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REGULAR PAPER

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Examining interaction techniques in data visualization authoring tools from the perspective of goals and human cognition: a survey

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Abstract We review the state-of-the-art interaction techniques of visualization authoring tools. The visualization tools tend to help users in the creation, exploration, or presentation of visualizations. Also, they allow users to craft expressive designs or extract data from visualizations. The review presents the interaction techniques integrated into the tools for those mentioned above five high-level goals. We cover each goal's tools and summarize how a sequence in the independent interaction techniques leads to the goal. We also discuss how well researchers had evaluated the usability and intuitiveness of interaction techniques. We aimed to reflect on the strengths and weaknesses of the evaluations. To that end, from the perspective of human cognition, we reviewed the goals, procedures, and findings of evaluations. Principally, human cognition is engaged when they perform tasks in a tool. The interaction techniques bridge the gap between human cognition and the goals they want to achieve from the tool. To sum up, in this review, we present a novel triad 'goals-interaction techniques-cognition' taxonomy. Besides, the review suggests the need for further work to enhance tools and understand users.
Graphic Abstract

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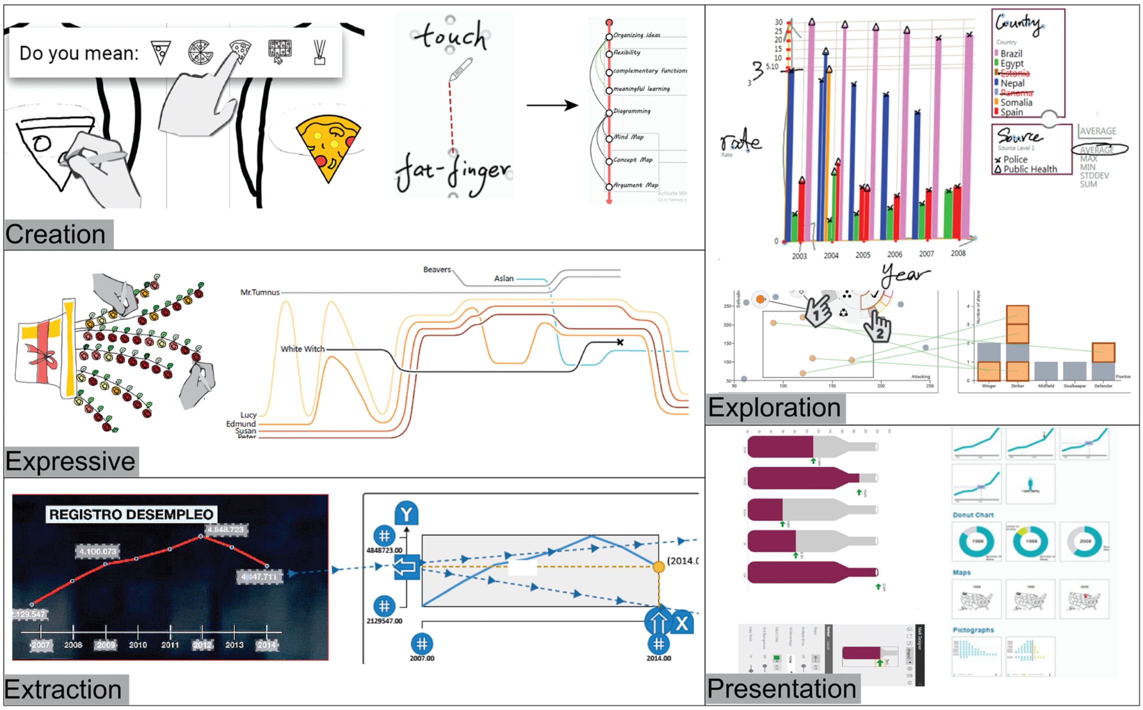

Keywords Visualization authoring tools · Interaction techniques · Cognition · Evaluation · Exploration · Creation · Presentation · Expressive

1 Introduction

The development of data visualization authoring tools (DVAT) is often goal oriented. For instance, the goal of a tool can be to help users analyze data (e.g., Yalcin et al. (2018); Wongsuphasawat et al. (2017)) or create expressive representations (e.g., Ren et al. (2019); Xia et al. (2018); Kim et al. (2017a)). The central aspect of a DVAT is that the achievement of the goal is through interaction techniques. The interaction techniques can also boost users' skills, performance, or knowledge about the data when they work on their goal in a tool (Roberts et al. 2017; Lee et al. 2019; Dimara and Perin 2019). The multi-level typology (Brehmer and Munzner 2013) and the science of interaction (Pike et al. 2009) help understand the relationship between goals and interaction techniques. However, merely this relationship may not be sufficient for crafting novel tools or providing users with a better experience. Appropriate consideration of human cognitive processing is indispensable. In fact, human cognition is engaged while users are working on their goals, and interactions create a bridge between cognition and the goals (Brehmer and Munzner 2013; Liu and Stasko 2010; Pike et al. 2009; Lam 2008).

The strength of interaction techniques suggests that, in a DVAT, they should turn out as an effective means to support human cognition. Mainly, in a shift from the user's mental model to the desired result (Liu and Stasko 2010), interaction techniques can reduce the cognitive load or confound the cognitive abilities (Green et al. 2008). First, here we describe the mental model from the perspective of InfoVis. The mental model refers to what is in the human mind. It can be a suitable mapping between the data and visual items, or interactions and representations for data visualization (Liu and Stasko 2010). Inspired by the relation between the mental-model/human-cognition and goals, visualization researchers have identified the cognitive activities that users use in the goal (see Table 1). Users face difficulty if the interaction techniques make it difficult to follow the cognitive activities or take them away from the goal (Patterson et al. 2014; Ceneda et al. 2019). Thus, a tool can compete with others for the results, but its practical significance depends on how well the interaction techniques minimize the cognitive load. A low cognitive load reduces the chances of making mistakes and overlooking features. Researchers emphasize evaluations that measure

