How the Preattentive Process is Exploited in Practical Information Visualization Design: a Review

How the Preattentive Process is Exploited in Practical Information Visualization Design: a Review

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ABSTRACT

This review aims at analyzing the recent literature to find how the preattentive visual process is currently used in information visualization, in particular, to improve the cognitive process in chart comprehension (i.e., perceptual effectiveness). The purpose of our literature review is to provide an overview of how concepts related to the preattentive process are used pragmatically in recent researches. We searched different bibliography sources, between 2010 and 2021, getting **29** articles that fit the review focus. In general, we discovered that the research work on exploiting the preattentive process in information visualization is currently not thoroughly explored.

The main contribution of the paper is the analysis of the papers, from which we identified two categories of research directions according to the primary uses of preattentive concepts: 'preattentive attributes as design components,' and 'the preattentive process as a measuring tool,' with a gap between these two approaches. The review also highlighted two limitations in the current research literature: most works tend to focus on a particular chart type, only, with difficult to generalize results, and the manipulation of preattentive attributes is done implicitly, without providing to the graph designer the suitable awareness over the design decisions impact.

We finally present a proposal about how to use the knowledge about the preattentive process in the first stages of design in information visualization, to start closing the above mentioned gap with the graph designer.

KEYWORDS
Information Visualization; Human Computer Interaction; Preattentive Process; Preattentive Attribute; Highlighting

1. Introduction

Pirolli and Card (1995) said that humans minimize the effort to get the necessary information gain as animals minimize the energy expenditure to get the required sustenance gain. They use this analogy to explain that it is crucial to reduce the cognitive process's cost to maximize cognitive productivity in the process of seeking relevant information. In information visualization, one way to reduce this cost is using Visual Analytics (VA) systems. Visualization systems are designed to support information seeking over a large amount of data, using different visual techniques (e.g., bar charts, scatter plots) that were created to boost the efficiency with which knowledge can be

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gained (Ware, 2013). However, visualizations can also be confusing and misleading, particularly for complex, multidimensional data sets that do not have a natural visual representation (Matzen, Haass, Divis, Wang, & Wilson, 2018).

According to (Ware, 2013), to design graphic representations of data, in VA systems, human sensory capabilities (visual perception and cognition) must be taken into account in such a way that relevant data elements and data patterns can be quickly perceived and processed (by visual working memory). The above means that *relevant data* should be *highlighted* using visual elements such as color, size, shape, or motion (Liang & Huang, 2010). Relevant data is defined as a selected group of data that could be chosen by users or by an algorithm Alves, Obraczka, and Lindberg (2020); Dzolkhifli, Ibrahim, Affendey, and Madiraju (2008), and represent data that is important to the object of study. The highlighting of data is mainly related to the first step in visual perception, i.e., the Preattentive Process (Rodrigues, Balan, Traina, & Traina, 2008): when we see an image in the preattentive moment, we unconsciously focus our visual attention on a specific area. This process is the first connection that a observer makes with the graph, and therefore it impacts his subsequent cognitive process Rodrigues, Traina, de Oliveira, and Traina (2006).

(Liang & Huang, 2010) presented a survey about the highlight definition and classification in information visualization. According to them, the highlighting technique is reduced to the use of color and light, also it *has been limited to basic viewing aid in most applications* (Liang & Huang, 2010). Their research was conducted in 2010, and eleven years later, we argue that the same issue remains open. Currently, VA systems have default designs (available graph types) and color schemes to help users customize the graph to highlight relevant data. For instance, Tableau gives the user a list of suggested graphs according to the data type Mackinlay and Winslow (2009). The user can then modify some attributes of the selected graph design, such as color, size, or detail (glyph) within the option's attributes in the design space determined by the VA system. However, especially for novice users, it is not easy to understand the effect over the perceptual and cognitive processes of the modifications to chart types and visual elements allowed by the VA (Grammel, Tory, & Storey, 2010), or whether relevant data is actually highlighted in default designs.

This paper aims to analyze how visual perception fundamentals, particularly the preattentive process, impact cognitive productivity. The preattentive process, on which the paper is focused, is only a part of the vastly more complex visual-cognitive process; however, being the first phase of the process, it has high importance in the attention behavior on InfoVis images. To analyze the research landscape on this topic, we made a literature review focused on how the preattentive visual process is used in information visualization, in particular, to improve the human cognitive process. Therefore, in selecting and analyzing the papers, rather than on the theory of how preattentive concepts impact the attention process, we focus on how these concepts have been used to improve data understanding (cognition) in information visualization. In other words, the purpose of our literature review is to provide an overview of how concepts related to the preattentive process are used *pragmatically* and implicitly in recent researches.

In general, we found that the preattentive process is currently used to highlight specific data, often in an 'implicit' way limited to specific data sets or visualization techniques. Also, the preattentive concepts are used to measure graph effectiveness. Besides, we noticed that in most cases, the research in preattentive on InfoVis *does not directly involve the graph designers.* The preattentive notion is still at the research level (patterns, standards), but we did not find specific studies that seek to bring this knowledge to the graph designer. This designer's oblivion is one of the most relevant issues found in the conducted research. Finally, we claim that future research should further develop how to integrate attention predictions models (evaluation) as a design tool in VA systems to support graph designer decisions.

2. Key Concepts

In the literature review, we notice that different authors exploit the preattentive process differently, which gives different interpretations to related concepts in the InfoVis area. For the sake of clarity, these concepts meaning, in the context of the present paper, is reported below.

Visual Attention *Visual attention is the umbrella term used to denote the various mechanisms that help determine which regions of an image are selected for more detailed analysis* (Healey & Enns, 2012). The term attention refers to the process that allows one to focus on some stimuli at the expense of others.

Preattentive According to Treisman and Gormican (1988), in the human visual process *a visual scene is analyzed at an early stage by specialized populations of receptors that respond selectively to such properties as orientation, color, spatial frequency, or movement, and map these properties in different areas of the brain.* The term "Preattentive" includes all factors influencing this selection mechanism: the process (how it works) and the attributes (which visual elements influence the process).

Preattentive Process Humans can simultaneously perceive a large number of visual attributes (e.g., color, orientation, shape) to direct their visual attention. Preattentive perception is done in parallel: each visual attribute is computed in parallel and then combined to select specific regions that are perceived without any conscious effort (Few, 2004). The preattentive process is fast (200 to 250 ms) and unconscious, in contrast to the attention process, which is done serially and is slower and conscious.

