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The State of the Art in User-Adaptive Visualizations

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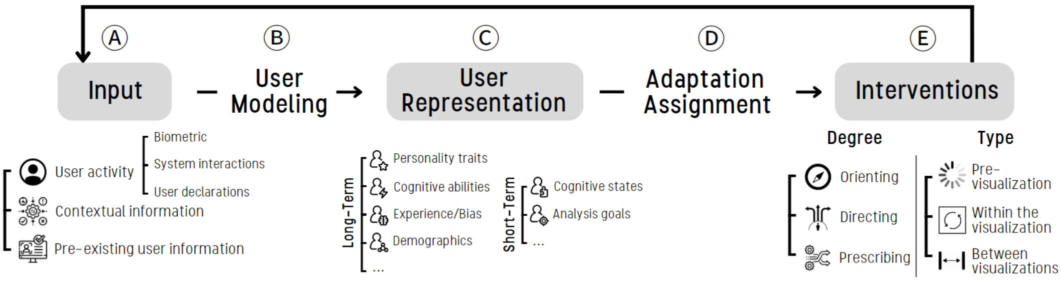

Figure 1: *Taxonomy of the components in user-adaptive visualizations.* Ⓐ ***Input*** *describes what type of information about the user is captured.* Ⓑ ***User Modeling*** *specifies how that information is processed to create a model of the user.* Ⓒ ***User Representation*** *describes the set of user characteristics that drives the system's adaptation.* Ⓓ ***Adaptation Assignment*** *defines how the information in the user representation is processed to make decisions on how to adapt, and* Ⓔ ***Interventions*** *captures the degree and type of adaptation.*

Abstract

Research shows that user traits can modulate the use of visualization systems and have a measurable influence on users' accuracy, speed, and attention when performing visual analysis. This highlights the importance of user-adaptive visualization that can modify themselves to the characteristics and preferences of the user. However, there are very few such visualization systems, as creating them requires broad knowledge from various sub-domains of the visualization community. A user-adaptive system must consider which user traits they adapt to, their adaptation logic, and the types of interventions they support. In this STAR, we survey a broad space of existing literature and consolidate them to structure the process of creating user-adaptive visualizations into five components: Capture Ⓐ ***Input*** *from the user and any relevant peripheral information. Perform computational* Ⓑ ***User Modeling*** *with this input to construct a* Ⓒ ***User Representation****. Employ* Ⓓ ***Adaptation Assignment*** *logic to identify when and how to introduce* Ⓔ ***Interventions****. Our novel taxonomy provides a road map for work in this area, describing the rich space of current approaches and highlighting open areas for future work.*

CCS Concepts

• General and reference → Surveys and overviews; • Human-centered computing → Information visualization; User models; • Information systems → Personalization;

1. Introduction

Data visualizations have long been used to amplify human cognition and help make sense of the vast amount of data. However, recent research has shown that the visual analysis process itself is not universal [Ott20]. Each user experiences a visualization through their own lens, as defined by their past experiences, personality traits, cognitive abilities, and more. Moreover, studies investigating the effect of user traits on visual analysis have shown that they can have a measurable influence on users' accuracy, speed, and attention when performing tasks (e.g., [CCTL15, COSM20, OCZC15]).

These findings suggest that it can be highly beneficial to personalize visualizations to specific user needs and preferences. The field of *user-adaptive visualizations* investigates how visualizations can adapt to the characteristics and preferences of the user [CCTL15]. This is similar to what the general research field of user-adaptive systems [Jam07] does for other types of interactive systems, such as recommenders and intelligent tutoring systems. Such adaptation can enhance the overall effectiveness of the visual analysis process, as was, for instance, shown by Lallé et al. [LWC20]. Additionally, in adapting to the user, these interventions can help reduce cognitive overload [ZK09, PYO*13] and improve data discovery rates [MHN*22].

Despite the potential benefit of such a system, only some existing visualization tools instantiate this concept completely. This is partly because realizing such a system involves addressing, in a very different context, the challenges that have been targeted by research in user-adaptive interaction for other domains. These challenges include addressing which user properties are relevant for personalization, how a system can capture and infer these properties reliably and obtrusively to often limited and noisy input data, and how to make suitable adaptation assignments from this information and deliver the adaptations effectively while maintaining user control and acceptance. This STAR aims to curate the collection of research often siloed in sub-disciplines, focusing directly on enabling *user-adaptive visualizations*. In the context of this STAR, we define user-adaptive visualizations as visual analysis systems that sense and maintain a representation of the user and produce an intervention that adapts to that user representation. Interactive visualizations that simply respond to clicks, drags, or other forms of user input without maintaining a user representation and adapting based on it are not considered user-adaptive within the scope of this review.

Personalizing visualization systems to specific users can also be achieved to some degree through user-driven customization, namely by providing users with tools and affordances to customize different aspects of a visualization. However, this approach is fundamentally limited by the knowledge and expertise of the user, which often does not include a detailed understanding of the strengths and weaknesses of different visual encodings or an awareness of their own cognitive load and analysis patterns [LC19]. With user-adaptive visualizations, the burden of making 'optimized choices' can be transferred to the system. The degree of guidance in an adaptive system can vary from non-invasive orientations, such as recommendation systems [WMA*16], to more prescriptive approaches, such as highlighting interventions [BLIC21] and legend placement [GKG*18]. Systems that support both user control and computer-driven interventions are called *mixed-initiative* systems [Hor99]. A successful mixed-initiative system enhances user cognition, improving users' ability to perform complex tasks [Ott20]. However, achieving an ideal balance between customization and adaptation is non-trivial. Such systems must know when to adapt and when to allow the user to take control, and provide customization tools that are lightweight and do not burden the user. Ultimately, a good mixed-initiative system must successfully manage the dialogue between the system and the user.

In this STAR, we organize the space of user-adaptive visualizations by deconstructing the adaptation process into five main components as shown in Figure 1: *input*, *user modeling*, *user representation*, *adaptation assignment*, and *intervention*. Further, we showcase the different evaluation methods implemented in user-adaptive visualization research in Section 10. These methods include quantitative measures (e.g., accuracy or performance metrics) and qualitative evaluations (e.g., user surveys, interviews, or focus groups). Overall, this work provides a framework for organizing and understanding the space of user-adaptive visualizations and can help researchers design and evaluate these systems. By understanding the different components of user-adaptive visualizations, we can better design and implement systems that provide users with effective and personalized visual analysis experiences.

2. Comparison with related surveys

Although there are no previous surveys on this topic, four are closely related. In particular, Liu et al. [LCO20] surveyed the impact of individual differences (i.e., user characteristics) on the use of data visualizations from papers published between 1987 and 2020. They classified the literature into four categories: individual differences or traits, types of visualizations, tasks the user had to perform, and measures recorded from the interactions. From these, the individual differences are the only category that resembles one of our components—namely, user representation. Moreover, the authors focused solely on personality traits and cognitive abilities as these are "invariant characteristics that distinguish one person from another" and are considered stable in the long term [LCO20]. In contrast, this STAR expands the perspective of individual differences by considering short-term characteristics that may vary throughout an analysis session (e.g., cognitive load and analysis goals).

Ceneda et al. [CGM19] surveyed and categorized the relevant literature on visual analysis systems that provide user guidance (i.e. when the user guides the system) and system guidance (i.e., when the system guides the user) to achieve an analysis objective. They organized the prior work based on (1) the analysis objectives defined by the user, (2) the intervention degree provided by the system, (3) the guidance inference made by the system based on user input, and (4) the guidance direction the user provides the system for future help. We extend Ceneda et al.'s characterization of guidance by also investigating different types of interventions, such as pre-visualization, within-, and between-visualization.

Xu et al. [XOW*20] focused their survey on analyzing user interactions and visualization provenance from 2009 to 2019. Specifically, they focus on answering the following three questions: (1) why analyze provenance data, (2) what data to encode, and (3) how to analyze the captured data. The value of provenance data to adaptive systems is very high as it helps inform them of the user's actions and infer relevant user characteristics. We build on the work done by Xu et al. [XOW*20], who focused their survey on the analysis of interaction and provenance data to include an analysis of how provenance data is used to infer the user representation, a backbone component of user-adaptive systems. User characteristics derived from provenance data can range from high-level characteristics such as analysis goals to low-level cognitive abilities such as visual literacy and cognitive abilities.

Most recently, Zhou et al. [ZWG*23] surveyed content recommendation capabilities within visual analytics platforms. The authors specifically studied how content recommendations surfaced to users and proposed a four-dimensional design space to describe these capabilities. Such dimensions are directness, forcefulness, stability, and granularity. These dimensions help characterize the interface design choices for displaying recommended content to users. In addition to the four dimensions, there are other important factors to consider in the design space. These factors include the location of the recommendation display, the temporal dynamics of content updates, and the level of detail or specificity in the recommended content. These factors play a role in determining how recommendations are presented and how users interact with them. While Zhou et al. only focus on the dimensions that characterize a design space in visual content recommendations, our work focuses on the entire workflow of user-adaptive visualization systems, from gathering user input to providing an intervention.

Our work builds on these prior surveys in three ways: (1) providing a pipeline that unifies the different components of user-adaptive visualizations, (2) taking a more granular categorization for each topic covered in the prior surveys, and (3) considering how the literature evaluates the success of a user-adaptive visualization.

3. Survey Methodology

3.1. Scope

User-adaptive visualizations are distinguished by their ability to sense and maintain user representations, which subsequently inform tailored interventions. Therefore, papers included in our core corpus must demonstrate a clear connection to this central concept. To assemble our core corpus, we considered papers that contain a system that tracks input to construct a user representation. This inclusion criterion is driven by the critical notion that user knowledge acquisition is at the core of user-adaptive visualizations. This selective approach ensures that our literature review remains faithful to the essence of user-adaptive visualizations, where the system's adaptability and personalized interventions hinge on its understanding of the user, achieved through the capture and analysis of user-related data.

It's important to note that our inclusion criterion for the core corpus is based on the existence of these components rather than the level of sophistication in data collection or modeling. Nevertheless, to enhance the discussion in some less-studied subcomponents, we also address some studies that do not necessarily meet this criterion—or are in a field other than information visualization—to offer a more holistic view of related state-of-the-art approaches that can inform user-adaptive visualizations.

3.2. Corpus

We first employed an exploratory phase aimed at grasping the language and nuances typical of the field which we explain in Appendix A. Our methodology consisted of a process to systematically identify relevant literature published in the past 20 years, as shown in Figure 2. It included a widespread and systematic search including *web scraping top tier conferences and journals*, *scoring papers based on the keywords and phrases identified in the preliminary phase* , and *manual review of filtered papers*.

Web Scraping: We scrapped data from the following ten top-tier journals and conferences, spanning the years from 2003 to 2023,

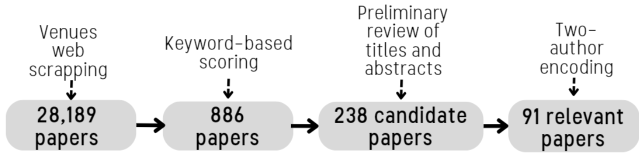

Figure 2: *Overview of the process implemented to come up with the final corpus of 91 relevant papers.*

Table 1: *The set of keywords and phrases generated by phase 1 to inform phase 2.*

User	Adaptive	Visualization
individual traits	computer-generated visualization	visual analytics
individual differences	generate visualization	visual
user representation	aided visualization	visualize
user abstraction	adapt visualization	visualization
user model	individual traits	infovis
user traits	tailoring	
user skills	personalization	
cognitive	recommend	
personality	intervention	
mixed-initiative	adaptation	
	adaptive	
	guidance	

resulting in a dataset containing 28,189 papers. The selection of these venues was guided by their reputation for publishing high-quality research, their relevance to user-adaptive visualizations, their propensity for featuring cutting-edge work, and their representation of various interdisciplinary perspectives.

- Computer Graphics Forum (CGF, including EuroVis proceedings),
- IEEE Transactions on Visualization and Computer Graphics (VIS, including IEEE InfoVis),
- ACM Transactions on Graphics (TOG),
- ACM Transactions on Interactive Intelligent Systems (TiiS),
- Computers & Graphics (CG),
- Proceedings of ACM User Modeling, Adaptation and Personalization (UMAP),
- Proceedings of ACM Advanced Visual Interfaces (AVI),
- Proceedings of ACM Computer-Human Interaction (CHI),
- Proceedings of International Joint Conference on Artificial Intelligence (IJCAI),
- Proceedings of Intelligent User Interfaces (IUI).

In particular, CHI publishes an extensive array of papers across diverse fields annually. Consequently, we selectively retrieved papers by applying a fuzzy search algorithm to the session names, choosing those that scored more than 70 in relevance with the keywords from Table 1. Fuzzy search allows for partial matches, providing relevance scores for each paper within each keyword category.

Scoring Papers: We then scored each paper—based on its title and abstract—by implementing a fuzzy search over sets of representative keywords for each of the components of interest: User, Adaptive, and Visualization (Table 1). This approach ensured a nuanced assessment of paper relevance. To identify highly relevant papers, we established two threshold criteria. Firstly, papers were selected if they achieved a score greater than or equal to 90 for each category. This initial criterion resulted in a subset of 157 papers. Secondly, we selected papers with a visualization-related score of 95 or higher, coupled with a score of 95 or higher in at least one other keyword category. This less stringent criterion produced a subset of 858 papers. We united the two subsets, yielding a combined set of 886 papers. These thresholds were defined considering the trade-off between the relevance and the diversity of the papers selected.

Manual Review: To further refine the corpus, the first author reviewed the titles and abstracts of this subset of papers after discussing 10% of them at random with the senior author for calibration to help identify specific guidelines to evaluate the remaining 90%". The ones that were irrelevant (e.g., topics unrelated to information visualization nor user-focused) were excluded at this stage. Following the initial review, 238 candidates for relevant papers remained, with the potential to be within our scope.