Table 1 The table presents a summary of the cognitive activities (in the context of InfoVis), which users use when working on the goals and the prevailing interaction techniques for each goal

Goals	Cognitive activities	Interaction techniques
Creation	Users spend time in selecting the variables and choosing the appropriate representation (Lam 2008). Continuously refine the output unless they find consistency in the visualization and their mental model. The final result is not merely for a specific problem (Crapo et al. 2000).	Create, draw, generate, encode, manipulate, link, refine, filter, pan and zoom, reorder, arrange
Expressive	The mental model serves as the foundation for achieving creativity and innovation in the design (Liu and Stasko 2010). Novel designs motivate users' interest in exploring other ideas (Brehmer and Munzner 2013).	Create, encode, linking, lay out, reorder
Exploration	Think about the objectives (Yalçin et al. 2016). Capture the implications according to the objectives and enhance the mental model (Crapo et al. 2000). Create and manipulate visual representations, and after interactions, assess changes (Yalçin et al. 2016). Search all possible relationships (Pike et al. 2009). Prefer to start from overview and then move to details (Brehmer and Munzner 2013). Unintentionally pick up cues from the representation for retrieving the information, and use those cues while exploring other visualizations (Patterson et al. 2014). Make use of the previous mental model and create a representation of the data for better understanding (Kim et al. 2017b). In a visual representation, focus on what is important, and should not be missing, and what is unimportant that should be removed (Crapo et al. 2000).	Generate, select, filter, annotate, pan and zoom, overview-to-detail, reorder, brushing-and-Linking, lay out
Presentation	Heavily rely on specific view and, while creating a visualization, are biased towards that view (Crapo et al. 2000). Prefer to communicate a succinct story of the data (Brehmer and Munzner 2013).	Generate, create, manipulate, bind, lay out
Extraction	Users focus on retrieval cues such as color, shape (Patterson et al. 2014).	Extract, refine, bind

the costs and benefits of interactions in the shift between the goal and human cognition (Satyanarayan et al. 2019; Yalçin et al. 2016; Brehmer and Munzner 2013; Pike et al. 2009).

We can observe users' experience with the interaction techniques through metrics such as the response time, accuracy (the two are the primary measures of users' performance), information recalled, ratings, and preferences. These metrics are suitable for evaluations based on cognitive activities (Patterson et al. 2014). Prior experience of users with related tools can influence the observations (Liu and Stasko 2010). Mainly, experience improves the mental model (Pike et al. 2009), due to which the expert users follow a well-coordinated approach. While non-experts rapidly shift their focus from one interaction to others (Crapo et al. 2000). The cognitive activities that we identified in the literature were stated independently of the users' experience. However, we considered this aspect in the review of evaluations.

This review has two main contributions: First, we summarize the relationship between the goals and interaction techniques of DVAT. Despite the taxonomies that shed light on the relationship (Brehmer and Munzner 2013; Pike et al. 2009), no study has thoroughly reviewed it in the DVAT (see Sect. 2.1). Second, we summarize the evaluations of the tools. The evaluations done by prospective users are a valuable source of judging interaction techniques from the perspective of human cognition (Isenberg et al. 2013; Tory and Moller 2004). Previous works show that researchers had assessed the tools based on their personal experiences (see Sect. 2.2), yet no study has reviewed the evaluations presented in the paper of each tool. In our review, based on the cognitive activities and the guidelines given in the literature, we aimed to identify the strengths and weaknesses in the evaluations of interaction techniques. We hope the summary will make readers understand how well researchers had assessed the usability and intuitiveness of the interaction techniques and what the users' expectations were.

Section 4 (main section) is comprised of five subsections that present the high-level goals of the DVAT we have identified in the literature. *Creation* supports the effective ways of creating visual representations for the data. *Expressive* supports the methods that bring customization in designs and present data expressively. *Exploration* helps users in reading visualization and making sense of the data. *Presentation* provides methods that generate expressive presentations quickly. *Extraction* delivers effective ways to extract information from the existing representations. In each subsection, we have described the interaction techniques and identified the sequence in them. Then, we have summarized the evaluations.

Before moving to the main section, in Sect. 3, we describe the methodology of our review and cover various interaction techniques of visualization authoring tools. In Sect. 5, we discuss the guidelines for the interaction techniques and their evaluation and shed light on the scope of future work. Finally, in Sect. 6, we conclude our review.

2 Related work

In this section, we first summarize the previous reviews of the DVAT. We discuss their limitations in reviewing the interaction techniques from the perspective of the goals of the DVAT. We then describe the literature that defines the relationship between the goals, interactions, and cognition.

2.1 Guiding interaction techniques

There are several earlier reviews of the DVAT. Here we discuss why they cannot provide a detailed direction on the interaction techniques for the varied goals served by the tools.

Pantazos and Lauesen (2012) had highlighted the issues users face in the creation and manipulation of visualizations. The study is significant for assessing the impact of the issues on cognitive abilities. Although the review focus on creating visualizations, it does not explain how tools used the interaction techniques. Shen et al. (2014) had identified seven types of interaction techniques for interpreting visualizations and discussed why sketch-based interactions are more intuitive and responsive. Nevertheless, the study does not cover varied goals. In addition, the cognitive activities for interpretation/sensemaking/understanding are a part of the exploration. So, we have not covered them independently. Mei et al. (2017) had classified the interaction techniques of the tools as fixed, configurable, and fully customized. The study guides the quality metrics for the design decisions that could lead to a better tool. However, the goals and interaction techniques were not explicitly covered. Méndez et al. (2018) had suggested a design space that was like a qualitative lens for estimating a tool's level along two dimensions, agency and granularity. The design space shows the level of users' control over the tool. The authors had also classified the tools as top-down and bottom-up. However, the paper does not aptly describe interaction techniques. The review by Tong et al. (2018) provides a concise summary of the literature on storytelling tools. The authors had classified the literature along various dimensions, including two goals: memorability and interpretation. They assessed the importance of visual representations generated from the tools to achieve the goals and reviewed the evaluations of the cited tools. However, the survey does not cover interaction techniques. Satyanarayan et al. (2019) had evaluated and compared the DVAT from the perspective of human cognition. The interactions and goals were the primary focus of the review. However, it covered only three tools that allow users to create expressive representations. Thus, it does not aptly describe the linkage between the different goals and interaction techniques.