The preattentive process can be represented algorithmically by two types of computational models: *Bottom-up* (or *stimulus-driven*, or *global*) and *Top-down* (or *goal-directed*, or *local*). These computational models simulate the mechanism used to detect the salient visual subsets in the human vision system (Li & Gao, 2014).

Bottom-up Model It *measures how different an element is from its neighbours* (Healey & Enns, 2012), and tries to simulate a natural visual perception process. This model uses low-level features such as color, texture, size, contrast, brightness, position, motion, orientation, and shape of objects that influence visual attention. Although the information from each fixation influences our mental experience (Healey & Enns, 2012), the bottom-up process operates without prior knowledge about the image content (Itti & Borji, 2014). To predict the highlighted elements, the bottom-up model usually adopts *saliency map* algorithms.

Top-down Model It *is a user-driven attempt to verify hypotheses or answer questions by "glancing" about an image, searching for the necessary visual information* (Healey & Enns, 2012). This model uses high-level features, context-dependent features such as faces, humans, animals, vehicles, text, etc. The top-down preattentive model uses prior knowledge about the scene and/or about a given task (Itti & Borji, 2014). Usually, eye-tracking is adopted to measure and validate these models' results (Elsa & Neenu, 2017).

Saliency The Saliency of an item —be it an object, a person, a pixel, etc.— measures how easy it is visually identified and arises from its contrast and separation relative to other objects or the background (Li & Gao, 2014). Thus, saliency detection is considered to be a critical attentional mechanism, which guides visual attention.

Formally, the *Perceptual Saliency* is the degree to which a target stimulus "pops out" in a set of stimuli (Kerzel, 2009). Thus, for example, if the target stimulus differs by a single attribute (e.g., color) from the other objects, it is more salient; meanwhile, if it differs by a combination of attributes (e.g., color and form), it is less salient. Alternatively, the *Visual Saliency* may be defined as the nature or quality of a viewed object which gives it relevance or importance to the observer ("Visual Salience", 2009).

Preattentive Attributes or Features They are straightforward visual elements perceived without conscious attention. According to different authors, there are different sets of attributes, classified in different ways. According to the definitions found in (Chih & Parker, 2008) and (Ware, 2013), Preattentive Attributes are classified in four groups: *Form*, which bundles line orientation, length, width, collinearity, size, curvature, spatial grouping, blur and numerousness; *Color*, including hue and intensity; *Motion* including flicker and direction; *Spacial position* made up of 2D position, (stereoscopic) depth, depth or convex/concave shape from shading. The authors also use the "visual element" concept in the literature to refer to preattentive attributes. In this context of InfoVis, visual elements are used to represent data and attract attention and highlight important information.

Highlighting : *The goal of highlighting is to make essential data points more visually prominent* (Waldner, Karimov, & Gröller, 2017). Highlighting in InfoVis is used to guide the user in exploring the data, for instance, through visual elements to help the observer focus on relevant data or link data across multiple views (Waldner et al., 2017). Also, highlighting may be used to ensure the comprehension of charts with excessive information density (Ware, 2013).

These concepts have been developed since 1980 when Treisman and Gelade (1980) presented the *feature-integration theory of attention*, which describes the Preattentive Process from a computational perspective. Since then, the preattentive concept has been mostly used for object detection in all kinds of images (landscapes, photos, videos, etc.). However, in InfoVis, the preattentive concept is not widely used in a structured way yet.

Another important key concept for our study is the *visualization development stages* in InfoVis. According to Mazza *et al.* (Mazza, 2009), the design process stages in InfoVis are:

Preprocessing and data transformations , this stage involves extracting data from a data source and converting them into a structured format that a visualization application can use.

Visual mapping , in this stage, the graph designer defines which visual structures are used to map the data and their location in the display area. In the visual mapping stage should be defined three structures: *spatial substrate* is the axes selection which defines the physical data representation space; *graphical elements* are everything visible that appears in the space (e.g., points, lines); and *graphical* *properties* are the graphical attributes which the human vision is very sensitive (preattentive attributes).

Views creation , this is the last stage. In this stage, the views are the final results of mapping data structures with visual attributes. Also, this stage has a refined process based on data design objectives (e.g., explore, communicate).

The design process described above is used for usual data visualization design not related to the research of new techniques or approaches. For this review, when we mention *"early design stage"* we are referring to the Visual Mapping stage explained previously. Represents an initial design state because it has not yet been presented to the final observer, nor has any validation been performed. On the other hand, when the design process is related to the research approach, we will refer to this as *long-term* design. Long-Term being understood as the time that must elapse while the graph is being made and its validation.

For information visualization, according to the comprehensive review by (Liang & Huang, 2010), the preattentive concepts have been studied since 1987. Some remarkable authors have done extensive work on how preattentive attributes can be used to visualize information to improve its comprehension or to integrate more data in a single graph. For example:

- Ware and Beatty (1988): the authors conducted a study that probes the usefulness of color in enabling human observers to perceive clusters of points in a multidimensional space.
- Ware (1988): provided some rules about how to create color sequences (scales) for different InfoVis contexts considering the contrast and form (e.g., shape of surface maps).
- Healey and Enns (1999): the authors created a method that combines color and texture features effectively, increasing the number of attributes that can be simultaneously visualized.
- Bartram and Ware (2002): they presented a study of how motion can be applied to filtering and brushing for visualizations incorporating multiple groups of data objects.
- Rodrigues et al. (2008): established that preattentive stimuli are the first step in the visual expression process in InfoVis and explored how this preattentive selection supported the graph cognition process.

These studies presented above are seminal papers, which are currently being used as a baseline for using the preattentive attributes to represent data in InfoVis, and upon which most of the more recent research works are based, implicitly or explicitly. Thus, for this survey, we are particularly interested in the applications of the preattentive concepts, previously presented in the seminal papers, on information visualization techniques (i.e., graphs, charts, infographics, etc.).

3. Methodology

This paper aims at analyzing how the preattentive visual process is used in information visualization, mainly to improve the cognitive process in chart comprehension (i.e., perceptual effectiveness). We carried on a literature review to identify the key recent research papers in this field by adopting a systematic review protocol starting from the following Research Question, oriented to improve the observer's cognitive process in graph comprehension:

- (RQ) *How is the preattentive visual process used in information visualization?*

Although the graph concept includes all 2D and static statistical data visualizations for this study, as explained below, graphs with different characteristics (*et al.* 3D or dynamic) have slightly different attention processes.

