and tooltips.

Lessons Learned: The overall analysis of the prototypes indicates some clear tendencies among participants. However, the analysis of the individual prototypes shows that the participants' solutions vary considerably. The participants generally do not stick to one idea but distinctly combine different features. They typically combine more and less intrusive features, sometimes targeted at more or less experienced users. Machine learning or AI features (especially chatbots) are usually added as an auxiliary feature. Gamification is often used with the explicit goal of motivating users to interact with the onboarding system and overcoming users' annoyance with intrusive onboarding. Step-wise introductions or practical examples are also seen as a possibility to engage users. Again, the idea is to overcome the annoyance of the users with more intrusive forms of onboarding.

4 DISCUSSION & FUTURE WORK

This investigation aimed to identify what kind of visualization onboarding users of visualizations found annoying and intrusive, and what would be more acceptable. This research question is based on previous research (Pohl et al., 2023) indicating that users of visualizations are sometimes not aware that they need help and, therefore, come to erroneous conclusions about the data presented to them. While there is some research on users struggling with visualizations (Börner et al., 2016; Galesic and Garcia-Retamero, 2010; Rezaie et al., 2024; Lee et al., 2017), this specific issue has, to the best of our knowledge, not yet been addressed in research. In the next paragraph, we present lessons learned based on our research.

User Skepticism Towards Active Assistance. The participants generally indicated that they were pretty skeptical about visualization onboarding, especially systems actively trying to assist them. Many participants mentioned that they preferred to find out how the system worked themselves, following a trial-and-error strategy (cf. Mahmud et al. (2020); Andrade et al. (2009)).

Preference for Subtle, Contextualized Nudging. Participants preferred unobtrusive onboarding methods such as tooltips, concise tutorials or videos, and small pop-ups in unused screen areas. These methods were seen as minimally disruptive and helpful. Some users also mentioned MS Word's spell-check as a positive example of a system's unobtrusive but active help. They argued that something similar should be developed for visualizations (e.g., systems that indicate the next necessary step in the interaction process through subtle highlighting). Participants argued that visualization onboarding should preferably be in situ (integrated into the system) so that their workflow would not be interrupted.

Pop-ups that appeared repeatedly, covered large parts of the screen, or were difficult to close were seen as highly annoying and intrusive. Participants also criticized long and complex tutorials with unnecessary information. Nudging should be adapted to the context, they said.

Borderline Cases. While participants preferred less intrusive solutions, they argued that in some cases, intrusiveness might be annoying but helpful. It depends on the situation whether intrusiveness is acceptable. Participants found it appropriate that the amount of nudging for inexperienced users and during interaction with complex visualizations could be higher. In this case, compulsory tutorials might be helpful. Pop-ups (e.g., with hints of the day) appearing in unused areas of the screen were deemed acceptable provided that this does not occur frequently, and that the pop-ups disappear by themselves. In all these cases, the text should be short. Some users would also find it acceptable for a chatbot to give advice, thus interrupting the workflow.

This finding suggests that onboarding systems should be adaptive, offering more guidance to novices and less to experienced users, thus tailoring the onboarding experience to the user's level of expertise.

Potential of AI-driven Visualization Onboarding Methods. Participants were open to the idea of AI-driven onboarding systems that could monitor user activity and provide context-sensitive hints or alternative solutions. In detail, they imagined that an AI system might monitor their activities and offer hints or alternative ways of actively solving a problem to assist users. Participants mentioned wanting to ask the AI questions and discuss solutions with this system. AI-driven onboarding is a more acceptable form of nudging than many others. To what extent this can be realized with existing generative AI models, like ChatGPT, is an open question. First attempts have been made to solve this problem (Joshi et al., 2024; Zhao et al., 2024), but future work will show whether such ideas are realistic. This is certainly a promising area for future research.

Misalignment Between Users' Expectations and Visualization Realities. Most participants apparently use a model from more conventional systems to reason about problems with visualizations. This model assumes one clear and identifiable path to the solution to a problem. The system can detect any deviation from this path and either show an error message or an inappropriate result. As mentioned above, this does not always apply to visualizations. Interaction with visualizations is an exploratory process (Battle and Heer, 2019), and often no clear path to the solution can be identified. Visualization systems, therefore, are sometimes unable to identify appropriate or inappropriate user behavior or assess the validity of the insights generated by them. Many participants expected the system to always provide feedback when errors occured. Visualization onboarding systems should also raise awareness of this problem.

Potential of Combining Different Features of Onboarding. In developing their prototypes, participants systematically combined various features of onboarding systems. They usually combined more and less intrusive features to provide different possibilities for user onboarding. Using gamification and practical examples can counterbalance the negative effects of more intrusive onboarding.

4.1 Limitation

While our study was limited by the demography of the participants, who were primarily data science students, it is important to note that these students are the future data scientists, many of whom also work part-time in the field. We also conducted an investigation with professionals from a software development company and found that they were also very skeptical about more intrusive visualization onboarding and preferred subtle nudging (tooltips and very short tutorials) (Potzmann et al., 2023). This aligns with other research findings (Stoiber et al., 2023b; Baur and Stephaner, 2018). Further research should address this issue more systematically, offering a wealth of potential for future exploration.

Our approach mainly addresses the attitudes of potential designers/users and a sketch-based approach similar to constructive visualization by Huron et al. (2014). An alternative approach would be to ask study participants to solve tasks and use observation to determine whether users apply onboarding, and what specific features they use. However, we would like to point out that this is a very challenging approach. Researchers need detailed knowledge about the users' level of experience to construct appropriate study material. If this material is too easy so that participants do not need onboarding, no appropriate results can be gained. In addition, tasks have to be developed specifically so that users are compelled to use various onboarding features. Furthermore, to get detailed insights about the users' cognitive strategies, thinking aloud or conducting interviews would be necessary to explain why users adopt certain features of the onboarding system, or not. Nevertheless, the results of such an investigation would be interesting.

5 CONCLUSION

We conducted an empirical study on the acceptance of more intrusive forms of visualization onboarding. The participants of our study accepted only very subtle forms of intrusion. It seems that AI-based approaches might be more acceptable than traditional forms of assistance. In contrast to existing visualization onboarding solutions in visualization, we suggest visualization onboarding integrated into the system. This also conforms to research on help systems.

ACKNOWLEDGEMENTS

This work was funded by the BMK under the ICT of the Future program (#874018), the Austrian Science Fund (10.55776/I5622), as well as by the Austrian Federal Ministry of Labour and Economy, the National Foundation for Research, Technology and Development, and the Christian Doppler Research Association.

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