Interaction taxonomies proposed in the literature have focused on bridging the gap between why users want to interact with a tool (goal) and how they could achieve the desired results (interaction techniques) (Brehmer and Munzner 2013; Pike et al. 2009; Yi et al. 2007). They have also suggested the most suitable sequence in the interactions, i.e., Overview first, zoom and filter, then details on demand (Shneiderman 1996). The relationship between the goals and interaction techniques is described as a shift from high-level to low-level categories (Brehmer and Munzner 2013; Yi et al. 2007) or a shift from representational intent to interaction intent (Pike et al. 2009). Based on these concepts, we propose a novel taxonomy of the interaction techniques of DVAT. Our taxonomy reveals a comprehensive vocabulary of the interaction techniques used for the various goals. We have also identified a plausible sequence in the interaction techniques.

2.2 Interactions and cognition

Humans high-level cognitive abilities, such as ideation, understanding, and reasoning, are engaged when interacting with visualizations in a tool (Patterson et al. 2014; Ceneda et al. 2019). The interaction techniques principally create a bridge between what users achieve from the tool and what is in their minds (Liu and Stasko 2010). The cognitive load that users feel with the tool can be evaluated by observing how fondly they discuss the interactions (Norman 2013). The term interaction comprises of multiple steps: focusing on a goal, users think a process, and after executing it, assess the results (Norman 2013). Lam (2008) had identified the impact of each step on the cognitive experience. Furthermore, visualization researchers have stressed taking the guidelines from HCI, as they could lead to the development of interaction techniques that users' experience as intuitive and useful (Tory and Moller 2004; Scaife and Rogers 1996). Here we list a few of them. (1) Interactions that feel closer to real-life practices and render visualizations quickly supports human cognition (Pike et al. 2009; Tory and Moller 2004). (2) In the analysis, the shift from aggregate to details, with zooming, panning, or overview-to-details, can increase the cognitive burden since users need to save more information in the working memory (Tory and Moller 2004). (3) Too many interactions for a goal, with a lack of predictable sequence, create a cognitive overload. Specifically, if interactions cause a simultaneous change in multiple representations (Lam 2008). (4) Providing interactions that are suggested/preferred by prospective users can ease the cognitive load (Patterson et al. 2014). (5) Reveal the relevant interactions on the selection of an object (Yalcin et al. 2018). Considering the importance of the cognitive aspect for a worthy experience with interaction techniques, researchers evaluated the interactions of visualization authoring tools (Satyanarayan et al. 2019; Pantazos and Lauesen 2012; Lam 2008). They had judged the tools based on their personal experience (Satyanarayan et al. 2019) or had conducted user studies (Pantazos and Lauesen 2012) or had reviewed the critical reports (Lam 2008). However, an assessment of approximately fifty DVAT that is based on personal experience or user studies is not a feasible option.

The evaluations of the tools done by prospective users are a valuable source of making judgments from the perspective of human cognition (Isenberg et al. 2013; Tory and Moller 2004). Yet, no study has comprehensively reviewed the evaluations of the DVAT. In this paper, we review how the evaluations have inducted the cognitive aspect and assessed users judgment about the interaction techniques when they work on the goal. To that end, we considered the cognitive activities for the five goals (see Table 1). Through this review, we aim to identify the strengths and weaknesses of the evaluations. The depth, diversity, and significance of the findings obtained from the evaluations are evidence of strengths. In contrast, the findings that though are important but are not collected are evidence of weaknesses.

3 Methodology and vocabulary of interaction techniques

With the help of query terms, such as data visualization authoring tools, sketch-based data visualization tools, and interactive visualization tools, we have selected 48 papers that present DVAT. Our major selection was from the three main venues. Our major selection was from the three main venues: IEEE Transactions of Visualization and Computer Graphics (TVCG), ACM CHI, and Computer Graphics Forum. We reviewed the selected papers in three stages: the identification of goals, the identification of interaction techniques for each goal, and the selection of evaluations for each goal. The next section covers the stages. This section provides a complete vocabulary of the interaction techniques we identified in the 48 DVAT. We have summarized the purpose of each interaction technique. Our summary reveals multiple definitions for some interaction techniques, suggesting a need for the unified vocabulary across the literature.

1. `Create / Draw / Sketch`. In two different ways, the literature defines `create`, (a) users can freely add a predefined element on the canvas, and (b) can add an element/glyph by sketching it on the canvas. Likewise, `draw` or `sketch` allows users to add an element that depicts their thoughts.
2. `Generate / Compose / Build`. `Generate` can cause an automatic creation of the visualization of the loaded data. With the `compose` or `build`, elements or images can be arranged as visualizations. The two interaction techniques are mainly based on the relationship between the independent units of the visual representation.
3. `Manipulate / Encode / Refine`. All of the three techniques can enhance the physical appearance of visual representations. The `manipulation` and `encoding` are generally used at the element level. In contrast, the `Refine` is used to enhance the overall view of the representation.
4. `Linking / Bind`. `Bind` is commonly used to define the mapping between visual elements and data attributes. `Linking` can define the mapping in varied ways, such as between the element and attribute, the encoding and attribute, the different elements, the different annotations, and the annotations and visualization.
5. `Reorder / Arrange / Lay Out / Move / Rotate`. `Reorder` can change the sequence of multiple views or elements with minimum spatial transformations. In contrast, the `arrange` and `lay`

out can provide users considerable freedom in managing the layout of the visualization. The lay out is commonly used for free and diverse spatial transformations. Move and Rotate can also enhance the arrangement. They are applied to an element, and the rest are arranged accordingly.