The review protocol consists of the following three phases, detailed in the next sections: search strategy (3.1), selection (3.2), and classification (3.3).

3.1. Search Strategy

In this step, we create and develop a search strategy that consists of three sub-phases: the selection of search *sources*, the construction of the *search string*, and the definition of *filtering criteria*.

Based on the review subject, i.e., information visualization, four *sources* of information have been selected, namely: ACM Digital library, IEEE Xplore, ScienceDirect, and Springer Link. These information sources were selected because of their high relation with the topics of information visualization in computer science SCImago (2021) since most conferences and journals relevant to the Research Questions publish their papers in these sources. On the other hand, other sources such as Pubmed were not considered since they approach the preattentive process from a more theoretical and neuroscientific approach, while we are looking for papers where these theories are applied.

Regarding the construction of the *search string*, we performed a search using the keywords: *preattentive* and its spelling variation *pre-attentive*, and *information visualization* and its related term *data visualization*. The search results were scarce, and for this reason, the search was expanded by adding the keyword *data highlighting*. In InfoVis, the 'highlighting' term denotes the focus data in a graph, a concept close to the preattentive process's output. With this new keyword, the search results improved from 161 to 306 articles. The final *search string* therefore adopted in this study was: `(''pre-attentive'' OR ''preattentive'' OR ''data highlighting'') AND (''information visualization'' OR ''data visualization'')`. This *search string* was applied in the *Metadata* search field, that includes document title, author(s), publication title, abstract, and index terms. We did not find duplicate articles among the results obtained because each source was limited to articles by one publisher only. We are aware that many works where the preattentive process is exploited implicitly may have been excluded from the search; this is consistent with our goals of finding papers that *explicitly* tackle preattentive.

About *filtering criteria*, items should be in at least one of the following knowledge areas: Computer Sciences, Human-Computer Interaction (HCI), Information or Data Visualization, Data Analysis, and User Interfaces. We chose these areas because preattentive is a concept related to human process cognition, extensively explored in HCI and User Interfaces areas. Information and Data Visualization are areas focused on the communication of data visually. Another filter criterion concerned the period of the published research, and we selected the period between 2010 and 2021, inclusive. The preattentive process was discovered in the 1980s and had been widely researched after that. However, this research aims to discover the current impact of the preattentive process in InfoVis's design stage, not its fundamentals, and we focused on the last decade. Concerning the documents type, only items that represented articles in conference proceedings or journals were considered.

3.2. Selection

The second step consisted in analyzing the articles and selecting those that could answer the research questions. First, we *refined* the article list by removing those related to concepts outside the research scope. Then we *selected* the articles that met the research questions.

To *refine* the obtained articles list, we discarded the articles associated with the development of salience prediction algorithms, virtual reality, dynamic and 3D graphics, theoretical articles, vision problems (e.g. blurred vision or hypertropia), and surveys. We manually looked for these concepts in the article's title, keywords, and abstract to apply this filter. Also, we dismissed Saliency prediction algorithms because these articles present experiments and developments of attention prediction algorithms, but not how the Saliency cognitively impacts the observer in the specific InfoVis domain. Also, there are currently several papers that summarize and evaluate those saliency algorithms. We excluded Virtual Reality, Dynamic and 3D articles because those were beyond the scope of the research. We are concentrating only on static and 2D images for the current study because the attention process has been studied more extensively than those with dynamic behaviors. About theoretical and survey articles, our research focuses primarily on the practical use of preattentive concepts in the area of InfoVis rather than on its theoretical aspects.

During the *selection* sub-step, we identified whether the use of *preattentive* concepts in the paper was actually oriented at improving the cognitive process in graph comprehension (RQ). Moreover, for this research, the concept of preattentive had to be a primary topic within the article; in fact, several articles used the word preattentive only to indicate human visualization's theoretical basis but did not focus their research on its exploitation. Therefore, in this selection process, some questions were established to choose those articles that would give us more explicit information about the use of *preattentive* in InfoVis; in fact, several reviewed articles were not explicit in how they used preattentive in their research. The articles that responded to *at least one* of those four filtering questions (FQ) were selected to be analyzed. The filtering questions were:

- (FQ1) Are preattentive attributes used to improve the understanding of the graph?
- (FQ2) Are preattentive attributes used to draw the observer's attention to specific information?
- (FQ3) Are the presented article results about the cognitive influence of preattentive attributes?
- (FQ4) Are computational salience models used to measure the impact of the preattentive process?

These four questions helped us identify the articles focused on how variations in one or more of the preattentive attributes modify the graph comprehension. We thus avoided the large number of articles that focus on how to present specific data, such as weather data on a map, and do experiments on them, or propose new visualization techniques.

About FQ1 and FQ2, we are aware that the definition of "Preattentive Attributes" has different and considerably broad interpretations. For the purpose of this research, we adopted the definition established in section 2. Another clarification about FQ1 is the concept of "understanding of the graph", which includes the "graph cognition" process, without explicictly focusing on it.

Table 1. Search results

Step	IEEE	ACM	ScienceDirect	Springer Link	Total
Search Results	89	77	81	59	306
Refined Filter	73	59	68	48	248
Selected Articles	11	9	2	7	29

In addition, we focused on those works that were applied instead of extensions of theoretical concepts. This approach was because many papers study the influence of the preattentive cognitive impact, but they do not work on the impact of those in practice, with real-world data or complex graphs (e.g., interrelated graphs).

To identify which articles answered our filtering questions, we performed a reading of each article's abstract, introduction, and conclusion. Besides, we looked up the concepts used in our "search string" in the full text of the paper and analyzed the context in which they were used.

Table 1 presents an overview of the selection process. The first row, 'Search Results,' shows the source whose results were used as inputs for the selected phase. The 'Refined Filter' numbers correspond to articles list refinement, discarding those related to concepts outside this research scope. Finally, based on the adherence to the additional questions presented above, 29 articles were selected to be analyzed.

3.3. Classification

The final step was to classify and summarize the concepts and techniques proposed in the selected papers. The classification was based on the main research question: *How is preattentive used in the information visualization design to improve cognitive graph comprehension?*. We start from the assumption that, in InfoVis design, the preattentive attributes are exploited to highlight relevant data or represent more data in a single graph. Nevertheless, on the other hand, the preattentive computational models (prediction algorithms) are used as a method of graph evaluation, in general, to measure the cognitive processes of the observer. Based on the main uses that emerged from the analysis, we established a classification with two types of uses of *preattentive* in InfoVis: (1) the preattentive attributes *as design components* and (2) the preattentive process as a *measuring tool*. In the Results section, this classification will be extensively discussed.