3.3. Categorizing Papers

We employed a structured process for organizing and analyzing the literature using computer-assisted qualitative and mixed methods data software, the MAXQDA 2022 [VER21]. This methodology involved several key steps. Initially, we uploaded the documents into the software program to facilitate systematic analysis. We adopted an open-coding method, which served as our primary tool for reviewing the literature.

During the open coding phase, we freely assigned labels to various aspects of user-adaptive visualizations. This initial coding phase enabled us to gain a deeper understanding of common themes and patterns within the literature. It was an iterative process, permitting us to extend, refine, and merge codes into coherent groups.

The first author and one of the senior authors thoroughly examined each of the 238 candidate papers' content independently. In cases where the two authors held differing opinions on the coding of certain papers, they engaged in discussions to resolve discrepancies and reach a consensus on the final selection. Papers deemed relevant were tagged for inclusion in this STAR paper. The final subset comprised 91 papers. These systematic steps were instrumental in constructing a comprehensive and representative final corpus of papers, ensuring that the ensuing literature review provides a thorough insight into the field of user-adaptive visualizations, as detailed in the previous subsection.

The ultimate outcome of this comprehensive coding process was the categorization of the data flow in user-adaptive visualizations into five main components with sub-categories as shown in Figure 1. Notably, three of these components, namely input, user representation, and intervention, were identified as inputs and outputs, while the remaining two, user modeling and adaptation assignment, were recognized as integral processes within the system.

The categorization of the papers in our final corpus that englobe the five components is reflected in Table 3, whereas the ones that only focus on the first three are reflected in Table 4.

Additionally, we conducted a separate coding for evaluation metrics and methods employed in our corpus of relevant papers. We classified the metrics into qualitative (i.e., system feedback, intervention feedback, self-reflecting user feedback, and user experience) or quantitative (user performance, eye-tracking, provenance-based, and cognitive load). On the other hand, we identified different evaluation methods, such as empirical user studies, case studies, use cases, and synthetic-user evaluation.

4. Overview of User-Adaptive Visualization Components

The primary contribution of this paper is a clear description of the components of user-adaptive visualizations, taxonomies to categorize the input, user representation, and intervention, as well as an overview of the different user modeling and adaptation assignment processes used in such context. We group the literature into which components of user-adaptive visualizations they cover, namely: the **input** that is captured by the system, the **user modeling** approach employed, the **user representation** that is leveraged to guide the adaptation of the visualization, the **adaptation assignment** method used to translate the user representation into a visual adaptation, and the **intervention** made to adapt the visualization to the user, as shown in Figure 1.

Ⓐ The **input** captured by the system about the information around the user. This input can take many forms: user activity information that is gathered while engaging with the visualization, such as biometric data (e.g., eye gaze or heart rate) or system interaction (e.g., clicking, dragging, or answering questions); user declarations as answers to specific questions, such as questionnaires, psychological tests, or ratings; contextual information about the environment in which the interaction takes place, such as the time of day, or the device being used; and pre-existing user information, such as insights from social media.

Ⓑ The **user modeling** approach used by the system. This refers to how the input is processed to create the model of the user. Some examples include ready-made formulas that translate user input into a different representation of the user, and inference or learning models.

Ⓒ The **user representation** are the set of properties and user states that are modeled aiming to drive adaptation, such as personality traits, cognitive abilities, experience and biases, cognitive states, analysis goals, and demographics.

Ⓓ The **adaptation assignment** method used to translate the user representation into a visual adaptation. This can involve a variety of techniques, such as expert knowledge hard-coded in the method, and data-driven algorithms.

Ⓔ The **intervention** is employed to adapt the visualization to the user. This can take many forms, such as highlighting certain data points, changing the visual encoding of the data, or providing additional information or guidance to the user.

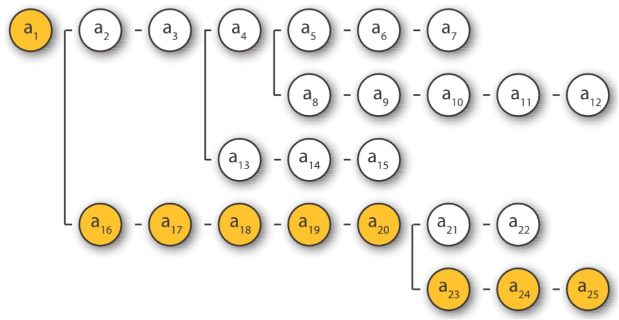

Figure 3: *Representation of the logical structure of the user's interaction with the visualization. The highlighted path represents the user's current line of inquiry [GW09].*

5. Ⓐ Input

The first component of user-adaptive visualizations is the input gathered from the user and the session. This could be either the first time interacting with the visualization system or after one or more interventions. This is then leveraged to generate a virtual representation of the user. This has historically presented a challenge due to the difficulty of capturing and analyzing information about the user and their environment [CNS05]. However, technological advances have opened up novel ways of sensing and tracking cognitive traits, physiological data, interaction patterns, and peripheral information on their environment, such as device type or time of day. As a result, some posit that adaptive visualization systems can provide more customized interventions and recommendations [XOW*20, Ott20]. We characterize the captured data into three types: *user activity*, *contextual information*, and *pre-existing user information*.

5.1. User Activity

User activity input is any information collected from observing the user during their session engaging with the visualization system, whether through interactions with the system, through sensors that capture biometric data, or user declarations provided by the user.

5.1.1. System Interactions

This refers to the information the user provides by interacting directly with the system. Examples of this data type include mouse movements and clicks [CH07, BOZ*14, OYC15, OCZC15, BGV16, VH16, CLRT20], keyboard input, menu selections, or other actions such as explicitly capturing user's analysis goals [BGV16]. Figure 3 shows a representation of the logical structure of the user's interaction with the visualization system [GW09].

User interactions have been proven useful to infer several user characteristics such as analysis goals, cognitive abilities, and preferences. In a study about predicting the user's analysis goals to perform directing interventions, Gotz and Wen [GW09] leveraged user interaction—or provenance—logs as implicit signals of the user's intent. They named their approach *Behavior-Driven Visualization Recommendation*, which extracts behavior patterns from sequences of user actions (e.g., queries, filters, or bookmarks) to drive the recommendation. Other interaction data (e.g., click rate, time to first click) was found relevant to predict a user's cognitive abilities at the beginning of the task, in contrast with eye-tracking data [CLRT20]. This result confirmed the possibility of relying on interaction data when it is not possible to gather biometric data, or it is possible but there is a need for an adaptation experience at the start of the visual analysis. Other work has relied on selections among visualization alternatives to predict the user preferences for the following tasks [Gra06, ML12]. In other fields (i.e., interactive interfaces, cognitive tutors), this input has been recorded to predict different user characteristics such as knowledge [CA95], learning [KC12], task performance [CMN80], or emotions [BGW*12].

System interaction data is highly reliable as it is readily available and not susceptible to external noise-generating factors, which represents advantages over biometric data which needs external sensors and is prone to noise (e.g., head movements, glasses) [CLRT20]. It can also support the calculation of implicit metrics such as provenance, the reading time of a specific text or prompt, or the response time when solving a problem or answering a question [ZK09]. On the other hand, this type of user activity input is not available in non-interactive visualization systems and it cannot capture the user's perceptual processes [CLRT20]. Even more, they require the user to actively engage with the visualization. This may not be feasible or even desired in circumstances where the visualization experience is expected to be passive but still with some degree of adaptation.

5.1.2. Biometric Data

This refers to information about the user's physical or physiological state. The visualization literature has captured several types of biometric data, including heart rate, respiratory rate, and skin conductance [CH09, PBC18], as well as facial expressions [CWEK15], and brain sensing data (i.e., fNIRS and EEG) [PYO*13, APM*11].

The most prominent biometric user input for information visualization research is eye-tracking data [SCC13, TCSC13, TSG*14, SCC14, LTCC15, GKG*18, SSV*18, CLRT20, SC20, BLIC21, CLRT20, LTC21, SLH*21, OKCP19], which may include the pupil and head distance data, in addition to the eye gaze information. Beyond the raw gaze data, some eye-tracking software includes clustering algorithms to determine the areas of the visualization the

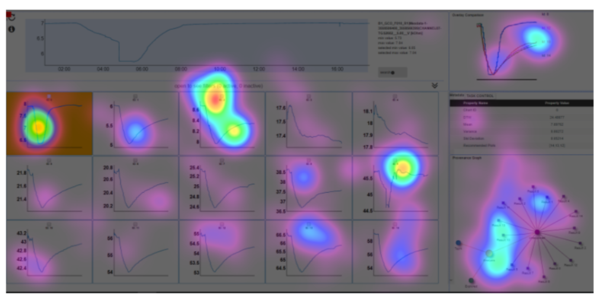

Figure 4: *Example of eye-tracking data as biometric input. The heat map represents fixation areas where the user spent the most time looking at [SSV* 18].*

user focuses on. This type of input is commonly used in visualization [GKG*18, SSV*18, TCC19, CLRT20, BLIC21, LTC21] as it is an indicator of how much of the data the user is processing [Ray09], and can serve as a proxy for the user's analysis goals. For example, Lallé et al. [LTC21] perform interventions according to the user's gaze fixation on specific references in a text. Figure 4 shows an example of how different areas of interest in the visualization are identified to inform the user modeling.

Eye-tracking data has been shown to provide insights into aspects of visual analysis such as success and confusion. In a study investigating user success in visual analysis, Spiller et al. [SLH*21] used eye-tracking data to assess both the effectiveness and efficiency of such predictions by varying the interval size of the gaze data collected. Summary statistics around fixations (i.e., the areas where the user's gaze focuses more) and saccades (i.e., the gaze paths between fixations) have also provided insight into levels of user confusion [LCC16a]. Other work has focused on how user characteristics influence eye gaze patterns in decision-making tasks with maps and deviation charts [LCC17], and analytic tasks with bar and radar charts [TCCH12, TCSC13], as well as with bar and line charts [OGGR16].

The body of work on emotion recognition in HCI often leverages facial recognition as a form of input from the user [CKC08]. This approach was applied to visualization by Cernea et al. [CWEK15], where the authors create standardized visualization of emotions, *emotion prints*, as read by facial expressions.

Among the few examples of collecting brain sensor data in visualization systems, Peck et al. [PYO*13] used fNIRS to evaluate visualizations by measuring the impact of visual design on the brain. They found that fNIRS is an effective input to model brain activity derived exclusively from visual design. Similarly, Anderson et al. [APM*11] were able to leverage EEG measures, along with user response times to visual tasks, to evaluate the burden different visualization techniques have on the users' cognitive resources.

Skin conductance has also been tracked in the context of user-adaptive visualizations, although on a much smaller scale. In a study focused on providing guidance to frustrated users in visual tasks, Panwar et al. [PBC18] measured users' arousal and valance from a combination of a galvanic skin response device and an eye tracker. The authors were able to classify a user's frustration state which then helped inform the interventions.

Biometric data is often captured continuously, with no explicit input from the user required [SLH*21]. As a result, it can provide rich data that captures variations in the user's state throughout the visual analysis process. The level of detail in this type of data supports adaptations to subtle changes in the user that may go undetected in self-reported measures. Additionally, biometric data can often be more objective than self-reported data.

5.1.3. User Declarations

User declaration is the form of input that encompasses explicit information provided directly by the user. It serves as a pivotal source of data that aids in adapting visualizations to align with individual user needs and preferences, especially in the early stages of an adaptive visualization system or when some user characteristics cannot be modeled indirectly through interactions. User declarations are typically self-reported through surveys (e.g. preferences, analysis goal, expertise) or gathered via specialized instruments, such as psychological tests or questionnaires, and encompass a broad spectrum of user-provided information, ranging from demographic details [ADHC*23] to more intricate aspects of the user's characteristics, including personality traits [CCH*14a], cognitive abilities [SCC13, TCSC13, SCC14, CCH*14a], expertise [TCSC13], and prior experiences [CH07, VH16, ADHC*23]. Additionally, users might explicitly state their goals and intentions when interacting with the visualization, specifying what insights they aim to gain or tasks they wish to accomplish.

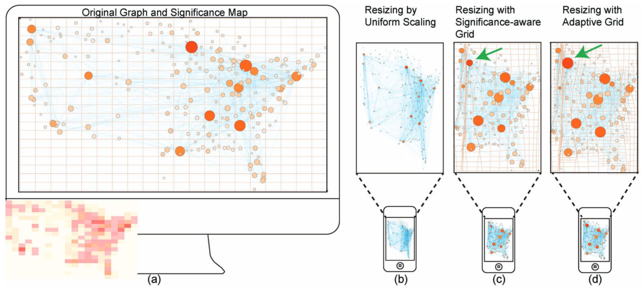

Figure 5: *An example of how the device used to display the visualization serves as contextual information for an intervention. In particular, the intervention reduces the visualization size while updating the design to maintain the significance of the data [WLLM13].*

5.2. Contextual Information

Contextual information refers to user-independent input specific to the situational context of the interaction session, including factors such as device type, operating system, screen size, and location. It can be dynamic between sessions, influencing how the system adapts in real time. For example, a system over a large weather-related dataset [ML12] leverages users' location, season, and time of day to personalize weather-related visualizations. By incorporating these elements, the authors were able to display only the most relevant weather data to the user, thereby improving the user's ability to analyze and interpret the information effectively.

Contextual information is also relevant for responsive visualizations, which can adapt based on the device screen size [DGDLM15]. Figure 5 shows ViSizer, a framework for resizing visualizations while maintaining the significance of the regions by adapting the design to the screen size [WLLM13]. Research that investigates the impact of contextual cues, such as screen size, on visual analysis can provide valuable insight for user-adaptive visualizations. For example, Jakobsen & Hornbæk [JH13] studied the effect of large displays on user interaction and found that the benefits of larger displays may be countered by implementing multi-scale navigation techniques (i.e zooming and focus+context). In another example, Alves et al. [ARG*20] analyzed the effect of wearing glasses/contact lenses during the visualization experience, and they found that neither had a significant effect on the experience.