6. Repeat / Partition. Repeat can generate multiple representations of an element or a visualization. In contrast, the partition can divide a visualization into multiple. Both techniques are based on the link between the attributes and the elements.
7. Filter / Scale / Overview-to-detail / Pan and Zoom. Filter and scale can help users to extract the required information from a visualization. In the filter, the source and the sub-view(s) can be displayed simultaneously. With the overview-to-detail, multiple views with the hierarchical relationships and varying levels of details are generally presented simultaneously. Pan and Zoom, is specifically useful in the narrative. It presents a focused and refined view.
8. Brushing and Linking / Highlight. The techniques clarify the connection between multiple views of data.
9. Annotations / Tags. Annotations can be used to enhance the representation or provide textual input. Tags describe the annotations/comments.
10. Extract. It provides data or a selected part of a visualization/image.

The definitions do not provide a detailed description. We covered the salient purpose(s) of each technique. In addition, the techniques, such as editing (manipulating the physical appearance) (Ren et al. 2014) and add (load new elements/image from existing ones) (Wang et al. 2018b), have not been covered explicitly. However, we mention them under the heading of the related techniques. Table 2 shows the interaction techniques according to the goals of the DVAT cited in this paper.

4 Nexus of three: goals—interaction techniques—cognition

At the first stage of the review, we have inspected the introduction and major contributions of each selected paper. We picked the major goals that the authors took into consideration. We chose only one main goal in all but one, and in total, we found five goals. In the second stage, we reviewed the interaction techniques for each goal. Finally, we assessed the evaluations of interaction techniques. Primarily, users' comments are one of the major sources of assessing the strength of evaluations. We have coded the users' comments and presented them as a thematic network (Attride-Stirling 2001). The network is good to grasp an overview of how deeply users observe and their preferences. Subsections cover each goal.

4.1 Creation

The design processes supported by the DVAT are a) an element to the desired visual representation and b) a predefined template to the desired view. Here the element represents a glyph, or an icon, or a visual mark.

4.1.1 Element-to-Visual Representation Process.

Generally, it has three steps.

S1 Users either create an element by selecting from a predefined set (Bishop et al. 2019; Chen et al. 2019; Kim et al. 2019b; Shu et al. 2020) (Fig. 1a) or draw/sketch it (Kim et al. 2019a) (Fig. 1b). They can also present each category with a different element (Kim et al. 2019a). Users' drawing experience can impact sketching, which can be handled by suggesting elements based on sketches (Kim et al. 2019a; Chao et al. 2010). Furthermore, linking an element with an attribute propagates it on the canvas for each data value. Users can also set the link for each element one by one (Bishop et al. 2019).

S2 Users manipulate the physical properties or encode the data attributes with the visual channels. In the case of a link, changes in an element propagate to all connected elements (Fig. 1c). The on-demand appearance of the menus and the gestures resulting in the precise selection are suitable for this step in small screens (Bishop et al. 2019).

S3 Users drag elements freely to arrange/lay out them or sketch a path that defines the layout of a group (Chen et al. 2019). The purpose of free arrangement and sketching is to help users in brainstorming, rapid ideation, and designing a narrative structure (Kim et al. 2019b; Lu et al. 2019;

Table 2 The table presents the categorization of the selected visualization authoring tools in terms of the goals and interaction techniques

GOALS: ■ Creation, ■ Presention, ■ Expressive, ■ Extraction, □ Exploration

VOCABULARY OF INTERACTION TECHNIQUES

	Create \ Draw	Generate	Build \ Compose	Anotate \ Tag	Encode Manipulate	Refine	Filter	Overview-to-detail	Scale	Linking \ Bind	Pan and Zoom	Extract	Highlight	Brushing & Linking	Select	Reorder	Move \ Rotate	Repeat \ Partition	Arrange \ Lay Out
Bishop et al., 2019	Creation				Creation					Creation									Creation
Chen et al., 2019	Creation				Creation														Creation
Cui et al., 2019		Creation																	
Kim et al., 2019a	Creation				Creation														
Kim et al., 2019b	Creation			Creation			Creation				Creation								Creation
Lu et al., 2019	Creation																		Creation
Romat et al., 2019a		Expressive			Expressive														Expressive
Romat et al., 2019b				Exploration			Exploration		Exploration				Exploration						Exploration
Sicat et al., 2019		Creation			Creation		Creation												
Tang et al., 2019		Expressive			Expressive											Expressive			Expressive
Wang et al., 2019					Presention														Presention
Kim et al., 2018																Exploration			
Koytek et al., 2018														Exploration					
Liu et al., 2018	Expressive				Expressive					Expressive								Expressive	Expressive
Wang et al., 2018a		Creation															Creation		
Wang et al., 2018b		Presention								Presention									
Xia et al., 2018	Expressive				Expressive														Expressive
Yalcin et al., 2018															Exploration				
Alper et al., 2017	Creation													Creation					Creation
Amini et al., 2017		Presention			Presention					Presention									Presention
Brehmer et al., 2017					Expressive														Expressive
Jung et al., 2017						Extraction						Extraction							
Kim et al., 2017a	Expressive				Expressive					Expressive								Expressive	Expressive
Nacenta and Mendez, 2017										Extraction		Extraction							
Ren et al., 2019	Expressive				Expressive					Expressive									Expressive
Saket et al., 2017					Exploration														Exploration
Sarracino et al., 2017			Creation			Creation													
Satyanarayan et al., 2017	Creation						Exploration	Exploration						Exploration	Exploration				
Wongsuphasawat et al., 2017		Exploration																	
Fulda et al., 2016		Creation			Creation	Creation													
Satyanarayan et al., 2016	Creation																		
Xia et al., 2016	Creation				Creation					Creation						Creation			Creation
Choi et al., 2015				Exploration							Exploration				Exploration				
Wongsuphasawat et al., 2015		Exploration																	
Zhao et al., 2015			Presention	Presention															Presention
Ren et al., 2014	Expressive				Expressive					Expressive									
Satyanarayan and Heer, 2014a	Creation			Creation															Creation
Satyanarayan and Heer, 2014b	Expressive				Expressive					Expressive									
Zgraggen et al., 2014				Exploration			Exploration			Exploration									
Lee et al., 2013	Presention						Presention												
Bostock et al., 2011	Creation																		
Browne et al., 2011							Exploration												
Willett et al., 2011				Exploration						Exploration									
Chao et al., 2010	Creation									Creation									
Andre et al., 2007								Exploration											
Heer et al., 2007				Exploration			Exploration			Exploration	Exploration								
Mackinlay et al., 2007		Presention																	
Viegas et al., 2007		Presention		Presention															