Table 2 shows the list of the selected articles with their classification (Design Component, or Measuring Tool), year, and authors names, in chronological order. The "FQ" column represents the Filter Question (see Section 3.2) with which each of the selected articles satisfies.

4. Results

During the literature analysis process, in particular, in the Classification step, we observed that the focus on the preattention process was mainly exploited in two ways (see column 'Classification' in Tab. 2). The first (preattentive attributes as Design Components) uses the knowledge about the capability of the preattentive attributes as part of the graph design components. This implies manipulating these attributes to achieve different goals, such as instantly identifying relevant data or connecting

Table 2. Selected Articles

Title	Authors	Classification	FQ
Improving focus and context awareness in interactive visualization of time lines	Luz and Masoodian (2010)	Design Component	1, 3
Context-preserving visual links	Steinberger et al. (2011)	Design Component	1, 2
Matse: the microarray time-series explorer	Craig et al. (2012)	Design Component	1
Stacking-based visualization of trajectory attribute data	Tominski et al. (2012)	Design Component	1
Leveraging cognitive principles to improve security visualization	Dunlop et al. (2012)	Design Component	1, 2
Onset: a visualization technique for large-scale binary set data	Sadana et al. (2014)	Design Component	1
Applying feature integration theory to glyph-based information visualization	Cai et al. (2015)	Design Component	1
Comparing color and leader line highlighting strategies in coordinated view geovisualizations	Griffin and Robinson (2015)	Design Component	1, 2, 4
Supporting supervisory control of safety-critical systems with psychologically well-founded infovis	Ostendorp et al. (2016)	Design Component	1, 3
Using typography to expand the design space of data visualization	R. Brath and Banissi (2016)	Design Component	2, 3
A space optimized scatter plot matrix visualization	Wang et al. (2016)	Design Component	1
Cognitive benefits of a simple visual metrics architecture	King et al. (2016)	Design Component	1, 2, 3
Font attributes enrich knowledge maps and information retrieval	R. a. Brath and Banissi (2017)	Design Component	1
Keshif: rapid and expressive tabular data exploration for novices	Yalçın et al. (2018)	Design Component	1
CorFish: Coordinating Emphasis Across Multiple Views Using Spatial Distortion	Richer et al. (2019)	Design Component	1, 2
GeoBrick: exploration of spatiotemporal data	Park et al. (2019)	Design Component	1, 2
Guidelines for cybersecurity visualization design	Seong et al. (2020)	Design Component	1, 3
Photographic High-Dynamic-Range Scalar Visualization	Zhou et al. (2020)	Design Component	1, 2, 3,
Comparing averages in time series data	Correll et al. (2012)	Measuring Tool	1, 2, 3
Does an eye tracker tell the truth about visualizations? findings investigating visualizations for decision making	Kim et al. (2012)	Measuring Tool	2, 3, 4
Individual User Characteristics and Information Visualization: Connecting the Dots Through Eye Tracking	Toker et al. (2013)	Measuring Tool	3
Highlighting interventions and user differences: informing adaptive information visualization support	Carenini et al. (2014)	Measuring Tool	1, 2, 3
Eye tracking to understand user differences in visualization processing with highlighting interventions	Toker and Conati (2014)	Measuring Tool	1, 3, 4
Towards Facilitating User Skill Acquisition: Identifying Untrained Visualization Users Through Eye Tracking	Toker et al. (2014)	Measuring Tool	1, 3, 4
Enhancing infographics based on symmetry saliency	Yasuda et al. (2016)	Measuring Tool	2, 4
Pupillometry and Head Distance to the Screen to Predict Skill Acquisition During Information Visualization Tasks	Toker et al. (2017)	Measuring Tool	1, 2, 3
Mitigating the Attraction Effect with Visualizations	Dimara et al. (2019)	Measuring Tool	2, 3
Eye-tracking reveals how observation chart design features affect the detection of patient deterioration	Cornish et al. (2019)	Measuring Tool	1, 3, 4
Incidental Visualizations: Pre-Attentive Primitive Visual Tasks	Moreira et al. (2020)	Measuring Tool	1, 3, 4

data between graphs. The second way (preattentive process as a Measuring Tool) uses the preattentive process as a measurement technique, either using predictive models or instruments such as eye-trackers. Such measurement is generally used to assess attention on portions of a graph or determine the impact of preattentive attributes. Both categories are relevant to the scope of this survey, as they both aim to understand or improve the cognitive processes of the graph observer.

In this context, we present a synthesis of the selected articles grouped according to their classification in the current section. The studies presented in this section are limited to those articles selected in Table 2. Although we excluded the seminal papers (see section 2) of the results, it is essential to point out that the concepts already investigated for them (in the previous decade) are used as a basis for the papers presented in this section.

4.1. Preattentive Attributes as a Design Component

It may seem evident that preattentive attributes such as color, shape, or size are always used as design components in a data analysis image, often implicitly. Nevertheless, for this literature review, we interpret the use of these attributes as an explicit attempt, at design time, to steer and focus the observer's attention and help them in the cognitive process of graph interpretation. We did not focus on using visual elements to distinguish diverse data in a graph, only in its visual attention characteristics. Preattentive attributes highlight relevant information in the reviewed literature, linking graphs or representing several data sets in one graph. Besides, color, shape, and size are the most common preattentive attributes used for this.

Within this Design Component category, we established three more subcategories to organize the different modalities in which the preattentive attributes are employed. These subcategories are: *Core Preattentive Attributes*, *Unusual preattentive attributes* and *Preattentive attributes into design methodologies*. Regarding the use of core attributes, we described all articles that used known attributes such as color, size, shape, or the combination of these attributes such as Glyphs. In the subcategory of unusual preattentive attributes, we report those articles that use the preattentive process concept on non-usual elements, for example, text. Finally, we also find that the preattentive attributes as a design component can be part of design methodologies, e.g., highlighting rules for relevant data.