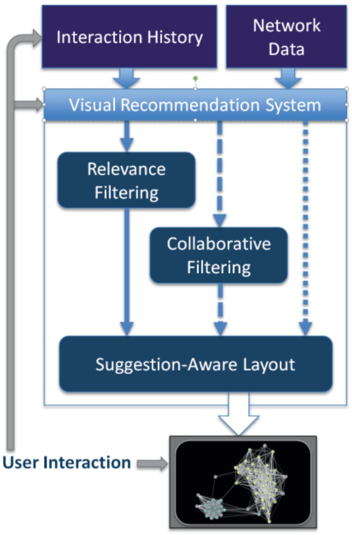

Figure 6: *An example of a workflow for saving user interaction data and leveraging it in future sessions within a network data visualization recommender system [CLWM11].*

5.3. Pre-existing User Information

Pre-existing user information involves input derived from external sources that exist prior to the current session, including user demographics, historical interaction data, social media profiles, and other integrated datasets from outside the immediate system. This input type provides an understanding of the user based on accumulated data over time and from various sources. For example, Mouine & Lapalme [ML12] predicted a user's preferences and needs based on the history of the preferences and interactions of similar users. The authors used clustering to group users who were similar to the current user and then set the visualization variables according to the visualizations of those users. Similarly, Crnovrsanin et al. [CLWM11] developed a visual recommendation system that saves the interaction history of a user for future input to collaborative filtering to help users navigate network data. Figure 6 shows their system's workflow where the user interaction does not only inform the current intervention but also gets stored for recommendations in future sessions.

However, a downside of relying on pre-existing user information is that external information sources may not be maintained regularly and are susceptible to becoming outdated and inaccurate. This paper, among others [Ott20,PYH*12,LCO20], maintains that a person's state, traits, and experience influence their behaviors. Thus, further studies are needed to evaluate the limitations of this data.

Summary and Open Areas

The space of possible input sources is vast, lending to numerous possibilities for what a potential adaptive system can detect. In this section, we categorized this input space into what we can observe from the user, their environment, and historical or demographic data. Much of the existing work in the visualization literature has aimed to collect information that would aid in the understanding of the user and her task, with disproportional attention to learning from mouse and keyboard interactions [XOW*20].

This focus on commonly available input devices has, so far, led to a somewhat narrow set of possibilities for what we can learn from observation. In particular, the community has made impressive strides in developing real-time adaptive systems by analyzing the provenance of data elements and system actions. In other words, the existing methods can track what someone is looking at or paying attention to by observing mouse and keyboard interactions or eye gaze (e.g., [BCS16,OGW19,LTC21]).

In contrast, physiological sensing has great potential for use in a visual analytics setting to learn *what* someone is doing and provide insights into *why*. For example, eye-tracking can help bridge the gap in the future because it can provide information about fixation positions (the *what*), and we can also measure cognitive load (the *why*) using pupillary dilations [Kli10]. Further, prior work already demonstrates how to use eye-graze data in the real-time setting, with Lallé et al. [LTC21] introducing an interface that automatically highlights the visualization elements that correspond to the portion of the text the reader is currently viewing.

However, capturing high-resolution biometric data (e.g., with fNIRS or skin conductance) does not come without challenges.

First, the time and logistics of setting up sensors on or near users for each visual analytics session. Second, biometric sensors are often costly and limited in availability [CLRT20] and must be precisely calibrated to provide valuable data. Eye-tracking, however, can overcome many of these challenges given the recent commercialization of eye-tracking products, and eye movement input is faster than other input devices (e.g., the user has to think about moving the mouse before acting) [Jac93,JK03].

Furthermore, the process of collecting input data, especially in the context of biometrics, can be notably challenging in today's technological landscape. Biometric sensors often necessitate controlled environments that resemble laboratory conditions. This controlled setting is essential to ensure the reliability and accuracy of biometric data, as factors such as ambient light, noise, and user comfort can significantly impact the quality of collected information. Calibration and quality control of input data, particularly within research settings, are paramount concerns. Researchers must meticulously manage and validate data to mitigate inaccuracies and ensure that the collected information is trustworthy, ultimately contributing to the effectiveness of user-adaptive visualization systems.

6. Ⓑ User Modeling

The second component of user-adaptive visualizations is the user modeling technique leveraged to build the user representation. This representation is then used to drive the visualization adaptation.

Explicit User Modeling Techniques involve directly transforming user-provided inputs, such as manually entered data or questionnaire responses, into the user representation.

One such technique that is quite common in user-adaptive visualization research is a declarative approach where a characteristic that will be part of the user representation is collected explicitly from the user through direct input. This one-to-one mapping involves obtaining specific information directly from the user, such as demographics [VHW87, SCC13, TSG*14, SCC14, GKG*18], explicit analysis goals [MZJS18, WMA*16], personal visual preferences [BGV16], and confusion [CHTS13].

Unlike general interaction feedback, this technique specifically entails the user's deliberate input of known characteristics that are then used in the adaptation process. For example, users might explicitly select the variables they want to analyze [WMA*16] or choose the paragraph of text they want to focus on [MZJS18]. These explicit selections can be directly incorporated into the user representation as analysis goals to guide the adaptive behavior of the system, as shown in Figure 7.

The main advantage of this approach is its ease of implementation and interpretation as it directly maps the input to the user representation. This enables the system to perform interventions based on explicit and accurate data, with no inference, learning, or scores being calculated. This method allows researchers to gather data that could otherwise be hard to calculate, learn, or infer with more sophisticated models. For instance, determining the age and gender of a user, or their color-scheme preference, based solely on their behavior during the visualization task is highly non-trivial.

This mapping presents a challenge when attempting to gather more intricate data about the user. This includes cognitive abilities, inherent biases, and even analysis goals that may change during the visual exploration process. It can be difficult to accurately relate this information to the system, as the user may not be fully aware of their own traits or it may feel invasive to ask for this information during the interaction. Moreover, complex user modeling, such as machine learning, is required to infer and learn how user input can give rise to their characteristics.

The other common explicit technique is questionnaire-based modeling. It is used to infer information about the relevant user's characteristics by asking a set of questions to the user and deriving a user representation from their answers. This differs from aforementioned mapping in that the user does not explicitly provide the information that will be part of the user representation.

In information visualization, the most common custom-made questionnaires are the ones that ask users for their preferences on visual characteristics on a Likert scale [SLC*20]. In one study that examined how user characteristics affect hierarchical relationship understanding, Ziemkiewicz & Kosara [ZK09] asked participants to rate how well certain statements described two hierarchical groups. The participants also ranked visual metaphors. The authors then inferred their verbal metaphor preference by calculating a score for each group. Other questionnaires have been built to assess different user characteristics. For instance, Carenini et al. [CCH*14a] leveraged this method to measure the users' expertise level with simple bar graphs as well as complex ones. However, the authors did not find any significant effect related to these prefetched expertise levels and expressed that there could have been some bias when self-reporting.

On the other hand, questionnaires-based modeling has been extensively leveraged to identify which user characteristics to measure and adapt to [TCCH12] in user-adaptive visualizations. In this regard, a type of user modeling questionnaire that has been widely used is standardized tests from other fields (e.g. psychology), which provide a robust way of assessing different user characteristics. For instance, in one of the first studies on this topic, Conati & Maclaren [CM08] conducted a user study to evaluate whether spatial abilities—tested with the Kit of Reference Tests for Cognitive Factors [EFH76]—and other user characteristics influence the effectiveness of two alternative data visualization techniques. The goal was to ascertain whether these individual user differences may be used as predictors of visualization effectiveness in choosing among the two alternative visualizations for a given task. They showed that the cognitive ability known as perceptual speed can predict which of the two target visualizations is most effective for a given user, suggesting that adapting visualization selection to this trait may improve user experience. Similar user studies have relied on other standardized tests to identify the relevance of specific user characteristics for other possible types of personalization in visualization research. For example, Lee et al. [LKY*19] leveraged a visual aptitude and reasoning test (i.e., Visualization Literacy Test [LKK17]) to study the correlation between visual literacy and different user characteristics. They found that the need for cognition had a positive correlation with the user's visual literacy, indicating that users who enjoy cognitive endeavors are likely to be good at reading and interpreting data visualizations.

Once the relevance of specific user characteristics that can be assessed via standardized tests has been established, a user-adaptive visualization could be designed by making each new user (i.e., a user with partial or no user representation modeled by the system) take the corresponding test and build the user representation from this input. However, subjecting users to the added onus of filling out questionnaires might not always be possible or desirable. Additionally, modeling a user representation from questionnaires must contend with the biases associated with any self-reported user information [CCH*14b]. Thus, researchers have looked at inferring the relevant user characteristics from less explicit types of inputs via machine learning, as we discuss in the next subsection. In this case, the user representation created by the questionnaire is used as ground truth labels to train the machine learning models (e.g., [SCC13]).

Implicit User Modeling Techniques involve the process of inferring user characteristics by analyzing observed behaviors and interactions with the visualization system. The most common approach is through machine learning models that leverage labeled data (i.e., supervised learning) or unlabeled data (i.e., unsupervised learning) to train and make predictions on new, unseen users. In the context of user-adaptive visualizations, the objective is to use existing data to train models that can infer the characteristics that will be part of the user representation from input information (i.e., user activity, contextual information, pre-existing user information, or a combination of them) [XOW*20].

There are several types of machine learning algorithms, each of which differs in terms of the mathematical approach they employ to solve the problem. The ones that have been applied the most in the context of user-adaptive visualization systems are regression algorithms, classification algorithms, clustering algorithms, and nat-

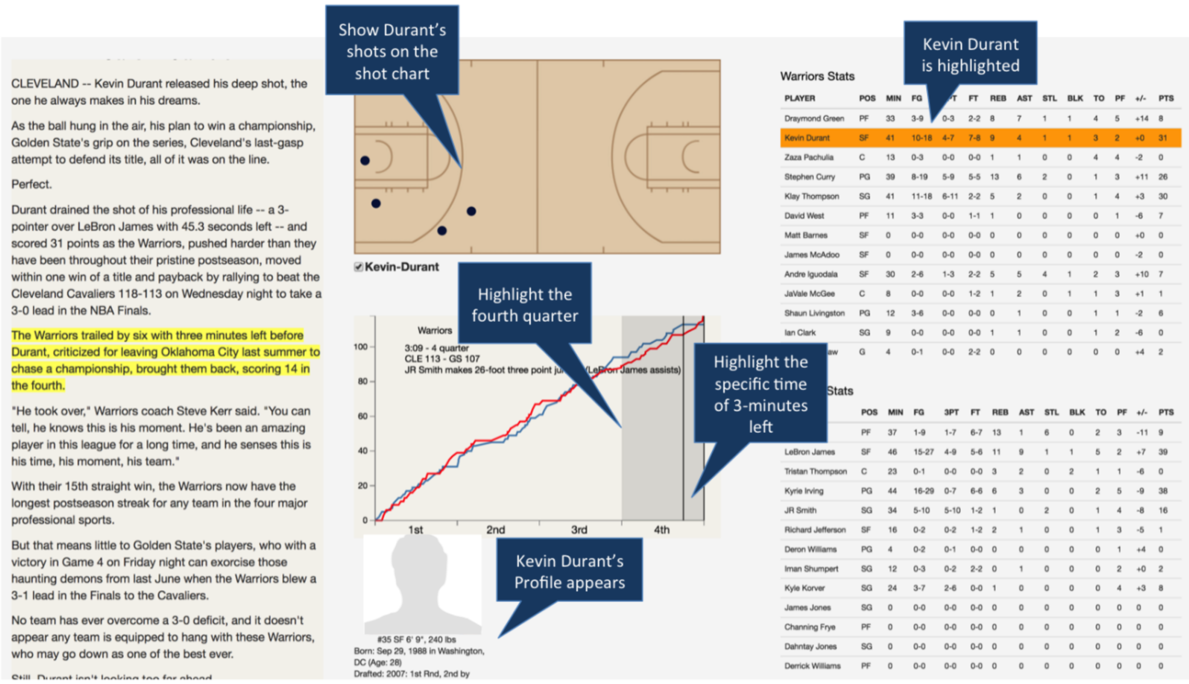

Figure 7: *Example of one-to-one mapping of the user's analysis goal directly from their interaction with the system by selecting the paragraph they want visual assistance for. The system extracts the relevant data from the text and performs an intervention to the visualizations [MZJS18].*

ural language processing. Regression algorithms rely on supervised learning to predict continuous output, aiming to model a mathematical function from an observed pair of input and output. Applied in the user-adaptive visualization context, they can predict user characteristics that are measured on a continuum numerical range from input data.

In a visualization study about predicting the user's learning curve measured by the response time, Lallé et al. [LTCC15] implemented stepwise linear regression models with eye-tracking data and long-term user characteristics such as locus of control as input. The authors affirm that being able to fit learning curves is especially relevant for user-adaptive visualizations because they model the user's initial expertise and their learning speed, two user characteristics that can be very informative when choosing the interventions to improve users' engagement and performance.

When creating a user representation to drive adaptation, regression algorithms are best suited when a finer granularity of the user characteristic being modeled is needed or beneficial to inform the personalization. However, the finer-grained the prediction, the harder it is from a machine-learning standpoint because it requires larger amounts of training data. Sometimes it may be sufficient to model the target user characteristics based on discreet categories derived from the original continuous values. For instance, most of the user studies to ascertain the impact of user characteristics that we described in the previous subsection managed to detect an impact for characteristics that were binarized based on the median split of standardized test results (e.g., [SCC13, SCC14, CLRT20]), suggesting that it is sufficient to represent these characteristics categorically in the user models.