Interaction techniques cover the complete vocabulary mentioned in Sect. 3, and they are arranged according to the similarity in their usage

Shu et al. 2020) (Fig. 1d). Users can arrange the visual elements linked with each other in the form of a hierarchical narrative structure (Lu et al. 2019; Kim et al. 2019b; Chao et al. 2010).

In addition to the interaction techniques used in the three steps, with `filter`, `pan and zoom`, and `annotations`, users can further refine the representation (Kim et al. 2019b). In short, interaction

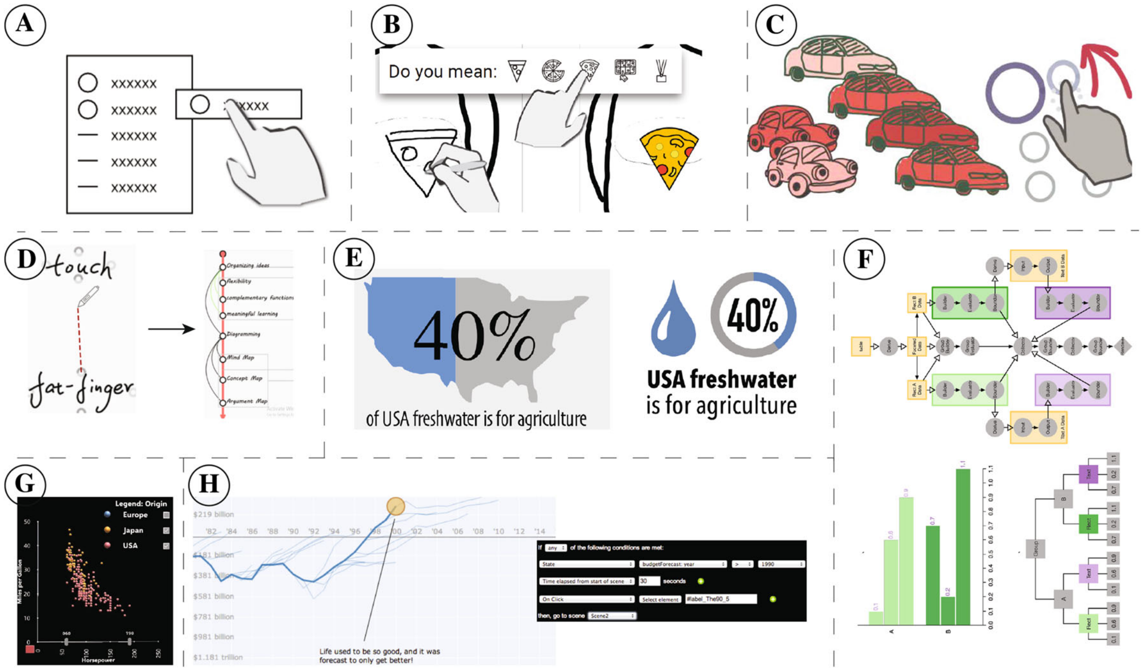

Fig. 1 In creation, users create an element (**a** (Kim et al. 2019b), **b** (Kim et al. 2019a)) or generate the visualizations with automatic methods (**e** (Cui et al. 2019), **g** (Sicat et al. 2019)) or use the programming for diverse designs (**f** (Satyanarayan et al. 2017)). Users encode the elements with data-bindings (**c** (Chen et al. 2019)). They apply conditional arrangements with direct manipulation (**d** (Lu et al. 2019)) or menus (**h** (Satyanarayan and Heer 2014b))

techniques of this process support the creation of external representation, close to the mental model present in the human mind (Lu et al. 2019). Tools like Reactive Vega (Satyanarayan et al. 2016), Vega-Lite (Satyanarayan et al. 2017), and D3 (Bostock et al. 2011) are also based on the element-to-visual process, as they provide the primitive building blocks, and users use them for creating diverse interactive visual representations (Fig. 1f). However, these tools require programming expertise. Both programming and interactive designing can be combined in one tool (Mei et al. 2018; Li et al. 2018; Boussejra et al. 2019).

4.1.2 Template-based Representation Process

In the process, few interactions and less direct manipulation are required. Users enter the data, and the system `generates` a single (Sicat et al. 2019; Mei et al. 2020) (Fig. 1g) or a set of representations (Cui et al. 2019; Zhu et al. 2020) (Fig. 1e). Users are not required to manually define the mapping between elements, data attributes, and visual channels. However, they can control the visual appearance and the amount of information visible (Sicat et al. 2019). The techniques, like `move` and `rotate`, are used to enhance the layout (Wang et al. 2018a). Users can also `build` varied representations by arranging independent elements (Sarracino et al. 2017). They can then `refine` the most appropriate. Thus, the template-based approach is suitable for the rapid prototyping of designs (Sicat et al. 2019). It is also ideal for quick refining and reordering hierarchies in the narrative structure (André et al. 2007; Satyanarayan and Heer 2014a) (Fig. 1h). However, the automatically generated narratives are not compelling. Additionally, users prefer the creation of a progressively evolving narrative (Shneiderman 1996; Shu et al. 2020).