4.1.1. Core Preattentive Attributes

According to Bartram, Patra, and Stone (2017) *color is preattentively observed, this characteristic makes it particularly useful in conveying qualitative and quantitative information in images, maps, graphics illustrations, and diagrams.* Color is the most common preattentive attribute used to improve the comprehension of the graphics. Currently, several color schemes are available and have been studied and validated and are widely used in InfoVis (Bianco, Gasparini, & Schettini, 2015). For instance, Park et al. (2019) present GeoBrick, a technique for exploring Spatio-temporal data. In GeoBrick, each region is comprised of multivariate data, which is encoded into a simple shape with a unique color scheme. They use three linked views: abstract, map, and comparative views. For Abstract View, the authors use glyphs to show multiple variables for a central variable (e.g., region in a map) in a specific period. They assign a color to each glyph section to represent a variable, which is also the upper limit of colors that humans can distinguish simultaneously. For the color used in glyphs, they selected ColorBrewer schemes commonly used for maps (Brewer, 1996). In similar research, but in a different context, Yalçın et al. (2018) use colors to link graphs and highlight relevant information in dashboards, and Craig et al. (2012) use spatial grouping and colors to enclose related information on large scale microarray time-series data. Also, Correll et al. (2012) present a study where they use color as a preattentive attribute to improve the performance in the 'detect sub-range' task of time series. Their proposed to encode data using color rather than position and draw the user's attention into a large region of color. They used the perceptual averaging theory that suggests: "color encodings would afford reliable determination of averages, as averaging over a range could be performed by the perceptual system instead of as a mental computation" (Correll et al., 2012). This latter study showed that the participant task performance was better using the color attribute than the standard line graph encoding. Recently, Zhou et al. (2020) used the glares to make high-value regions (of a few pixels) more pronounced in HDR (high dynamic range) visualizations. They considered that glares pre-attentively steer attention and focus the visualizer's attention onto high-value features.

Furthermore, color is used at the contrast level to highlight data, but also, the blur is used to make some data more visible than others. For instance, Luz and Masoodian (2010) tested some designs techniques to improve the focus and context awareness capabilities of standard Gantt charts. They use blur to avoid attention on non-focal items. In this study, the "blurring" technique yielded improvements in user performance.

Although the color is the most used preattentive attribute, it is used with other attributes to enhance the range of attention and give more information with a single representation in specialized InfoVis graphs. Tominski et al. (2012) present an approach that integrates space, time, and some preattentive attributes to improve the visualization of Trajectory Attribute Data. Trajectory graphs represent data in a route between two points on a map, such as environmental attributes, land cover, and others. Authors use color and spatial position as preattentive attributes. They use a color-code based on ColorBrewer (color schemes for maps), which provides a renamed color scale for several data classes. Tominski et al. (2012) also used spatial position (grouping) preattentive attribute, which divides a broad set of trajectories into manageable portions and focuses the attention on interesting subsets of trajectories. In this approach, the highlight is related to a behavior interaction, and the observer selects a point between spatial and temporal in the color trajectory band.

The Converged Security Visualization Tool design is an additional example of preattentive attributes combination to highlight relevant information Dunlop et al. (2012). This tool uses preattentive attributes to identify and analyze threats from multiple detail levels supporting the information overload in security data analysis. For instance, high-risk machines require immediate attention, and to achieve this, the tool uses three visual features that activate preattentive detection: curvature, color, and size. Cai et al. (2015) made a detailed study of how to use preattentive attributes to improve a particular type of visualizations, combined different preattentive attributes. Cai et al. (2015), used a set of glyphs named RoseShape, to optimize the visual search in information visualization. RoseShapes combines three preattentive attributes: color, size, and shape. In the experiment, color and size were used to highlight the essential information. For the RoseShapes with the same size and color, shapes were the preattentive attribute to differentiate them with more o fewer petals. As contributions, the authors emphasize that basic shapes (circles, rectangles, or triangles) are limited for visual diversification of semantics, unlike RoseShapes, either winding periphery and slim petals or smooth edges and plump petals.

Another frequent use of the preattentive attributes is on Coordinated Views. Coordinate views are visual techniques used to highlight observations across the graphs (Griffin & Robinson, 2015). The authors present a comparative experiment using two highlighting strategies for coordinated-view geovisualizations. The authors point out that some information visualization systems have widely used colored outlines or fill to highlight observations in coordinate views, but other visual strategies could be used, such as leader lines. This paper describes the results of an experiment designed to compare user performance with two highlighting methods; color and leader lines. Leader line strategy draws lines out from the selected observation to its counterparts in other views. Other related work with coordinated views is presented by Steinberger et al. (2011). To highlight these complex visualizations, Steinberger et al. (2011) propose visual links that adapt to color context, minimizing the visual interference of relevant information. To achieve this, they adjust the appearance of visual links using some color highlight techniques. First, a link color is automatically selected, maximizing the color difference between the link color and its vicinity. Second, if the automatically selected color did not generate contrast between the links and their vicinity, a halo-like glowing effect is added around the link. The last adjustment identifies where the text is, and in those points, changes the link color and puts the line behind the text. The results indicate that this approach is more visually attractive than the other tested techniques.

The use of preattentive attributes in Coordinated Views to highlight relevant data was also studied by (Sadana et al., 2014), Wang et al. (2016), and (Craig et al., 2012). These three studies use the preattentive attributes in a typical way, by changing color to get more detail about one set of data in coordinated views. Finally, in more recent research, Richer et al. (2019) presented CorFish, a method for coordinating spatial distortion across multiple views. CorFish uses a distortion technique (or magnification) that alters preattentive elements (size, position, and shape) to make selected data more visually prominent. Additionally, they applied the cue-based technique that modifies other visual properties (color, transparency) or adds decorations (contour, halo).

4.1.2. Unusual preattentive attributes

Due to the many ways to represent data in InfoVis, preattentive attributes are not only used in specific charts (bars, boxplot, and others) but they can also be manipulated on text visualizations (e.g., Knowledge Maps). One example is the research presented by R. a. Brath and Banissi (2017): they use font properties, such as bold and italic, to make some text visually preattentive and to add more information into textual displays. This research explores the broad range of alternatives to combine all text attributes to represent multi-attribute labels. However, this approach has some hesitation regarding the aesthetic appeal and time to understand, and each attribute is used to represent different information. One more example is presented by R. Brath and Banissi (2016), who made a systematic exploration intending to include text (font) as a preattentive attribute in InfoVis. However, they argue that literal encoding is part of the design space. An example they give is: "replacing a dot on a scatterplot with an alphanumeric character preserves the initial reading of the scatterplot, increases data density by adding additional information with the character, and allows for the perception of associative micro-patterns—local adjacencies that would otherwise require interactive techniques to reveal."