A supervised machine learning user modeling able to predict user characteristics as categorical values is a classification algorithm. Work in user-adaptive visualizations has successfully leveraged traditional machine learning models such as logistic regression, decision trees, and random forests for these classification tasks. For instance, logistic regression proved to be the winning classifier to predict users' high and low levels of cognitive abilities such as perceptual speed and visual working memory from user gaze data [SCC13, SCC14, GC15] in visualization studies involving users working with bar graphs.

Random forest proved to be the winning classifier in predicting users' confusion from both user actions and eye gaze when interacting with a ValueChart visualization [LCC16a], frustration from the user's eye-tracking data as well as skin conductance information when interacting with a visualization tool for scatter plots [PBC18], and learning curves from eye-tracking data when performing visual tasks over Bar Charts and ValueCharts [LCC16b]. Furthermore, Conati et al. [CLRT20] showed that a random forest user modeling approach could predict visual working memory from eye gaze data, as well as perceptual speed from a combination of interactions and eye-tracking, during visualization processing of deviation charts and maps. In all the studies above, several classifiers were compared to identify the most accurate, and although the random forest was the winner in many of the studies, trying multiple classifiers is still the recommended approach because we still do not have

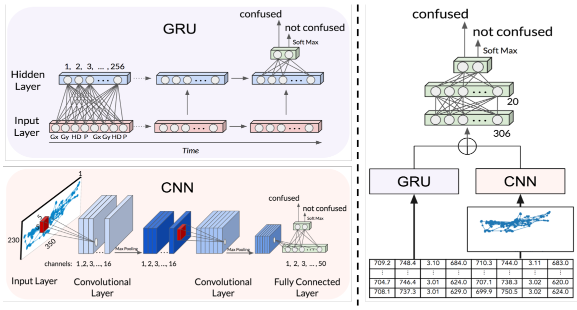

Figure 8: *Examples of neural network architectures as a machine learning user modeling method that binary classifies the user's confusion during the visualization task [SC20]. **(Left)** GRU and CNN architectures. **(Right)** VTNet architecture.*

enough results to generalize how input data, visualization, and task type might influence classifier performance.

There are also recent results on using deep learning models to classify user characteristics relevant to user-adaptive visualizations. This work is still limited because deep learning models usually require vast amounts of training data, usually unavailable in this domain, especially when looking at specialized input sources such as eye-tracking data. However, by using various data-augmentation techniques suitable for increasing the size of eye-tracking datasets, Sims and Conati [SC20] successfully used a deep learning model to improve the accuracy of classifying user confusion achieved in [LCC16a]. Their model is a visuospatial-temporal network (VTNet) (Figure 8) that combines a convolutional and a recurrent network to process raw gaze data both temporally and visually. Another work aiming to predict users' visual search task success from eye gaze data implemented MLSTM-FCN (Multivariate Long Short Term Memory Fully Convolutional Network) to analyze time series data from interactions with visualization systems [SLH*21]. Given that this neural network architecture analyzes time series, their dataset consisted of eye gaze data points with a frequency of 60 Hz. Moreover, the authors used full-length sequences to train the network and compared the results with sequences of shorter lengths, thus increasing the total training set. Classification algorithms are appropriate for constructing the user representation when the data on the dependent variable (i.e., the user characteristic being modeled) is categorically labeled with ground truth values. Getting these ground truth values, however, can be challenging, for instance when we want to predict short-term user states such as emotions or cognitive load, that evolve in real-time during visualization processing. An alternative is to look at unsupervised machine learning algorithms, which do not need labeled data. One such class of algorithms is clustering, which groups data points based on similarity metrics. Clustering has been used to model the user's visualization preference based on their interactions with the visualization system [ML12]. In this work, the authors vectorized the known users' input (i.e., the visual preference and contextual information) and implemented a k-means clustering algorithm, categorizing every system user into k groups. Based on the little information known, new users were classified based on their similarity to pre-established groups, allowing the visualization system to leverage information about the group's preferences and provide better interventions from the start. However, clustering algorithms also have caveats. For instance, this approach is sensitive to the choice of how many clusters there will be and, at the same time, the system may not have enough information to understand the similarities that explain the clustering if it lacks labels.

User-adaptive visualizations have also leveraged natural language processing (NLP) to extract insights. For example, Guesmi et al. [GSC*23] inferred user interest models from research publications, employing different techniques for keyphrase extraction and shedding light on users' research interests. Ahn et al. [ABH15] employed NLP methods over explicit user mention of important text fragments to calculate keyword scores and construct task models, revealing immediate user goals. Gou et al [GMHZ13] analyze tweets, inferring users' Big Five personality traits and offering insights into personality-driven interactions with visualizations.

While certain machine learning techniques like regression analysis and classification algorithms (e.g., random forests [LCC16a, CLRT17, PBC18], support vector machines [BOZ*14]) have been extensively explored for modeling user characteristics in user-adaptive visualizations, there exists a subset of methodologies that, albeit less researched within this domain, offer intriguing avenues for user modeling. Notably, some studies have ventured into employing machine learning algorithms such as neural networks [SC20, SLMK18, SLH*21], probabilistic generative models [GGLBY16, ZFF22], Markov chains [WBFE17], and recommendation algorithms [JTV18] to capture and represent user characteristics. Although less prevalent, these approaches introduce diverse and promising perspectives on user modeling in the context of user-adaptive visualizations. They warrant attention and further investigation as they may hold untapped potential for enhancing the adaptability and personalization of visualization systems.

Summary and Open Areas

In general, the decision of which user modeling technique to adopt should be based on assessing which method provides the most reliable representation of the user characteristics that need to be captured while minimizing the user effort in providing the necessary input.

For instance, for long-term user characteristics that do not change during the interaction and that are easy for users to self-assess (e.g. demographics, preferences), it might make sense to leverage one-to-one mapping or well-established standardized tests for more complex characteristics when they are available (e.g. for personality traits). Although this approach requires some effort on the user's end to explicitly provide the necessary input before starting to work with the target visualization, this must happen only once with the advantage of deriving representations that tend to be rather accurate. Still, there might be situations in which getting the input explicitly from the user upfront is not feasible, for instance, in the case of a walk-up-and-use system (as discussed in [CLRT20]) where it might not be realistic to ask users to spend additional time volunteering information. In this case, it is worthwhile investigating alternative data-driven approaches that can infer the relevant user characteristics from implicit input (e.g. interactions, eye-tracking data, etc.) [GC15, PBC18].

Considering data-driven approaches is even more important if the user traits to be modeled are short-term states that change during the interaction with a visualization, such as cognitive load and analysis goals because deriving these states from the methods that involve explicit user input (i.e., one-to-one mapping or questionnaires) requires interrupting the user during the interaction, which can be intrusive and unreliable. On the other hand, building accurate data-driven models for short-term states is also challenging because they need suitable training data. Hence, one important open area of research in this context is to investigate further the relative suitability of data-driven versus explicit-input approaches for different short-term states and a variety of visualization contexts.

It would be interesting to explore cognitive modeling techniques for user modeling, especially those that rely on having a computational model of the knowledge and skills that are needed to process a given visualization effectively. Such techniques allow inferring from observable user behaviors which knowledge and skills the user has mastered or is missing, and they have been successfully used to drive adaptive interventions in applications such as Intelligent Tutoring Systems (e.g., [Woo09]). One main advantage of these cognitive modeling approaches is that they are highly interpretable, unlike most data-driven approaches, meaning it is easier to show the user the rationale underlying the system's predictions (e.g. [BKA*18]). This is important to address the lack of comprehensibility, one of the possible drawbacks of user-adaptive interaction [Jam07].

7. © User Representation

A user representation describes the set of user characteristics the system has of a particular user [DG94]. This information is described in the form of user characteristics, usually called individual differences [VHW87]. In this paper, we categorize them into long-term characteristics (e.g., personality traits, cognitive abilities, experience/bias, demographics), and short-term ones (e.g., cognitive states, analysis goals). The former represents information about the user that is stable, at least for the duration of the session interacting with the visualization system, whereas the latter describes characteristics that are likely to change within any one session. It is important to note that these categories are not mutually exclusive and can exhibit correlations. For example, low working memory capacity—a cognitive ability—can be correlated with higher levels of cognitive load—a cognitive state—, influencing how a user interacts with the visualization system.

7.1. Long-Term Characteristics

When considering long-term characteristics (i.e., those not expected to change during the analysis session) user-adaptive visualizations only need to capture and integrate them once.

7.1.1. Personality Traits

Personality traits are the user characteristics regarding thinking and behaving [All37]. The two most common personality traits studied in the context of user-adaptive visualizations are *locus of control* [COSM20, GF10, ZCY*11] and *need for cognition* [LCT19, CM08]. Additionally, two personality traits from the Five-Factor Model [MJ92] (i.e., extraversion, neuroticism, openness, conscientiousness, and agreeableness) have been shown to have an effect on visual analysis (e.g., [GF10, ZOC*13, BOZ*14]). Lastly, conscientiousness was studied by Alves et al. [ADHC*23] and its role in visualization-supported decision-making.

Locus of control measures the degree to which the user perceives outcomes due to their own behavior or external forces [Rot66]. While this characteristic is usually measured on a continuous scale, visualization researchers often discretize it into categories to better understand trends. The most common way to classify the spectrum is in either *external* (i.e., low) or *internal* (i.e., high) locus of control, with the rare addition of a *intermediate* (i.e., medium) class (e.g., [COSM20]).

Locus of control has been studied within the context of visualization research by analyzing its effects on users' interactions with visualizations. Differences in locus of control can have an effect on performance in both data exploration tasks [GF10, ZOC*13, OYC15], and visualization styles [GF10, ZCY*11, ZOC*13].

For data exploration tasks, Ottley et al. [OYC15] found a strong correlation between locus of control and analysis strategies with hierarchical visualizations. In their study, individuals with an external locus of control outperformed those with an internal locus of control when exploring dendrograms. Additionally, the authors found that when the visualization offered guided or restricted exploration, users with an external locus of control were more efficient. Locus of control can also play a role in different levels of visual complexity. Sheidin et al. [SLC*20] found that users with a high locus of control perform better with complex and less familiar visualizations, whereas users with a low locus of control do not. The authors provide clear guidelines for adaptive systems on which interventions to provide based on users' locus of control. They also caution against interventions that switch between visualizations during analysis to avoid cognitive overload. Studies like these provide valuable information for future research in user-adaptive visualizations.

Locus of control has also been investigated in relation to other aspects of visual systems design (e.g., visual encoding, spatial arrangement, and interaction). In work investigating the impact of the layout of hierarchical visualizations, Ziemkiewicz et al. [ZCY*11] found that participants with an external locus of control performed equally well with both implicit and explicit layouts. Conversely, participants with an internal locus of control performed significantly better with implicit and familiar layouts. The authors hypothesize that visualizations with a highly explicit and unfamiliar visual structure may be more overwhelming for an external locus of control user. Someone with an external locus of control may be more willing by nature to adapt her thinking to the external representation. These findings agree with Sheidin et al. [SLC*20] and suggest that adaptive systems can leverage more complex and unfamiliar visualizations for users with high (internal) locus of control.

Need for cognition describes the inclination a user has towards cognitively demanding tasks [LTC21]. Even though this is measured continuously, people's need for cognition is usually assessed as *low* (i.e., prefer tasks with less mental effort) or *high* (i.e., prefer to solve problems that require effortful thinking and enable them to learn new information).

Research in visualization has examined whether user characteristics, such as need for cognition, can help the adaptation assignment process select the most effective visualization for the individual [CM08]. Over two alternative visualizations (radar graph and multiscale dimension visualizer), the authors showed that users' cognition needs were a good predictor of each visualization's effectiveness. If the system detects the user has a low need for cognition, the authors suggest implementing an intervention, such as providing help or clarifications.

This user characteristic has been found to be correlated to other characteristics relevant to visualization research. For example, Lee et al. [LKY*19] measured the correlation between different user characteristics related to visualization (i.e., visual literacy, numeracy, need for cognition, and visualizer-verbalizer cognitive ability). The participants' visual task involved answering questions based on different information visualization techniques (i.e., bar chart and stacked area chart). The authors found that there is a positive correlation between the user's need for cognition and their visual literacy.

The Five Factor Model has been analyzed in many visualization research studies by measuring their correlation with different aspects of visualization tasks. However, only two of these factors have been found to be relevant in such analyses: *Neuroticism* and *Extraversion*. Neuroticism captures how prone the user is to experience negative emotions. Extraversion is the degree to which the user is assertive, sociable, and outgoing. Both have been found to be good predictors of task efficiency [GF10] and task accuracy [ZOC*13]. For instance, Green & Fisher [GF10] found that those who are highly neurotic or extraverted tend to be more adept at manipulating interfaces and identifying targets. Additionally, research has shown that it is possible to predict these two factors based on users' interactions with the visualizations, with up to 95% accuracy [BOZ*14].

7.1.2. Cognitive Abilities

Cognitive abilities are the characteristics of the user's cognitive process that influence how the user understands and processes information. As long-term traits, these remain constant during the interaction with a visualization system.

Perceptual speed describes how quickly a person can accurately compare similarities and differences of objects [Ott20].

In evaluating the effectiveness of visualization based on user characteristics, Conati et al. [CM08] asked users to complete multiple visualization tasks using two different types of visualizations. In a comparative numerical task, the authors found a significant correlation between the users' perceptual speed and their performance. There has also been some work aimed at detecting perceptual speed using eye tracking and interactions of the user [CLRT20]. The authors found that perceptual speed could be predicted most accurately with both types of data simultaneously, which they attribute to the number of visual comparisons the user makes. Adaptive visualizations that capture eye gaze can leverage these findings to infer perceptual speed and make appropriate interventions.