Both processes can be integrated into a single tool. A representation created on loading the data can be considerably modified (Kim et al. 2019b) or used as a reference (Alper et al. 2017) in the integrated tool. The reference visualization is specifically helpful for users with a limited visualization experience (Bishop et al. 2019). Regardless of the process a tool follows, it can be based on the WIMP interface or direct manipulation. Direct manipulation does not limit the tool's usage to a few interactions. Tools' developers have integrated the interaction capability in non-WIMP interfaces comparable to the professional WIMP interfaces. The direct manipulation-based object-oriented drawing (Xia et al. 2016) is a good example.

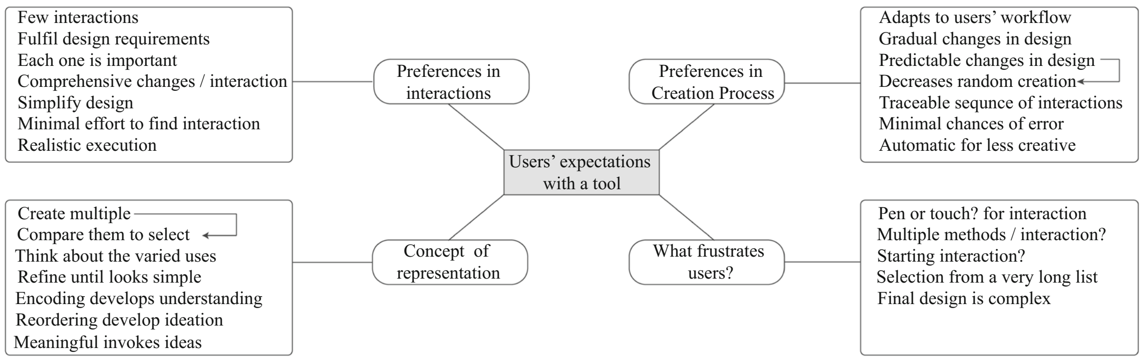

Fig. 2 A thematic network of users comments on tools for visualization creation

Evaluation. We have not reviewed the evaluations of the programming-based tools (Satyanarayan et al. 2017, 2016; Bostock et al. 2011), and user studies were not conducted for the two tools (Sicat et al. 2019; Chao et al. 2010). In the rest of the twelve papers, we found four common goals of the evaluations; a) enable users to create diverse representations (2/12), b) effective for users' needs (3/12), c) allow users to follow their workflow (7/12), and d) usability/usefulness/engagement of the tool (7/12). These goals are well consistent with the evaluation metrics (such as the extent to which the tool helps users create various visualizations, ease, and the number of actions required to create a visualization) (Amini et al. 2018) relevant to users' cognitive activities (Table 1).

Goals are commonly achieved through qualitative methods. The method is useful for collecting comprehensive feedback on users' experiences with interactions. Specifically, the evaluations based on users' needs (Satyanarayan and Heer 2014a; Wang et al. 2018a; Cui et al. 2019) report feedback on all interaction techniques. Moreover, experts in the related tools and visualizations provide more thorough reviews (Xia et al. 2016; Cui et al. 2019; Satyanarayan and Heer 2014a). They identify features that the tool should have or are not important (Cui et al. 2019; Lu et al. 2019). They discuss their experience with the lower-level tasks, such as the convenience in attributes mappings and the enjoyment in creating elements (Xia et al. 2016). Thus, findings from qualitative evaluations depict concerns that can impact the cognitive load and can make the interaction process different from the users' mental model. Figure 2 shows a collective view of feedback. The figure shows users focus on an individual element, well-refined output, flexibility in creating and modifying the views, and the purpose of visualizations created in the tool. Users' evaluations show a strong relationship with their cognitive activities (see Table 1).

The findings could be more significant if users are asked to perform lower-level tasks. In all except two (Bishop et al. 2019; Wang et al. 2018a), users reproduce or replicate a visualization or freely explore the tool. No doubt, these methods are significant. The time performance in replication clarifies how comfortably users create a visualization in the tool (Chen et al. 2019). Users discuss the problems they face in the creation process; for instance, they show surprise and frustrations, if the interactions' output goes beyond their expectations (Sarracino et al. 2017). Free exploration of the tool presents varied ideas that users can create. Simultaneously, due to the absence of lower-level tasks, we found that evaluations do not explicitly cover the users' satisfaction from the interaction techniques. For example, in the evaluation of DataSelfie, there is no observation on users' encoding experience (Kim et al. 2019a), the evaluation of InkPlanner lacks details on how users develop a link between the words and arrange them. The lack makes it difficult to estimate users experience with techniques that can refine views (Lu et al. 2019). Generally, users discuss overall experience and mention an issue only when they have a problem. Well decomposed tasks (e.g., identify how to layout visualization (Bishop et al. 2019), or arrange the elements based on color (Wang et al. 2018a)) can provide in-depth insight into the places where users feel difficulty. They can lead to evaluations that thoroughly reveal users' satisfaction with the intuitiveness and usability of the interactions.