4.1.3. Preattentive attributes into design methodologies

Our last finding in this category is that some researchers have included preattentive attributes as a fundamental part of InfoVis design methodologies. For example, Ostendorp et al. (2016) present a systematic method to derive a Human-Machine Interaction design for a safety-critical system's supervisory control task. This method uses Human Factor methods to focus the InfoVis design towards the human perception skills. Furthermore, they selected glyphs as a fundamental design element because more information can be held in working memory. In order to guide the designers, this method combines the information (data), the insight the human controller wants to have (e.g., temperature), type of information (e.g., quantitative, nominal, ordinal), and the most effective attribute. The most effective attribute is based on the effectiveness ranking of preattentive attributes considering the type of information. For instance, if the type of information is nominal, the possible visualization attributes are position, color hue, texture, connection, and so on. The evaluation showed that designs were significantly faster and more correct to perceive using Ostendorp *et al.* method. Another example can be found in the guidelines for Cybersecurity information visualization presented by Seong et al. (2020). In this methodological guide, the authors encouraged designers to "*take advantage of the human visual system's ability to do preattentive processing by seeking to encode information pre-attentively visually.*" Also, King et al. (2016) proposed a Visual Metrics Architecture to create dashboards. King *et al.* used preattentive attributes such as hue, intensity, and form to identify critical information as part of their proposed architecture. Besides, they established some rules that considered the pre-attentively property rank. For example, form and color are potent properties for preattentive detection; therefore, King *et al.* separate them to create diverse templates as part of its proposed Visual Metrics Architecture.

4.2. Preattentive Process as a Measuring Tool

The preattentive process can be predicted, and its impact can be evaluated using computational models such as saliency maps and eye-tracking (see Section 2). In this literature review, we found that eye-tracking is a common technique used in InfoVis to analyze perceptual and cognitive processes of visual tasks (Raschke, Blascheck, Richter, Agapkin, & Ertl, 2014). This experimental methodology has proven useful for human-computer interaction research and for studying the cognitive processes involved in visual information processing, including which visual elements people look at first and spend the most time on (Jacob & Karn, 2003).

On the other hand, saliency maps are not a commonly used technique, but they can also predict InfoVis's visual perception. There are many saliency algorithms (Elsa & Neenu, 2017), with a different approach, most of them based on the Itti-Koch biological model (Itti & Koch, 2001) (see section 2). These saliency map algorithms, according to Matzen et al. (2018) *can accurately predict where observers will look in a natural scene; they typically do not perform well for abstract data visualizations.* We found some articles related to modifying the original algorithm for InfoVis by transforming the image color characteristics and the salience algorithm's normal parameters.

Based on our investigation, in InfoVis, these two preattentive computational models (saliency maps and eye-tracking) have been used to evaluate the graphs observers' cognitive process (e.g., fixations, focus time) in order to establish design patterns. For instance, big industries in InfoVis, such as Tableau, use eye-tracking to find design patterns. For instance, Tableau Research and Design team (Alberts & Cotgreave,

2017) experimented with eye-tracking to discover key learning about Dashboards. They observed that dashboards with vast numbers showed a concentration of visual attention directly on the significant numbers. Also, they discovered that human-like figures get prime attention over other data. Concerning color manipulation, they detected that high visual contrast areas acted as guideposts throughout a dashboard. The eyes tended to jump from one high contrast element to the next. Thus, as we can see, this experiment has used eye-tracking to measure the impact of the preattentive process in a practical context, as the Tableau system is.

Use of the preattentive process measures to evaluate the cognitive process is the most common usage in InfoVis. According to Toker and Conati (2014), *"various cognitive abilities such as perceptual speed, verbal working memory, and visual working memory have been shown to impact user performance and/or user subjective experience with Infoviz task."* Also, Healey and Enns (2012) explain that the human visual system is strongly related to cognitive and memory processes that take action in data comprehension and interpretation. Based on these statements, InfoVis uses eye-tracking to get insights into observers' cognitive process when reading the graph and to solve a definite task. With this measuring technique, InfoVis creators can know which is the focus of attention of the graph and the performance in its comprehension. An example of this evaluation of the cognitive capability was presented by Carenini et al. (2014) and Toker and Conati (2014). Both works focus their preattentive evaluation on the intervention of "marks" (lines or arrows), "hue", and "width" attributes to improve the visualization process in bar charts. With these dynamic changes, authors suggest alternative visualization, guiding users to do a specific task. The experiment result was that highlighting interventions improve visualization processing compared to receiving no intervention. Also, no single preattentive attribute is the most effective overall, depending on the user task.

Another investigation found in this perspective was made for Kim et al. (2012). In this research, Kim et al. (2012) did an eye-tracking study to investigate *how visual aids influenced the participants' browsing behaviors and decision-making strategies that eventually influence decision quality.* With eye-tracking studies, they evaluated how data highlighting has some cognitive process effects in decision making. They used the SimulSort visualization technique created to support multi-attribute decision-making. With this technique, two items can be linked in a table representation by comparing the highlighted cells' vertical positions (with cells filled with a different color for each item), unlike the regular reading of tables where rows compare items. SimulSort highlights the position of the item value (row) in each sort attribute (column). The results demonstrated that with the use of this highlighting technique, decision-making quality had an improvement. In addition, SimulSort provided pattern information (color highlighting) for quicker browsing and promoting compensatory decision-making strategies. With the eye-tracking results, Kim et al. (2012) verified that different stimuli configurations, rather than the tasks themselves, could affect information-processing strategies when people made choices.

Furthermore, the preattentive process could change when users have previous knowledge: Fabrikant, Hespanha, and Hegarty (2010) present the results of an attentive experiment with novices and trained users on weather map reading. They wanted to know *whether perceptually salient elements draw novice observers' attention (bottom-up processing) or whether their attention is directed by domain knowledge of meteorology (top-down processing).* They chose full-color weather maps, including surface temperature and pressure, because of their potential complexity for spatial inference making and attractiveness. As a result, the accuracy of response significantly increased after participants learned the task-relevant weather principles. About eye fixation patterns, the authors found that participants spent more time on thematically relevant items such as a closed pressure system (color code) and less time on items as a legend after learning weather principles. Thus, the authors conclude that visual attributes (preattentive attributes) affect viewing behavior, especially in novice observers. Besides, the authors say that matching thematically relevant information with a significant perceptual salience improves the efficiency of making inferences from the graphic display.