Visual working memory describes the ability to remember an object's orientation, configuration, and location [Ott20].

A number of researchers have attempted to predict cognitive abilities—including visual working memory—from eye-gaze patterns to inform future research on adaptive visualization designs. For instance, Steichen et al. [SCC13] were able to predict visual working memory with 58.92% accuracy. According to Steichen et al. [SCC13], visual working memory is inversely proportional to the time to first fixation, meaning users with high visual working memory scan different visual areas quickly. A different study, also aimed at detecting cognitive abilities based on eye-tracking data and user interactions [CLRT20], suggests that eye-gaze data alone is more accurate than interaction data or a combination of both in predicting visual working memory.

This characteristic has also been studied in accordance with the user's ability to process a given visualization. Conati et al. [CCTL15] performed a study where the users had to do diverse visual tasks with bar charts or radar graphs. The authors found that people with low visual working memory struggled with understanding the use of certain characteristics of the visualization system, such as radio buttons and drop-down menus.

Verbal working memory refers to the ability to remember speech-related information [Ott20], and it is measured by the quantity of verbal information that can be temporarily stored and used in working memory [MZJS18].

In a study on the influence of cognitive abilities and personality traits on visual perception, Sheiden et al. [SLC*20] found that users' perception of different visualizations has interaction effects with visual working memory. On domain tasks, users with high verbal working memory were faster than those with low verbal working memory when interacting with stream visualizations. When it came to synoptic tasks, the authors found no effect on verbal working memory and visualization, as every user was faster with the line visualization.

Several different factors, including user characteristics, highlighting interventions, and task complexity, have been examined to determine how gaze behavior is affected while analyzing bar graph visualizations [TC14]. The researchers concluded that users with low verbal working memory took longer than those with high working memory to process some of the textual elements of the graph. They argued that interventions that enhance their ability to process textual information (e.g., questions and legends) related to visual tasks might benefit them.

Spatial ability is the ability to mentally represent and manipulate representations of objects in two or three dimensions [Ott20].

Research in visualization has found a correlation between spatial ability and visual comprehension and a preference for verbal descriptions [OPH*16, MOC21, BWH*23]. Velez et al. [VST05] found a positive correlation between visualization comprehension and spatial abilities. Moreover, they found that the general population exhibits a wide range of spatial abilities, suggesting that visualization designers should consider spatial ability to accommodate audience diversity. Researchers found in a different study that people with higher spatial ability rated all verbal descriptions lower than people with lower spatial ability, suggesting a dichotomy between spatial and verbal thinking [ZK09].

Other cognitive abilities hold potential relevance in this field. These include spatial memory [VST05, CLRT17, TCC18, LC19], visual disembedding [VST05, CM08, TCC18, SLC*20], visual scanning [CLRT17, LC19, CLRT20], reading proficiency [TCC18, LTC21], verbal IQ [TCC18, LTC21], cognitive style [RKB*17, SFN20], color difference perception [Sza18], numeracy ability [MDF12], computational literacy [RMB11], and musical sophistication [JTV18]. While these cognitive attributes have the potential to influence how users engage with visualizations and comprehend complex data, their exploration and incorporation into user-adaptive systems have been comparatively limited in research thus far.

7.1.3. Experience/Bias

Experience describes prior knowledge of a specific task, domain, or visualization. Bias, on the other hand, is the user's preconception based on their experience. They encompass knowledge that may affect the user's behavior when faced with familiar problems.

Expertise is the user's level of proficiency with the visualization or task. It refers to the user's knowledge of specific concepts, their ability to apply the knowledge in practice, or their ability to extrapolate knowledge to new related tasks.

A user's visual expertise affects how they interact with the visualization. Toker et al. [TCSC13] used bar and radar graphs to study user characteristics and gaze behavior. Users with bar expertise tended to access labels more, while users with radar expertise tended to access legends more. According to the authors, these findings are important for developing user-adaptive visualizations because they provide interventions similar to what experts would provide.

There is also a relationship between domain expertise and spatial ability. This type of expertise has also been studied in visualization research. Downing et al. [DMB05] observed a relationship between domain expertise and spatial ability when studying their influence on searching tasks. Even though the analysis didn't show a significant effect between them—which the authors grant to the disproportion of domain experts among their participants—, the results showed that users with high expertise and spatial ability performed best, while those who scored poorly performed worst.

Visual literacy is the ability to read and interpret visual information effectively, efficiently, and confidently [BRBF14].

Studies show a correlation between visual literacy and people's ability to learn unfamiliar visualization [LKK17, PO23] and their self-reported rating for the ease of understanding a given set of visualizations. Visual literacy was also shown to be an influential factor in user-adaptive interventions for magazine-style narrative visualizations. An analysis of eye-tracking-based interventions (i.e., highlights) for comprehension tasks revealed that low visual literacy users most benefited from them [LTC21]. The authors suggest user-adaptive interventions can mitigate potential disadvantages as low visual literacy users achieved higher accuracy on the task when they received interventions—while maintaining the same overall time—compared to high visual literacy users. Building on these results, Barral et al. [BLIC21] studied gaze behaviors generated by adaptive interventions in the context of users' visual literacy levels. As a result of these highlighting interventions, the authors found that users with low visual literacy could better comprehend the visualization by concentrating on relevant regions.

Cognitive bias is defined as the errors in judgment or the irrational behavior that may come from automatic heuristic strategies in the decision-making process [Ell18]. It is well known that visualization plays an increasingly important role in decision-making. Therefore, the study of cognitive bias in user-adaptive visualizations is especially important since it may assist in mitigating adverse outcomes.

In a study to identify cognitive biases from the user's sequential decision-making during the analysis task, Wall et al. [WBFE17] observed and measured users' bias manifestations. The authors argue that bias detection can be used to mitigate negative effects during visualization tasks, a valuable resource for future user-adaptive visualization studies.

Other factors within the Experience/Bias category that have garnered relatively less research focus thus far. These include characteristics such as learning learning curve [Sin07, TSG*14, LTCC15], style [CM08], and political view [GGLBY16]. These lesser-studied aspects pertain to individual predispositions, attitudes, and learning patterns that can shape the user's interaction with visualizations. While these factors may not have been extensively explored in the context of user-adaptive visualizations, they offer intriguing avenues for further investigation into user behavior and preferences in this domain.

7.1.4. Demographics

Demographics are users' characteristics not related to their cognitive process, personality, or experience (e.g., age, gender, educational level, cultural background).

A gender-related pattern of visual preferences has been observed in visualization research. A study examined how users internalized visual metaphors (similar to verbal metaphors) based on their preconceived information structures and user characteristics, such as demographics [ZK09]. Despite the lack of a strong correlation between self-reported visual preference and performance, such a relationship still showed a strong gender effect.

Studies on adapting digital documents and images for color-deficient people will benefit user-adaptive visualizations. According to previous work, documents can be tailored to color-blind viewers using optimization methods [JH06]. In contrast, another study demonstrates that their algorithm allows users to interact with one variable—defined as color correction—to compute various color adaptations [JH07].

7.1.5. Visual Preferences

Visual preferences are the user's likes and dislikes related to visualization styles, layouts, or interactions.

Visual preferences are related to personality traits in the context of information visualization. It was previously shown that personality traits (e.g., the Five Factor Model and locus of control) correlate with preferences for idioms (i.e., different types of charts) within a variety of visualization contexts (i.e., hierarchy, evolution over time, and comparison) [ARG*20]. According to the authors, neuroticism, openness, and agreeableness have a correlation with user preferences for different idioms, such as horizontal bar charts. These results shine a light on the possibility of inferring user preferences by understanding other user characteristics and thus informing the intervention in a user-adaptive visualization system.

7.2. Short-Term Characteristics

7.2.1. Cognitive States

As opposed to cognitive abilities, cognitive states are the characteristics of the user's cognitive process that are more temporary. They can be influenced by external factors and change over time. In particular, they may change during the interaction with a visualization system. Even though cognitive states are volatile and hard to measure, they provide additional information about user performance that cannot be gathered from cognitive abilities [Ott20].

Cognitive Load is the amount of cognitive resources needed to perform a given task, and it's sometimes referred to as memory demand [HEH09].

The effectiveness of visualization has been measured by cognitive load. For example, Peck et al. [PYO*13] conducted a study using Functional Near-Infrared Spectroscopy (fNIRS) to compare the level of difficulty in interpreting bar charts and pie charts. They found that the performance depended on the individual. The study revealed that around half of the participants showed brain activity indicating that interpreting bar charts was more mentally demanding, whereas the other half showed the opposite results. Similarly, Anderson et al. [APM*11] analyze Electroencephalogram (EEG) data as users interacted with multiple visualization types. By objectively measuring the difficulty of different visualizations, they could determine which visualization was the most difficult. Figure 9 shows their experimental workflow that transforms EEG data into a single cognitive load time series for each sensor, which is then spatially combined to derive the overall cognitive load for the trial. User-adaptive visualizations could use this framework to choose various interventions depending on user cognitive load in real-time.

Contextual information input is also relevant for responsive visualizations, which can adapt based on the device screen size [DGDLM15]. Figure 5 shows ViSizer, a framework for resizing visualizations while maintaining the significance of the regions by adapting the design to the screen size [WLLM13].

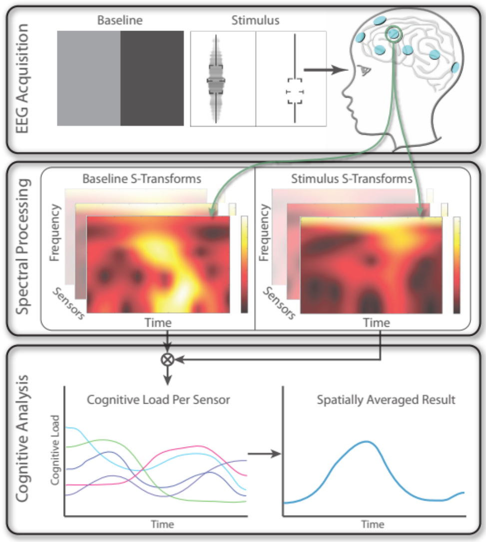

Figure 9: *Example of the workflow to transform EEG signals into an estimation of the cognitive load for a user during a visual analytic experiment [APM*11].*

Confusion refers to the user's lack of understanding. This characteristic has been found to hinder the user experience with information visualization, especially when the visualizations increase in complexity [LKH*16].

Several studies have invested their efforts in predicting confusion from eye-tracking data to inform future research in user-adaptive visualizations. Conati et al. [CHTS13] ran a user study to collect eye-tracking data from users interacting with ValueCharts, and self-reporting when they were confused during the analysis task. This data was then leveraged by Lallé et al. [LCC16a], who built a classifier to predict confusion in real-time from the user's eye-gaze data. Sims & Conati [SC20] were able to improve upon the previous work and more accurately predict users' confusion from their eye-tracking data when interacting with ValueCharts.

Other short-term characteristics within user-adaptive visualization research, cognitive load, and confusion have rightfully occupied a central place. However, it is important to acknowledge the presence of other cognitive states that have received relatively less attention in research but hold significance in understanding user behavior during visualization interactions. These underexplored cognitive states encompass frustration [PBC18], confidence [SLMK18], and attention [Sin07, WLMB*14, AAGP23]. Investigating these additional cognitive states could offer a more comprehensive understanding of user experiences and interaction dynamics in user-adaptive visualizations.

7.2.2. Analysis Goals

Analysis goals are tasks or specific objectives the user aims to accomplish using visualization (e.g., exploring data, finding patterns) [BM13]. Knowing these will facilitate the selection of the interventions for the user's needs.

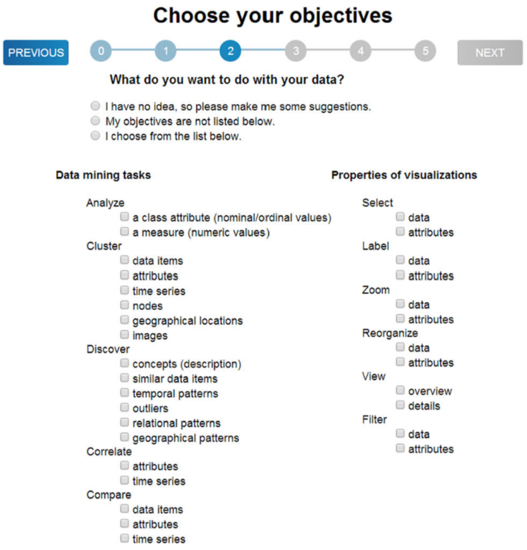

Figure 10: *Example of explicit analysis goals in VizAssist. The user selects their intent with the data, the tasks they aim to perform, and any wanted properties for the visualizations [BGV16].*

Research has been conducted to gain insights into the user's analysis goals either implicitly or explicitly. For example, Lallé et al. [LTC21] determined the analysis goal from the user's fixation on specific sentences in a text. According to a *post-hoc* survey of their participants, this technique provided personalized interventions based on their gaze fixations about 90% of the time. Additionally, Bouali et al. [BGV16] focused on guiding users to find visualizations relevant to their visualization task, based on explicit objectives. Figure 10 shows the questionnaire asking for their intent with the dataset, plus two characteristics of their analysis goals: the type of data mining they will perform, and the visualization properties they might require. With this information, the system selects the right intervention from a subset of possible visualizations.

Summary and Open Areas

There is a substantial body of work in the visualization of the various user representations we can capture and model in a user-adaptive system. In this paper, we have categorized the characteristics into long-term and short-term, motivated by considering the complexity of algorithms needed for practical adaptations. In particular, it may be feasible to use rule-based approaches when adapting to long-term traits, as they will remain unchanged during an analysis session. In contrast, short-term traits will likely evolve, necessitating continuous monitoring and more complex algorithmic solutions.