4.2 Expressive

Visualization tools that allow users to create expressive designs support flexible creation process and bring customization to the designs. Mainly, they enable users to a) freely create diverse designs, b) create charts

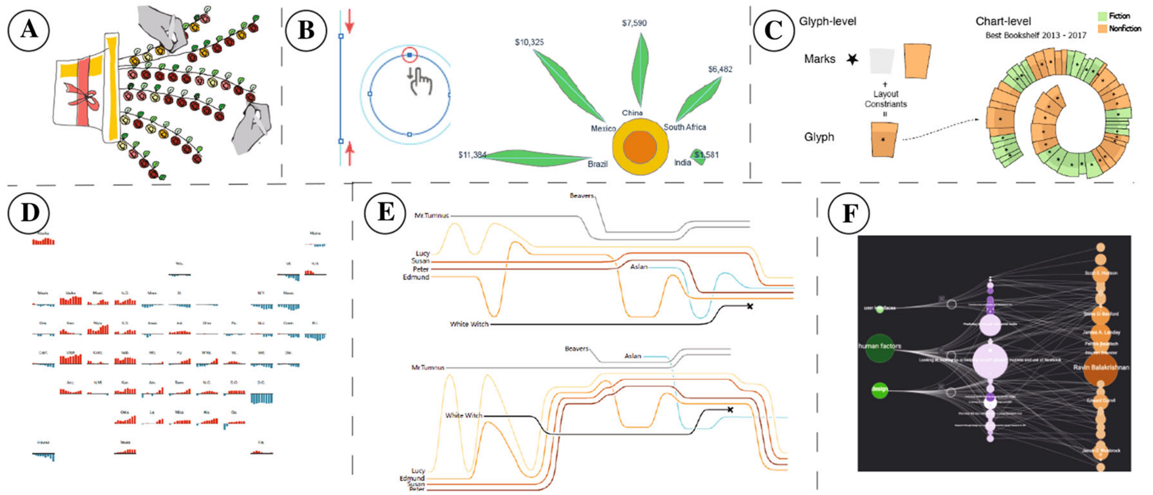

Fig. 3 In the tools for expressive designs, users create diverse elements, and apply varied arrangements (**a** (Xia et al. 2018), **b** (Kim et al. 2017a)). They bind an element with the multiple attributes (**c** (Ren et al. 2019)), customize the chart templates (**d** (Liu et al. 2018)), enhance the layout and encoding of the automatically generated representations (**e** (Tang et al. 2019), **f** (Romat et al. 2019a))

that portray considerable customization in templates, and c) enhance the expressiveness of an automatically generated representation. In any of the three cases, `create`, `encode`, and `lay out` play a major role.

4.2.1 Expressive and diverse designs

Freely created glyphs provide expressiveness and diversity in designs. With glyphs, users can portray their arguments and thoughts in design elements. Users `create` a glyph as a unique representation of their artistic thoughts. It comprises of a set of elements that can be added iteratively (Fig. 3a). Users can `encode` each element of the glyph independently, e.g., in the glyph of person, dress, and background can have a different color. The varied encodings are useful to link multiple data attributes with a single glyph (Chen et al. 2019; Xia et al. 2018). Glyph, when linked with data attribute(s), automatically propagates into multiple glyphs and freely drawn path `lay out` glyphs in impressive arrangements (Xia et al. 2018) (Fig. 3a). Data guides support the creation of data-driven glyphs (Kim et al. 2017a) (Fig. 3b). However, they limit extreme diversity in designs and layout.

4.2.2 Customized charts

With the help of freely created marks, users can go beyond the limits of a few chart templates (Liu et al. 2018). Predefined marks/glyphs can impact the expressiveness (Satyanarayan and Heer 2014b; Ren et al. 2014) but can be more informative than user-defined glyphs (Weng et al. 2020). In either of the cases, when the mark `binds` to the data attribute(s), it propagates into the visual representation (Liu et al. 2018; Ren et al. 2019) (Fig. 3c). A single mark can bind to multiple attributes, such data attributes assigned to the tip and base of the triangle. In this instance, triangles in the chart will have a different height and width. Primarily, in customized marks, users can control the anchor points. Additionally, they can `encode` multiple features of the mark, such as stroke color, width, and fill color. The fine-tuned encoding considerably enhances the expressiveness of the chart. In customized charts, the freedom to define layouts is limited. Techniques like `repeat`, `partition`, or `reorder` provide the layout configuration with minimal spatial transformations (Liu et al. 2018) (Fig. 3d). Iterative transformations at the data level (Satyanarayan and Heer 2014b; Ren et al. 2014) and the built-in functionalities (Ren et al. 2019) lead to the diverse and expressive, but controlled layouts. Nevertheless, users need to learn the transformations supported by the tool.

4.2.3 *Expressive and automatic designs*

To enhance the expressiveness of automatically generated visual representations, developers emphasize on the high-level appearance. First, algorithms generate the uniform layouts (Fig. 3e-top), and then users enhance the aesthetic quality with the help of interaction techniques. The improvements do not merely contribute to the expressiveness—they make the visualizations more revealing. Modified representations can portray features that might not be evident in the automatic layout. With `manipulate`, users can iteratively improve the physical appearance of the element(s) (Romat et al. 2019a; Tang et al. 2019; Brehmer et al. 2017, Tang et al. 2020). In `lay out`, they can alter the trajectory of the lines. The transformations impact the overall layout of the representation (Tang et al. 2019, 2020) (Fig. 3e-bottom). Fine-tuning of the layout contributes a lot to the expressiveness (Romat et al. 2019a; Tang et al. 2019; Brehmer et al. 2017, Tang et al. 2020, Pan et al. 2020) (Fig. 3f).

Evaluation. The timelines revisited (Brehmer et al. 2017) do not present the evaluation of the tool. In the remaining eight papers, we found three common goals of evaluations, a) can users understand how to use the tool (3/8), b) expressiveness of the designs (2/8), and c) usability of the tool for creating desired designs (5/8). These goals are consistent with the measures (such as how well the tool supports users' preferred workflow, how easy is learning interactions, the extent to which the visualization designed adheres to users' mental model, and the degree to which users accept the difference) that researchers suggested for evaluations while focusing on human cognition (Amini et al. 2018; Patterson et al. 2014; Tversky et al. 2006).

Goals are commonly achieved through the multi-stage evaluation: tutorials → practice → replication → free exploration. The first three stages provide a worthy judgment of users' experience as they ensure the usage of all interaction techniques (Romat et al. 2019a; Liu et al. 2018; Xia et al. 2018; Kim et al. 2017a; Tang et al. 2019; Satyanarayan and Heer 2014b). Although none of the evaluations we reviewed were comparison-based, participants with the experience of akin design tools had compared the interaction techniques with those of other tools. Thus, evaluators were able to collect a significant piece of evidence about the users' experience with various interaction techniques.