In a set of papers by Toker *et al.*, Toker and Conati (2014); Toker et al. (2013, 2017, 2014), the authors use eye-tracking to understand *"how sets of user characteristics, highlighting interventions, and task complexity impact gaze behavior during bar graph visualization processing?"* They performed the test with thirty-five subjects, characterized by three cognitive tests. The subjects performed 14 tasks, and each task consisted of presenting a radar/bar graph displaying the relevant data (highlighting interventions), along with a textual question. Toker *et al.* collected the information with eye-tracking while the subjects performed the tasks described above. Some results about highlighting interventions were: (1) highlighting interventions can improve visualization processing compared to receiving no interventions (task performance and usefulness); and (2) some specific visualization regions can cause low task performance in users with low values of specific cognitive measures.

Some studies present how it is possible to draw visual attention to infographic images, a different type of InfoVis images. Yasuda et al. (2016) approach uses symmetry salience to enhance local symmetry inherent in the layout of visual patterns. Symmetry saliency is an algorithm to detect a saliency region based on symmetry Gestalt principles. This principle allows schematizing visual images by approximating them as pairs of symmetric patterns extracted from object silhouettes. Thus, image saliency leads to a promising approach for improving visual images' readability with sharp edges such as infographics. Yasuda et al. (2016) enhance four infographic images: statistical charts, node-link diagrams, a tag cloud, and a city map. They perform an eye-tracking study to evaluate how much the approach can draw attention to a specified region of interest. The results showed that this approach could draw more visual attention to the selected region of interest. In another case, Dimara et al. (2019) present empirical evidence about how highlighted optimal choices could help decision-makers to focus on important information while ignoring distracting choices. They developed an experiment highlighting the *Pareto Front*, and their objective was to improve one objective by deteriorating one of the others in the graph. They found some evidence that highlighting the Pareto front helped participants to make faster decisions and weaken the attraction bias (decoy and distractor points).

The latest studies in this category are presented by Cornish et al. (2019) and Moreira et al. (2020). Cornish et al. (2019) conducted a study to investigate the established effects of observation chart design on patient deterioration detection. They evaluated participants' (doctors and nurses) ability to detect abnormal observations on paper-based chart designs in which preattentive attributes (color and marks) were present or absent. Participants made fewer errors and were faster when color scale and markings were included (observations) in the chart. On the other hand, Moreira et al. (2020) conducted a user study to test how simple visual tasks can be executed pre-attentively without a conscious process. The study tested some tasks, such as finding points in a vertical or horizontal position, line length, and color luminance. The results showed that the horizontal task is the most accurate and faster to execute pre-attentively, and color luminance is the worst one.

Finally, most of the articles responded to QF 1 (see Table 1), confirming that concepts rested to preattentive attributes are implicly exploited for graph comprehension. However, less than half of the researches explored the possibilities of using preattentive according FQ2, FQ3, and FQ4, thus identifying potential areas for further research.

5. Discussion

This review mainly aimed at identifying *how the preattentive visual process is used in information visualization* (RQ), oriented to improve the observer's cognitive process in graph comprehension. The survey results indicate that the preattentive visual process is used implicitly in two ways: as a *design component*, and as a *measuring tool*. As *design component* means that researchers used the preattentive attributes for specific design objectives to emphasize data, represent several data sets in one graph, or linking data. On the other hand, as *measuring tool* is when the preattentive process concepts are used as a measure to validate design decisions or to graph redesign.

The novelty of this research is that the results provide a classification of the preattentive process concepts based on their different uses (Design Components vs Measuring). In addition, we found that in InfoVis area some design elements, not usually known associated to "preattentive attributes", are in fact used for highlighting or drawing attention to essential graph points: those could be considered as "implicit" preattentive attributes (e.g., glyphs). On the other hand, we presented how the preattentive process can be explicitly used as part of graph creation methodologies. Additionally, we made a classification in the use of validation methods of the preattentive process. We established that these measurements could be used to redesign the graphs or simply as a validation tool of design decision-making. However, we did not find any article that considered the end-user (the graph designer); although it is still a widely studied area, we have not found efforts to bring it closer to those who design graphs.

In this section, after a discussion over the two categories (Sections 5.1 and 5.2), we will also present possible future research about the level of expertise required to purposely use the preattentive attributes and use the preattentive process as a validation tool integrated into VA systems (5.3). Finally, we are going to propose possible approaches to cover them (5.4)

5.1. Preattentive as Design Component

The literature review confirmed that preattentive attributes are used in general to highlight data. This is consistent with has been mentioned in sections 2 and 4.1. Several articles demonstrated how preattentive attributes could be used to draw the observer's attention in specific data, using highlighting techniques Correll et al. (2012); Yalçın et al. (2018); Zhou et al. (2020). Color and form preattentive attributes categories are the most common highlighting techniques used to emphasize data, and at the same time, they optimize the visual search (Cai et al., 2015; Carenini et al., 2014; Park et al., 2019; Toker & Conati, 2014). We also detected that highlighting might be applied according to the data type (e.g., identify threats Dunlop et al. (2012)) or based on a design decision (e.g., Coordinate views Griffin and Robinson (2015); Steinberger et al. (2011)).

Preattentive attributes can also be used to enrich data. We identified two different techniques: adding more data and linking graphs. Adding more information in one InfoVis graph can be done by integrating, commonly, color and shape preattentive attributes (R. a. Brath & Banissi, 2017; Park et al., 2019; Tominski et al., 2012).

Integrating these attributes makes it possible to visualize different data in a single InfoVis graph. In the other technique, the preattentive attributes like hue, color, and marks are used to *link data*, which means showing the connection between graphs or displaying more details about the data (Craig et al., 2012; Dinkla, Westenberg, & van Wijk, 2012; Griffin & Robinson, 2015; Sadana et al., 2014; Steinberger et al., 2011).

Additionally, we found that in InfoVis, some visual elements could extend main preattentive attributes. We identified two possible new visual preattentive elements: Glyphs and Glares. Glyphs integrate diverse preattentive attributes like color, form, and orientation to present more information in one graph (Cai et al., 2015; Ostendorp et al., 2016; Park et al., 2019). We contemplate Glyphs as an attentive attribute because it integrates the most commonly used preattentive elements, and its preattentive impact could affect the understanding of the graph data (Ostendorp et al., 2016). The other, more recent, visual element is simulated *Glares* presented by Zhou et al. (2020). This technique uses brightness to guide the observer's attention to identify the most relevant information. In addition, this technique enhances the visibility of the secondary data because it generates a high contrast. We consider that Glares could be a new attentive attribute because it highlights specific data, and at the same time, the secondary data also get more attention. However, we acknowledge that those new attributes should deserve a thorough investigation as there is currently little literature on the subject. Further research is needed to establish the attention impact of these attributes in the preattentive visual-cognitive process.