Still, future work is needed to translate low-level observations of user behavior into user representations, as most of the existing literature uses "pre-existing" sources such as psychological surveys. Accessing the user's personality profile, background, and preference data in some expert scenarios is feasible. However, this information is likely unavailable in most usage scenarios. One possible solution is to develop real-time modeling algorithms that infer user characteristics from interaction observations. For example, Brown et al. [BOZ*14] showed how we might detect user attributes by analyzing their click stream data. Additionally, we have seen increased interest in developing algorithms to model user behavior (e.g., biases [WBFE17, MGO20], attention [OGW19], etc.) and investigating how we can use these techniques to improve visualization tools [BCS16]. We hope that this STAR bridges these two traditionally separate lines of research.

Analysis goals are inextricably linked to tasks. However, there exists multiple taxonomies, typologies, and frameworks to help visualization researchers reason about tasks [RAW*16, GMOB22], ranging from categorizing the low-level interactions that users perform with an interface (e.g., [YaKSJ07, BM13]), to classifying the higher level intents that often drive these interactions (e.g., [LTM17, BH19]).

Although recent attempts have been made to define tasks programmatically [BO24] and understand the relationship between the different proposed task models [GMOB22, GZ09], future work is needed to enable real-time task identification and tracking their evolution.

8. Ⓓ Adaptation Assignment

The adaptation assignment component defines when and how to personalize an intervention based on the user representation. This process must balance the benefits of adapting the visualization with the cognitive overload that can result from dynamic changes to the visual interface [CHTS13]. This section describes the main approaches used to make adaptation assignments in visualization research.

Expert knowledge defines the criteria that drive the adaptation decisions.

Expert rules are best suited for adaptation assignment processes based on the results of prior studies investigating the relationship between user characteristics and visualization choices. For example, Lallé et al. [LTC21] leverage prior work on the importance of cuing to help users process multimodal documents that combine text and graphics (e.g., see [CAS*18, MZJS18, RM15]) to devise a system that highlights specific parts of graphs in a magazine-style narrative visualization based on which part of the accompanying text the user is reading.

An implementation of expert knowledge to generate an effective visualization technique design is shown in VISTA [SI92] and can be leveraged in the user-adaptive context. When representing a wide range of magnitudes in a vector field, they used prior knowledge to inform that the arrows should indicate only the direction of a vector while letting characteristics like color and thickness indicate their magnitudes. Senay & Ignatius [SI92, SI94] leverage such knowledge to build composition rules, which are a set of conditions to combine different pairs of visualization techniques to display several data variables at once, as shown in Figure 11.

Data-driven algorithms leverage data to build mathematical models that will inform the adaptation assignment process.

For instance, classification algorithms can predict interventions as categorical output by leveraging the user representation along with the data and its properties. For example, Metoyer et al. [MZJS18] trained support vector machine classifiers based on the user's analysis goal to extract the four key narrative elements (i.e., who, what, when, and where) from news text. Then, the system transformed such information into graphics to show to the user as in Figure 7.

Boulai et al [BGV16] experimented with genetic algorithms to drive the adaptation decisions in user-adaptive visualizations. Genetic algorithms have been used to generate suitable visualizations in non-user-adaptive contexts [VSMAdB97, BP05, CBL12]. In this case, a genetic algorithm starts from a vector encoding of relevant visualization properties and generates a set (population) of possible solutions. A population is evaluated first based on predefined fitness criteria (e.g. suitability for data representation, ease of use), and the top-performing individuals are combined while introducing small random changes. This process continues until the visualization is satisfactory or a stopping criterion is met. VizAssist [BGV16] employs a variant of this approach called an interactive genetic algorithm where the fitness criteria include the user's preference over visualization properties, which allows the algorithm to evaluate visualizations to produce a new population. Then, the top-ranked ones are shown in Figure 12. This algorithm enhanced users' task performance, compared with a trial-and-error alternative where users manually adjust the interface's settings. However, the authors found that it doesn't improve their efficiency, as users spent a similar amount of time with both interfaces.

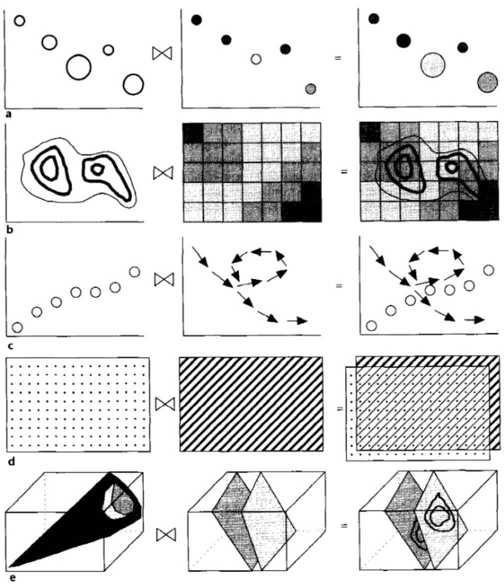

Figure 11: *Example of expert knowledge as composition rules to render new visualizations. In each row, the first two graphs on the left are the components for the composition, whereas the ones on the right result from applying the rules [SI94].*

Summary and Open Areas

Adaptation assignment approaches can broadly be categorized as either knowledge-based expert rules or data-driven algorithms. Knowledge-based rules have the advantage of being more interpretable and transparent. This type of approach is best suited for systems that build on the results of prior studies on the relationship between user characteristics and visualization choices.

On the other hand, data-driven algorithms are more scalable and can provide adaptations to more nuanced changes in the user representation. For example, a data-driven algorithm can respond to small changes in cognitive load, using mathematical models to calibrate the appropriate interventions.

The adaptation assignment component of user-adaptive visualizations is arguably the least researched area of the five components. As a result, there are plenty of possibilities for future work in this area. A particularly relevant direction for future work is using reinforcement learning algorithms for the adaptation assignment process. These algorithms must balance two distinct trade-offs: (1) deciding whether to adapt at any given moment and (2) exploiting specific interventions versus exploring new possibilities. Reinforcement learning has already been used in the field of adaptive user interfaces, such as for intervention planning [TBLO21], and to improve users' initial interaction with the system [ZWAD21]. User-adaptive visualizations can leverage these findings by utilizing user representations to train reinforcement learning models.

Another area where future work would be beneficial is combining expert rules and data-driven algorithms for adaptation assignment. Empirical data collected during studies can provide a valuable dataset of user representations, their interaction histories, and their performance and preference for specific visualizations. Data-driven algorithms can then be employed to extract rules and heuristics from this rich dataset. This approach leverages the implicit knowledge contained in prior studies and captures them in the form of rules and heuristics that can be modified as needed by experts.

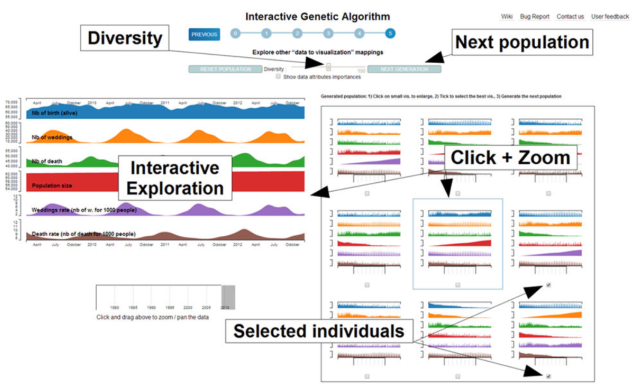

Figure 12: *Example of a data-driven approach to determining the intervention by implementing an interactive genetic algorithm based on user preference [BGV16].*

9. Ⓔ Interventions

The intervention component is the output of the adaptation assignment process and defines the strategies used to deliver personalized support in user-adaptive visualizations. Interventions can be categorized along two dimensions: **(1) the degree of intervention** [CGM*17], and **(2) the type of intervention**. The former determines the level of support provided to the user ensuring that the assistance is appropriately tailored to their needs without causing cognitive overload. The latter describes the method of delivering this support. This section describes the main approaches used to provide interventions in user-adaptive visualization research.

9.1. Intervention Degree

Intervention degree is the level of support provided to the user which could range from a suggestion within the visualization to making direct modifications to it, such as dynamically highlighting bars in a bar chart based on eye-gaze data over corresponding text [LTC21]. We follow the distinction made by Ceneda et al. [CGM*17], where the said degrees can be orienting, directing, or prescribing. Figure 13 shows the decision tree suggested by Ceneda et al. [CGM*18] illustrating the key difference between selecting among these degrees.

9.1.1. Orienting

Orienting entails interventions in the form of hints related to the current visualization. These are visual cues that suggest to the user an action to take next or a possible visualization change that might be helpful based on the user representation.

For instance, in a study dedicated to detect and respond to user frustration by leveraging gaze data and skin conductance sensors [PBC18] the system is able to orient the user towards relevant actions through contextual recommendations to alleviate frustration and maintain task focus.

In another study, the *Domino* visualization technique was presented as a method of presenting relevant data subsets and their relationships to the user's analysis goals [GGL*14]. A user receives hints as to what data is relevant to their current analysis state in this visualization system. The system allows them to arrange visualizations as they wish and to easily generate visualization techniques relevant to their analysis.

9.1.2. Directing

With directing, the systems put explicit emphasis on possible interventions as the next course of action. The system presents one or more curated alternative options based on the user representation, from which the user decides whether to pursue them.

To improve the efficiency of visual analysis tasks, Silva et al. [SSV*18] developed a user-adaptive visualization system that used visual recommendations as directed interventions. In this work, the user representation revealed the user's interest in multiple time series, so the system suggests different visualizations to assist them in achieving their analysis goals.

In Voyager, a well-known visualization system, Wongsuphasawat et al. [WMA*16] designed the system to display multiple relevant visualizations based on user interactions. Data-driven models (i.e., clustering and ranking algorithms) were used to make recommendations. As illustrated in Figure 14, Voyager includes two panels: (a) shows the exact match gallery, and (b) shows suggested visualizations. The user can choose to accept or reject suggestions, steering their analysis path accordingly.

9.1.3. Prescribing

Prescribing involves making decisions and performing mandatory interventions to the visualization. This type of intervention happens automatically and does not provide the user with a choice or selection. This intervention is common in user-adaptive visualization research to determine which intervention works best given the user representation.

For instance, based on the user's analysis goal inferred from fixation points, Barral et al. [BLIC21] implemented highlighting interventions as prescribed guidance (Figure 15) in a study about the relationships between visualization personalization, user representation, and eye gaze behavior. Most participants found this approach useful and easy to use, but half flagged it as distracting.

A different study also leveraged users' fixations to prescribe interventions to the visualization's legend by adapting its content and/or placement [GKG*18]. They demonstrated that their adaptive approach decreased users' time spent on the legend.

9.2. Type of Intervention

Aside from the degree, interventions can also be categorized based on how and when the interventions are applied. These types are pre-visualization, within an existing visualization, or between different visualizations.

9.2.1. Pre-Visualization

Interventions can happen even before modifying the current visualization the user is interacting with. Also known as dynamic back-end adaptations, these interventions take place in the background to provide support to the user without altering the current display [Ott20]. The design space for this type of interventions includes the optimization of data retrieval processes, the anticipation of user needs based on historical interactions, and the seamless integration of back-end processes to enhance the overall responsiveness of the system.

Pre-visualization interventions are typically used in user-adaptive visualizations to reduce response times, which improves the user experience. Battle et al. [BCS16] used a middleware layer between the backend and the visualization system to preemptively fetch data as the user explored the dataset. A 430% reduction in latency was found by dividing the visualization into tiles and pre-fetching data for the regions of interest, which were both similar to the context the user was interacting with and their past interactions, as shown in Figure 16.

9.2.2. Within an existing visualization

When an intervention is performed within an existing visualization, the current visualization being displayed to the user is

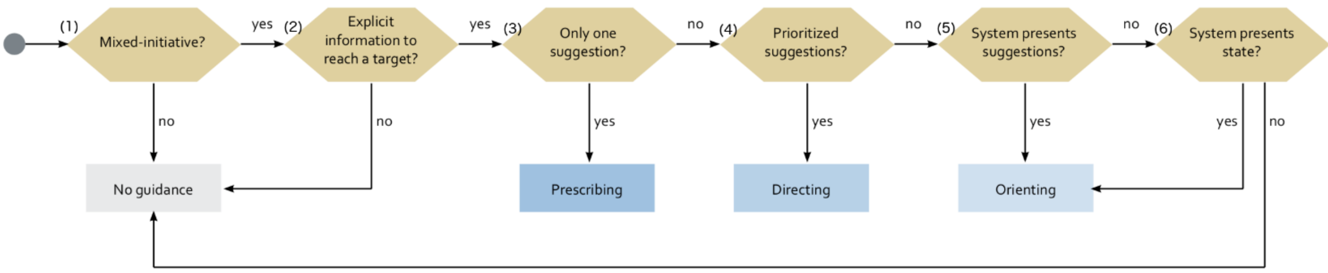

Figure 13: *A decision tree illustrates the key differences between the different degrees of guidance, showcasing that orienting entails presenting multiple suggestions, directing involves presenting prioritized suggestions while prescribing comprises presenting only one suggestion [CGM*18].*

modified. Several interventions of this type are common in the visualization literature, such as visual prompts (e.g., highlights and labels) [Mit97] and layout changes.

The relevance of a particular subset of data can be communicated effectively by highlighting interventions. Carenini et al. [CCH*14a] studied some types of highlighting (i.e., bolding, de-emphasizing, reference lines, and connected arrows), as shown in Figure 17. According to the authors, the effectiveness of such visual prompts on task performance depends on user characteristics and the complexity of the task.

Other works have also studied user characteristics and interventions. For example, the layout of file visualization systems was gradually shifted from an indented view to a containment view in a study aimed at evaluating the compatibility between users' locus of control and visualization style [ZCY*11]. Based on their findings, users with an internal locus of control performed worse with containment visualizations, whereas those with an external locus of control performed better.

Figure 14: *Example of directing guidance to the user by showing other visualizations of relevant data to the current state/query. By selecting a variable, the main gallery is updated showcasing: (A) the exact-match section containing multiple transformations and (B) the suggested section with the visualizations the system is recommending to the user [WMA*16].*

9.2.3. Between different visualizations

Interventions can happen between different visualizations. This involves switching between different visual representations based on the understanding of the user. For instance, the visualization chart type can be changed to better suit the user's preferences or analysis goals.

An example of user-adaptive visualization systems that perform this type of intervention was developed by Gotz et al. [GWL*10]. The authors built a user representation by inferring their analysis goals, which helped the system recommend alternate visualizations. A more appropriate alternative is recommended to the user based on patterns in the temporal data derived from their interactions, as shown in Figure 18. Other examples include the system implemented by Silva et al. [SSV*18], and Voyager by [WMA*16] (Figure 14) as mentioned earlier.

Summary and Open Areas

Choosing which type of intervention to use, within or between visualizations, can be guided by several factors. The first tradeoff to consider is the cognitive cost of changing between visualizations over the possible advantages of a data and task-appropriate visualization. Another factor to consider is the user representation the visualization is adapting to. The transient nature of short-term

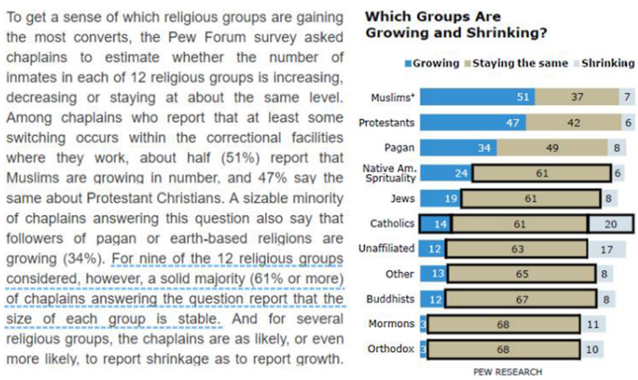

Figure 15: *A system prescribing the intervention by highlighting the relevant bars according to the fixation points of the user while reading the text [BLIC21].*

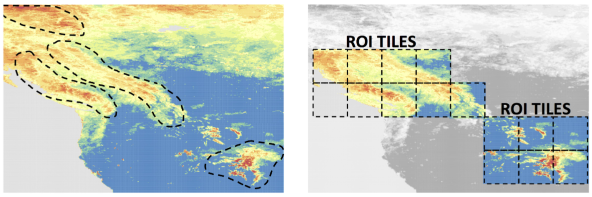

Figure 16: *Example of pre-visualization intervention by pre-fetching data of the region of interests based on the user's past interactions [BCS16].*

characteristics such as cognitive load or of some types of analysis goals are often best handled by within-visualization adaptations, which can incur a much lower cognitive cost to the user.

The design space of interventions in existing user-adaptive visualizations is largely restricted to either *modifying* or *switching between* existing visualizations. A vastly unexplored area for future research lies in automatically generating visualizations that are custom-made for each individual. This type of work has been done for interface generation, where the system generates "optimal" user interfaces given a declarative description of an interface, device characteristics, available widgets, and a user- and device-specific cost function [GWW10]. Specific to visualizations, Hullman et al. [HDA13] developed a system that automatically produces custom, annotated visualizations of stock behavior given a news article about a company. Their annotation algorithms are informed by a study of professionally created visualizations and take into account visual salience, contextual relevance, and detection of key events in the company's history.

Formalizing visualization design knowledge is critical for the automatic generation of visualizations. This formalization was done by Moritz et al. [MWN*19], who propose modeling visualization design knowledge as a collection of constraints in conjunction with a method to learn weights for soft constraints from experimental data. This and other work in this space (e.g., [DSK*14, KRD*22]) provide the foundation for the automatic generation of personalized visualizations, which would cater to an even broader spectrum of users since the design space of visualizations would be limited only by a specification of the visual encodings.

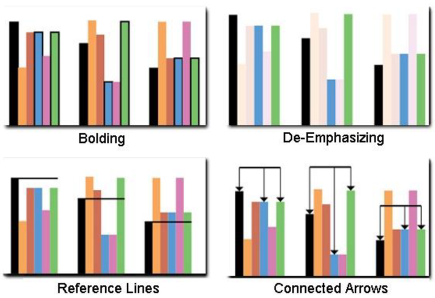

Figure 17: *Example of the within visualization intervention of visual prompt. Some potential highlights for bar charts are bolding, de-emphasizing, reference lines, and connected arrows [CCH*14a].*

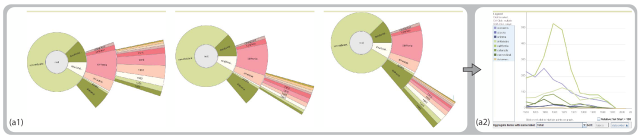

Figure 18: *Example of a between visualizations directing interventions. The left side (a1) represents the previous iterations of the user's interaction with the system, along with the current context. The right side (a2) shows the system's recommendations of a more appropriate alternative for the current task [GW09].*

10. Evaluation

In this section, we discuss the evaluation approaches applied to assess user-adaptive visualizations. Although empirical user studies are the most prevalent evaluation method in this field (i.e. lab-based or crowdsourced), researchers also employ several other methods to gain comprehensive insights into the impact and effectiveness of their visualization systems. Additionally, most works rely on quantitative metrics, especially user performance, to gain a better understanding of how well their visualizations meet the needs of the users.

10.1. Evaluation Metrics

Researchers employ a wide array of methods to assess user interactions and system performance. These include both qualitative and quantitative metrics, offering a multifaceted view of the user's experience and the system's functionality. In user-adaptive visualizations, success metrics evaluate user performance along with the effectiveness of the interventions provided. In the subsequent section, we delve into the various evaluation metrics used to gauge the quality, efficacy, and user-centric aspects of user-adaptive visualizations.

10.1.1. Qualitative

Qualitative evaluation metrics encompass the holistic evaluation of the user experience, encapsulating the nuanced aspects that quantitative metrics alone may overlook. They provide a lens through which researchers gain insights into the subjective aspects of adaptive interventions. These metrics involve system feedback—such as visualization preference and ease-of-use—intervention feedback—which delves into recommendation quality and relevance—, and self-reflecting user feedback—including assessments of user confidence.

Some studies perform qualitative evaluation by comparing the adaptive visualization and a non-adaptive version. For instance, Wongsuphasawat et al. [WMA*16] built Voyager, an adaptive system that displays multiple relevant visualizations based on the user's analysis goals and used *post-hoc* questionnaires to determine user preferences compared with PoleStar, a non-adaptive tool modeled on Tableau. 94% of the participants stated that they preferred Voyager for exploration tasks. Similarly, in a user-adaptive visualization system that suggested time series based on user preferences, Bouali et al. [BGV16] performed a user study with both their system VizAssist, and a manual interface. After performing statistical tests, the authors found that there was a significant difference in the users' preference towards VizAssist.

System Feedback is a prevalent qualitative approach that involves assessing user feedback on the system's overall performance, including aspects such as visualization preference (e.g. [ABH15, AHM16, VBCC18, JTV18]) and ease-of-use (e.g. [CLWM11,SSV*18]). This provides insights into the users' subjective experiences and satisfaction. A subset of system feedback is *intervention feedback*, which specifically evaluates the quality and relevance of interventions. Researchers often gauge feedback on the effectiveness of recommendations, assessing whether the suggested interventions align with users' needs and objectives by inquiring about the recommendations' relevance (e.g. [HKR*08, MDF12, BOH13, SPEB18, ZBNS21]) and quality (e.g. [KCGK16, MZJS18, PLW*23]).

Self-reflecting User Feedback forms an integral part of the qualitative evaluation by understanding user confidence and their perception of the intervention's utility. It sheds light on users' trust in the system's recommendations and their self-assessment regarding the usefulness of the provided interventions and how that helped their performance (e.g. [WQM*17, SLMK18, DAG22]).

User Experience encompasses a holistic evaluation, examining the overall journey of users interacting with adaptive visualizations (e.g. [Sza18, HKR*08, GSC*23, AAGP23]). This includes factors such as user satisfaction, engagement, and perceived value.

10.1.2. Quantitative

Quantitative evaluation metrics provide the foundation for rigorous assessment of user-adaptive visualizations. These metrics offer precise and measurable insights into user performance, system effectiveness, and the efficiency of adaptive interventions. Researchers delve into user-centric quantitative metrics—including accuracy, completion time, decision time, and search performance—, eye-tracking metrics—such as fixation count, fixation duration, visual comparison, and scan path—, provenance-based metrics—which analyze user interactions and events triggered during their interaction with adaptive visualizations—, and cognitive load metrics—that offer invaluable insights into the cognitive demands imposed on users. Lastly, model-related metrics assess the accuracy and coherence of user modeling and adaptation assignment algorithms.

For instance, Lallé et al. [LTC21] implemented a comparison of control and adaptive groups to determine how their intervention of highlighting magazine-style narrative visualizations based on the analysis goal affected users' performance. From multiple linear mixed models, the authors concluded that, despite an effect between performance and visual literacy, their interventions didn't translate into a significant main effect against the control group, suggesting that such interventions are not useful for all users. Bouali et al. [BGV16] also leveraged mixed models to measure the effect of the interventions on user performance. The authors found with VizAssist that the accuracy of the answers when engaging with the Interactive Genetic Algorithm had a significant difference compared with the manual interface.

User Performance offers objective measures of how effectively users navigate and interpret adaptive visualizations, including, for example, accuracy (e.g. [BGV16, PCQ*20, DKZH20, BWH*23]), completion time (e.g. [PYO*13, VH16, GKG*18, VST05]), decision time (e.g. [CCH*14b,DKZH20,ADHC*23]), and search performance (e.g. [HKR*08]).

Eye-tracking metrics delve into users' visual behavior, encompassing, for instance, fixation count and duration (e.g. [RKB*17, SFN20, BLIC21, SSV*18]), visual comparison (e.g. [LC19]), and scan path analysis (e.g. [SSV*18]). This provides insights into what users look at and how they explore visual content.

Provenance-based Metrics allow for a comprehensive understanding of users' interactions and decision-making processes (e.g. interaction strategy (e.g. [OYC15, KCGK16, WMA*16, WWZ*22]), interaction count (e.g. [KCGK16, CHTS13]), and the number of events triggered (e.g. [DAG22, ADHC*23])).

Cognitive Load assessment measures the mental effort expended by users during interactions. This includes quantifying the cognitive resources utilized to comprehend adaptive visualizations (e.g. [APM*11, PYO*13]).

Model-related Metrics focus on assessing the time performance (e.g. [WLLM13]) and accuracy (e.g. [HKR*08, LC19]) of adaptation decision-making models, as well as the accuracy of user modeling techniques (e.g. [Sin07, BOZ*14, SLH*21, CAGM22, FS22]).

10.2. Evaluation Methods

Evaluating adaptive interventions encompasses not only the choice of appropriate evaluation metrics but also the methods employed to gather and analyze data. Researchers employ diverse methods tailored to address specific research questions and objectives. In the following section, we delve into the intricacies of these evaluation methods, encompassing empirical user studies, case studies, use cases, and synthetic-s-user evaluation. The distinction lies in how these methods are applied to assess the unique success metrics of user-adaptive visualizations.

Most works in the user-adaptive visualization literature employ user studies with a limited number of participants. This allows for a controlled setting where the user not only interacts with the visualization system but also can respond to questions about their experience. Some of the most common empirical user studies in user-adaptive visualizations are *post-hoc* questionnaires that capture user insight during the analysis, as well as cognitive states such as cognitive load and frustration [TCC19, BLIC21, LTC21]. In a user-adaptive visualization study, Silva et al. [SSV*18] implemented interventions by directing users to other recommended time series based on their analysis. They applied diverse tests and questionnaires where they assessed the user's cognitive load and frustration, as well as their insights into the usability and functionality of the adaptive visualization. Their most significant finding was that users felt confident during the analysis task when selecting a visualization from the system's recommendations.

Empirical User Studies involve real-world experiments conducted with human participants to gather data, insights, and observations about their interactions with the visualizations. They offer a real-world understanding of how users interact with and benefit from adaptive visualizations and are often performed in controlled lab settings (e.g. [ABH15, ARG*20, SC20, BOH13, GSC*23, LQS*23]) or crowdsourced from diverse user populations (e.g. [GGLBY16, JTV18, EJLLW*22, BWH*23]).

Case Studies are in-depth examinations—usually by domain experts—of specific instances, scenarios, or examples of user-adaptive visualization systems to gain a detailed understanding of their performance, impact, and characteristics in real-world contexts (e.g. [MZJS18, PCQ*20, ZFF22]). They offer detailed insights into the contextual factors and outcomes associated with these interventions.

Use Cases involve the description of hypothetical scenarios or situations where a user interacts with a system or technology to achieve specific goals or objectives. It typically includes a detailed walkthrough of the user's actions, interactions with the system, and the expected outcomes in various scenarios (e.g. [CLWM11, GGL*14, SPEB18]).

Synthetic-User Evaluation simulates user interactions or behaviors using algorithms to evaluate how an adaptive visualization system responds. Researchers create algorithms that mimic user actions, such as responding to prompts (e.g. [HKR*08]) or selecting targets in visualizations (e.g. [KCGK16]), to assess the system's reactions.

Our corpus of surveyed papers indicates that evaluations of user-adaptive visualizations, whether qualitative or quantitative, happen *post-hoc*. That is, there is no evidence of user-adaptive visualizations that perform a reinforcement learning approach where the intervention are continuously evaluated and adjusted during the visual exploration. This is an open area for future research.