Finally, we noticed that the use of preattentive attributes in the graph design stages is highly implicit. In most papers, using preattentive attributes as design elements is shown as something implicit, something that the researcher, or graph designer, already knows, or some VA system already handles by default. The implicit use of these attributes revealed an essential gap between the theory and final users' intended use of this knowledge. Both expert researchers and VA systems are able to handle the impact of the preattentive attributes in the visual-cognitive process, but final users use them unconsciously. In most articles, it is clear that the studies are oriented to create standards or understand the attribute's attention behavior but do not help novice graph designers understand the visual-cognitive impact of their design decisions.

One of the tough challenges for researchers in this domain is to bring the implications of the preattentive attributes visual impact to the less knowledgeable in InfoVis design so that they can make better and more conscious design decisions.

5.2. Preattentive as Measuring Tool

Different techniques can measure the preattentive visual process, in InfoVis mostly with eye-tracking and saliency models. However, eye-tracking and saliency models were the techniques commonly adopted in InfoVis. Those techniques may identify the focus of the observer's attention in the preattentive and attention visual processes (see section 2. However, as stated in the methodology section, our study purpose was the practical use of preattentive process concepts without delving into how those techniques are developed or their effectiveness. In InfoVis, the preattentive measurement techniques are utilized to get insights about an observer's cognitive processes when they read a graph. In this study, we identified that these techniques could be employed both to measure the cognitive impact of preattentive attributes and as a measuring tool to support graph redesign.

About the use as a measure to determine the preattentive attribute cognitive impact, most of the studies found to belong to this category, e.g., Fabrikant et al. (2010); Kim et al. (2012); Toker et al. (2013, 2017, 2014); Yasuda et al. (2016). In those investigations, the researchers recognize the importance of highlighting relevant points on the graph so that the observer can detect them more efficiently. The preattentive attribute handling also helps the observer to make a more effective comparative analysis of the data. Other studies have used these preattentive measures to establish design patterns. For instance, huge numbers showed a concentration of visual attention in a dashboard (Alberts & Cotgreave, 2017).

Within the studies, we observed many that used the preattentive concepts to evaluate their designs or new techniques to prove their possible effectiveness. However, only a few articles used the concepts to evaluate attention and improve the design of the graph, focusing on the overall design decisions for the whole graph instead of an individual attribute. For example, Yasuda et al. (2016), they use symmetry salience (preattentive measure) to improve the graph visualization in the design stage.

5.3. Expertise level to handle purposely preattentive concepts

Although there is a significant theory about the cognitive impact of preattentive attribute manipulation, and as we showed above, preattentive also has more than one use in InfoVis, we noticed a gap between the theory and the needs of graph designers. For the purposes of this research, the *graph designer* are those who those who create InfoVis graphs daily, using any VA system. These graph designers come from different areas of expertise, for instance be designers by profession or experts in data analysis.

The results show that graph designers must have extensive knowledge about the preattentive process to understand how to use its attributes. For example, the VA systems have some visual elements, like color palettes, that have solid preattentive visual process fundamentals (Brewer, 1996; Egeth & Yantis, 1997). However, in those systems, the visual-cognitive process is implicit, applying standard shapes or colors scales without giving insights to the graph designer on how their use can affect the graph design objectives. Furthermore, in many cases, using existing visual elements in VA systems does not provide insights for a novice user. For instance, a novice graph designer does not know how to handle visual elements to reduce the cognitive process's cost and to maximize the observers' cognitive productivity.

In this research, we claim that the graph designer lacks relevance. However, a more in-depth search on this specific topic should be carried out. From this standpoint, bridging the gap between the graph designer and the preattentive attributes visual implications can be considered a relevant research topic.

5.4. Preattentive prediction as design measure tool

In section 5.2, we discussed how measuring the impact of preattentive attributes can be a promising tool for performing graph design improvements. Also, we pointed out that according to several studies, the focus of attention in an image affects the human cognitive process. Based on these assumptions, future research should further develop how to integrate these attention predictions models in VA systems to support graph designer decisions.

Currently, some researchers are developing new methods and algorithms to generate attention prediction maps specifically for InfoVis images (Bylinskii et al., 2017; Fosco et al., 2020; Matzen et al., 2018). Those algorithms are the first approaches to predict the visual and cognitive impact of preattentive attributes already in the graph design stage. As a first strategy, we have presented an exploratory approach on how to use a saliency model to assist the graph designer in drawing the observer's visual attention into the data that she considers most relevant (Barrera-Leon, Corno, & De Russis, 2020). We developed a tool to generate various charts depending on which relevant data was selected to focus, and the graph designer preferred color palettes. The results showed that it is possible to algorithmically drive the observer to focus on relevant information, handling some preattentive attributes such as color and orientation.

6. Conclusions

We conducted a review in order to find out how the preattentive concept is used in InfoVis in the last ten years. We found about 306 articles that mention the word "preattentive", but we only selected 29 in which the concept is used to improve the graph observer's cognitive process (graph comprehension). The research showed that the preattentive concept has been used in two ways in the InfoVis design. The first is at the design level, creating graphics with the awareness that each design element that is selected has a preattentively explicit capability. The second usage is to use preattentive as an evaluation tool to measure the impact of the preattentive attributes in the graph attention.

We conclude that the understanding the impact of preattentive attributes is only used implicitly, in other words, based on analyses of attention models developed more than 20 years ago. Furthermore, the knowledge of how to correctly handle this preattentive ability is only exploited by experts in the field of design or human vision. Novices, who design graphics daily, seem not to be a significant a target in current research.

On the other hand, we identified a gap between activities done at design time and at the graph's validation. The evaluation of graphs is done in laboratories, in controlled environments and is extremely time-consuming. Consequently, in our research, we did not find any tool that, at design time, may show the graph creator the impact that their design decisions might have on graph comprehension. This lack of knowledge of design decisions' possible cognitive impact is a starting point for future work. Currently, researchers are developing saliency prediction algorithms (human vision models) adapted for InfoVis. With these new algorithms, the graph creator could be given a first insight into whether her graph is expectedly impacting the observer, already during the creation process.

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