11. Challenges and Future Research

As with any complex problem, a major challenge in user-adaptive visualizations lies in comprehensively addressing all of the components involved: eliciting information from the user, developing a user modeling method, creating a user representation, determining when and what the precise adaptation is needed, and lastly, performing and evaluating the intervention made. Often, research in this field tends to focus on specific components rather than integrating all aspects systematically. Our taxonomy will provide a framework for future researchers to design adaptive systems that systematically address all the components.

Additionally, work in this field would benefit from leveraging advancements in related fields, such as educational and cognitive psychology. For instance, research in educational psychology can inform visualization researchers on how to incorporate user characteristics in learning abilities in its user model methodologies. Similarly, work done in learning systems and educational technology can shed light on successful adaptation models that conform to a broad spectrum of user personas.

System-driven adaptation vs. User-driven customization. Research in user-adaptive interaction often begs the question of why the system should drive the personalization (i.e., adaptation) instead of enabling users to perform the personalization themselves (i.e., customization). The main reason is that there is extensive research in HCI showing that users don't always want or know how to customize (see [LC19] for an overview). Lallé & Conati [LC19] provide initial evidence that this is also the case with visualizations.

AI-driven personalization, however, does not mean that the system unilaterally decides. Instead, it should be seen as a dialogue between the system and the user to help them understand how to use the system's features best, always leaving the user with ultimate control over what to do. In the context of user-adaptive visualizations, this will involve investigating how to design effective interface tools for the user to access and personalize the visualizations, but also enabling a system to monitor if and how the user leverages these tools and provides support as needed.

Risks and Limitations. This STAR asserts that by monitoring the user and intelligently tailoring appropriate information and guidance situationally, we can create next-generation user interfaces that better support the user's analytics process. However, one limitation is the potential to have missed relevant works due to our selection of specific venues and keywords used for the search. This could mean that some pertinent studies may not have been included in our review. Also, we have primarily focused on a single user, and future work is needed to examine how we can apply this pipeline to multi-user scenarios. Suppose, for example, two users are collaborating. How do we reason about adaptations? Moreover, customizing the visualization design may frame the user's mental model in the task and data relationships [ZK09]. How do we help collaborators bridge the gap between differing mental models of the same problem?

Although the ability to automatically infer individual characteristics will open many opportunities for tailoring visualization systems to suit the user better, collecting and storing such information can raise privacy concerns. Researchers and practitioners must know the potential ethical challenges ahead and take socially responsive steps to mitigate the effects. For example, future work should consider challenges such as managing user privacy in a way that is transparent, understandable, and approved by each user. Altogether, people's experiences with user-adaptive interfaces will depend on their confidence in appropriate data privacy, their safety from hacking, and their trust in guidance and suggestions. These are all vital areas of research that require substantial inquiry.

12. Conclusions

In this paper, we presented the state of the art in user-adaptive visualizations. We deconstruct the adaptation process into five main components: input, user modeling, user representation, adaptation assignment, and intervention. For each component, we provide an overview of guidelines and open areas of research. We also provide an overview of the different evaluation methods used to assess the trade-off between providing interventions and possibly inducing cognitive overload. This survey was done through a qualitative analysis of 91 papers published within the visualization research community.

Some of the components of the user-adaptive visualization process have been well-explored, while others provide rich opportunities for future work. In particular, there has been substantial work in understanding the relationship between user characteristics and both performance and preference for different visualizations. However, research on *when* to actively adapt the visualization is considerably less explored. Other areas of future work include capturing richer physiological data from the user, modeling user representations from low-level interaction traces, and generating personalized visualizations from design guidelines.

We believe our work can provide a road map for practitioners and researchers in this area, describing the rich space of current approaches and highlighting open areas for future work.

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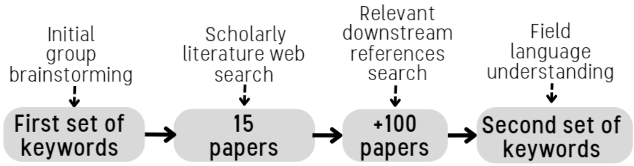

Figure 19: *Overview of the preliminary process implemented to come up with the set of keywords used in our main methodology.*

Appendix A

Preliminary Process for our Main Methodology

The first author together with one senior author reviewed representative papers on user-adaptive visualizations, adaptive interfaces, and user modeling. We followed both linear- and citation-search approaches. The linear search focused on finding an initial set of relevant papers based on specific keywords and phrases as shown in Table 2 in scholarly literature web search engines (i.e., Google Scholar and Semantic Scholar). We compiled this list of keywords and phrases to encompass the concept of adaptive visualization, spanning both its comprehensive and specific dimensions. After a first pass identifying relevant ones in terms of closeness to the user-adaptive visualization topic (15 papers), we moved on to the citation search by looking at the downstream references for each paper by reading the *related work* sections and discerning which ones seemed relevant to user-adaptive visualizations. This step brought the count of papers to just over 100, published between 1994 and 2022, for which we manually reviewed the title, abstract, introduction, and discussion/conclusion to understand the language and nuances representative of the field. The output of this first, exploratory phase (summarized in Figure 19) is a set of categorized keywords as shown in Table 1.

Table 2: *Initial set of keywords and phrases used for early exploration of user-adaptive visualization research.*

- user-adaptive visualization
- user-adaptive interaction
- adaptive visualization
- visualization generation
- visualization literacy
- visualization morphing
- user assistance in visual methods
- visualization recommendation
- visualization decision-making
- visual analysis recommendation
- adaptive information visualization

Table 3: *Selected papers based on their relevance to user-adaptive visualizations and that contain the five components. The filled boxes indicate the Ⓐ Input, Ⓑ User Modeling, Ⓒ User Representation, Ⓓ Adaptation Assignment, and Ⓔ Interventions present in the manuscripts.*

	Input					User Model.		User Representation							Ad. Asgmt.		Interventions					
	User Activity							*Long-Term*					*Short-Term*				*Intervention Degree*			*Type of Intervention*		
	Biometric Data	System Interactions	User Declarations	Environment Context	Pre-existing User Information	Explicit Modeling	Implicit Modeling	Personality Traits	Cognitive Abilities	Experience Bias	Demographics	Visual Preferences	Cognitive States	Analysis Goals	Expert Knowledge	Data-driven Algorithms	Orienting	Directing	Prescribing	Pre-visualization	Within-visualization	Between visualizations
Healey et al. (2008) [HKR*08]		●				●								●		●	●				●	
Gotz & Wen (2009) [GW09]		●					●							●		●		●				●
Gotz et al. (2010) [GWL*10]		●				●								●		●		●	●		●	●
Crnovrsanin et al. (2011) [CLWM11]		●			●	●								●		●			●		●	
Reinecke et al. (2011) [RMB11]		●			●	●	●		●		●	●				●			●	●	●	●
Mouine & Lapalme (2012) [ML12]		●		●	●	●	●					●		●		●			●		●	
Bostandjiev et al. (2013) [BOH13]		●				●				●	●					●			●		●	
Ahn et al. (2015) [ABH15]		●					●							●		●			●	●	●	
Mutlu et al. (2015) [MVTS15]			●			●						●			●	●		●		●		●
Bouali et al. (2016) [BGV16]		●				●						●		●		●		●				●
Graells-Garrido et al. (2016) [GGLBY16]					●		●			●						●		●				●
Battle et al. (2016) [BCS16]		●					●							●		●			●		●	
Kangasräääsiö et al. (2016) [KCGK16]		●				●								●		●		●			●	●
Mutlu et al. (2016) [MVT16]			●			●						●			●	●				●		
Wongsuphasawat et al. (2016) [WMA*16]		●				●								●		●		●				●
Saket et al. (2017) [SKBE17]		●				●								●	●			●			●	●
Wongsuphasawat et al. (2017) [WQM*17]		●				●								●		●		●				●
Göbel et al. (2018) [GKG*18]	●		●			●	●				●	●	●	●	●				●		●	
Jin et al. (2018) [JTV18]			●		●	●	●		●					●		●					●	
Metoyer et al. (2018) [MZJS18]		●				●								●	●	●			●	●	●	
Panwar et al. (2018) [PBC18]	●						●						●		●	●	●	●				
Silva et al. (2018) [SSV*18]	●	●					●							●		●		●		●		●
Srinivasan et al. (2018) [SPEB18]		●				●								●	●			●			●	
Vanderdonckt et al. (2018) [VBCC18]				●		●								●	●				●			●
Zhi et al. (2019) [ZOM19]		●				●								●	●	●			●		●	
Barral et al. (2021) [BLIC21]	●		●			●	●			●						●			●		●	
Lallé et al. (2021) [LTC21]	●		●			●	●	●	●	●					●				●		●	
Zong et al. (2021) [ZBNS21]		●					●							●	●			●			●	
Cao et al. (2022) [CLPL22]		●	●			●	●					●			●	●		●			●	●
Ceneda et al. (2022) [CAGM22]	●	●				●	●						●			●						
EPPerson et al. (2022) [EJLLW*22]		●					●							●		●		●			●	●
Monadjemi et al. (2022) [MHN*22]		●					●							●		●		●			●	
Wu et al. (2022) [WWZ*22]		●				●								●		●		●				●
Zhao et al. (2022) [ZFF22]		●					●							●		●		●				●
Andreou et al. (2023) [AAGP23]		●	●			●			●	●	●		●	●	●	●					●	●
Chen et al. (2023) [CYS*23]	●						●							●		●			●	●	●	
Guesmi et al. (2023) [GSC*23]					●		●							●		●			●		●	
Li et al. (2023) [LQS*23]		●					●							●		●		●			●	
Pandey et al. (2023) [PLW*23]		●				●								●	●			●	●		●	●

Table 4: *Selected papers based on their relevance to user-adaptive visualizations and that contain only the first three components. The filled boxes indicate the* ■ Ⓐ *Input,* ■ Ⓑ *User Modeling, and* ■ Ⓒ *User Representation present in the manuscripts.*

	Input					User Model.		User Representation						
	User Activity							*Long-Term*					*Short-Term*	
	Biometric Data	System Interactions	User Declarations	Environment Context	Pre-existing User Information	Explicit Modeling	Implicit Modeling	Personality Traits	Cognitive Abilities	Experience Bias	Demographics	Visual Preferences	Cognitive States	Analysis Goals
Velez et al. (2005) [VST05]			■			■			■					
Cohen & Hegarty (2007) [CH07]			■			■			■					
Singh (2007) [Sin07]	■						■			■			■	
Conati & Maclaren (2008) [CM08]			■			■		■	■	■				
Ziemkiewicz & Kosara (2009) [ZK09]			■			■		■	■					
Anderson et al. (2011) [APM*11]	■						■		■				■	
Micallef et al. (2012) [MDF12]			■			■			■					
Toker et al. (2012) [TCCH12]			■			■			■	■				
Conati et al. (2013) [CHTS13]		■				■							■	
Gou et al. (2013) [GMHZ13]					■		■	■						
Peck et al. (2013) [PYO*13]	■		■			■							■	
Steichen et al. (2013) [SCC13]	■		■			■	■		■					■
Toker et al. (2013) [TCSC13]			■			■			■	■				
Ziemkiewicz et al. (2013) [ZOC*13]			■			■		■						
Brown et al. (2014) [BOZ*14]		■	■			■	■	■			■			
Carenini et al. (2014) [CCH*14a]	■	■	■			■		■	■	■				
Conati et al. (2014) [CCH*14b]			■			■			■	■				
Gratzl et al. (2014) [GGL*14]		■				■								■
Steichen et al. (2014) [SCC14]	■		■			■	■		■					
Toker et al. (2014) [TSG*14]	■						■			■				
Waldner et al. (2014) [WLMB*14]		■					■						■	
Lallé et al. (2015) [LTCC15]	■		■			■	■	■	■	■				
Ottley et al. (2015) [OYC15]			■			■		■			■			
Ottley et al. (2015) [OCZC15]			■			■		■						
Asenov et al. (2016) [AHM16]			■			■							■	
Gotz et al. (2016) [GSC16]		■					■			■				■
Lallé et al. (2016) [LCC16a]	■	■					■						■	
VanderPlas & Hofmann (2016) [VH16]			■			■			■		■			
Conati et al. (2017) [CLRT17]	■						■		■	■				
Gotz et al. (2017) [GSC*17]		■					■			■				■
Raptis et al. (2017) [RKB*17]	■						■		■					
Wall et al. (2017) [WBFE17]		■					■			■				
Smith et al. (2018) [SLMK18]	■						■			■			■	
Szafir (2018) [Sza18]		■	■			■			■		■			
Toker et al. (2018) [TCC18]			■			■		■	■	■				
Lallé & Conati (2019) [LC19]			■			■		■	■	■				
Lallé & Conati (2019) [LC19]		■					■							■
Alves et al. (2020) [ARG*20]			■			■	■	■						
Conati et al. (2020) [CLRT20]	■	■					■		■	■				
Duchowski et al. (2020) [DKZH20]	■					■							■	
Monadjemi. (2020) [MGO20]		■					■			■				■
Padilla et al. (2020) [PCQ*20]	■						■		■					
Sheidin et al. (2020) [SLC*20]			■			■		■	■			■		
Sims & Conati (2020) [SC20]	■	■				■	■						■	
Steichen et al. (2020) [SFN20]	■						■		■					
Mosca et al. (2021) [MOC21]			■			■			■					
Spiller et al. (2021) [SLH*21]	■	■					■			■				
Delgado et al. (2022) [DAG22]		■	■			■		■						
Fu & Steichen (2022) [FS22]	■						■			■				
Alves et al. (2023) [ADHC*23]		■	■			■		■			■			■
Bancilhon et al. (2023) [BWH*23]			■			■			■				■	