Following replication of design, users comment on their experience at the element level, e.g., the ease in attribute binding or manipulation of an element. Users' comments help evaluators to assess the convenience with which users execute each technique. Without comments, it remains unclear (Romat et al. 2019a; Tang et al. 2019). A change in design beyond expectations is frustrating (Tang et al. 2019). Lack of comments makes it difficult to assess users' experience. Apart from comments, in replication, logging (Ren et al. 2019) and analysis of gaze behavior (Bryan et al. 2020) for each interaction technique and change in view also helps evaluators identify the problems.

The free-exploration approach is useful for measuring users' satisfaction with designs. In this approach, users use every feature of the tool to make visualizations—diverse and expressive. A study without this approach makes unclear how much diverse design users can create (Ren et al. 2019). Users generally admire a simple tool that enables them to create varied representations quickly. Additionally, a tool that supports their workflow. Collectively, users' comments (Fig. 4) reveal how deeply they focused on various tools' aspects that lead to innovative and meaningful designs, showing the strong engagement of users' cognitive activities (see Table 1). User feedback concludes that their satisfaction is associated with the basics of designs, not merely the overall design.

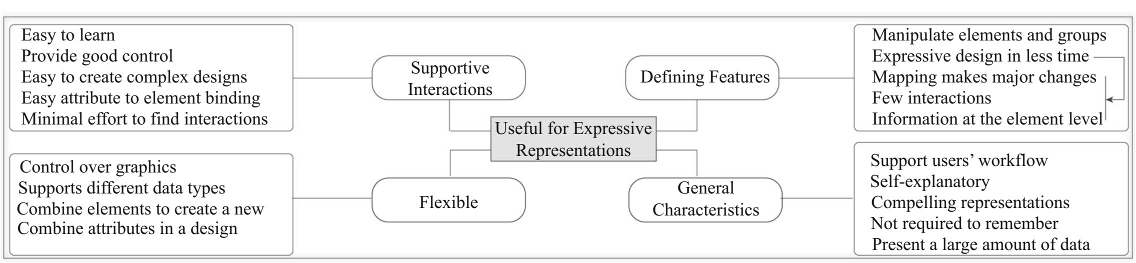

Fig. 4 A thematic network of users comments on tools for creating expressive representations

Fig. 5 In exploration, users first select the data attributes and marks (**a** (Wongsuphasawat et al. 2017)). They apply the interactions like filter (**c** (Zgraggen et al. 2014)), annotations/tags (**d** (Heer et al. 2007)), and brushing and linking (**f** (Koytek et al. 2018)) for the sense-making. Take the help of highlight in the simultaneous reading from multiple views (**b** (Yalcin et al. 2018)). Use the direct manipulation and textual input for flexibly interacting with the views (**e** (Browne et al. 2011),**g** (Romat et al. 2019b))

4.3 Exploration

Wide-ranging interaction techniques contribute to data exploration. In the following paragraphs, we have discussed them based on similarity in their purpose.

4.3.1 Identify attributes

Analysts generally first get familiarized with data attributes. A starting univariate summary of all data attributes provides a complete overview (Ghosh et al. 2018). Users can `generate` all possible views. Users get a wider view if the tool generates all recommended representations for their provided input (Wongsuphasawat et al. 2017). However, merely selecting attributes and views without/with-few interactions affect users' analytic skills (Wongsuphasawat et al. 2015). Freedom to define the encoding and visual marks develop users' interest in data exploration (Wongsuphasawat et al. 2017) (Fig. 5a).

4.3.2 Derive views

As users' knowledge of the data widens, they frame questions/hypothesis, which they answer/test by interactively deriving views from generated visualization(s). `Select` [e.g., Yalcin et al. (2018)], `filter` (e.g., (Zgraggen et al. 2014)), `pan and zoom` [e.g., Heer et al. (2007)], `overview to detail` [e.g., (André et al. 2007, Weng et al.2020)], and `scale` (e.g., (Romat et al. 2019b)) are important for the transformations and deriving views. With `scale` and `filter`, important information is kept in perspective (Romat et al. 2019b). A filtered view is significant in answering complex queries (Zgraggen et al. 2014) (Fig. 5c). `Overview-to-detail` reveals hierarchies (André et al. 2007). Concurrently, a sudden transformation can lead to less informative exploration. Techniques like `encode` and `lay out` take users' intent and provide an incremental transformation (Saket et al. 2017).

4.3.3 Externalize thoughts

`Annotations` and `tags` support hypothesis creation and collaboration of insights by allowing users to mark important findings in visualization or give the textual input that can transform the visual representation (Romat et al. 2019b; Browne et al. 2011; Choi et al. 2015) (Fig. 5e, g). `Tags` add a further description in the comments. Links between the tags and views help in tracking progress and in the collaborative analysis (Fig. 5d). Mainly, links create a story and support an incremental process for question answering (Willett et al. 2011; Heer et al. 2007; Zgraggen et al. 2014; Chotisarn et al. 2020).

4.3.4 Explore relations

Sense-making also includes a simultaneous reading of information from the sources with an obvious relation. `Highlight`, which commonly precedes other techniques, exposes the differences between the various regions of visualizations (Romat et al. 2019b; Deng et al. 2019). In a well-synchronized dashboard, `highlight` helps users to identify patterns, trends, and outliers in multiple-views effortlessly (Fig. 5b). Concurrently, an automatic connection impacts the decision-making (Yalcin et al. 2018; Hu et al. 2020) as tracking of the sudden changes is difficult. `Brushing-and-Linking` provides users fine control over the linking between multiple view (Deng et al. 2019). It also helps users to formulate complex queries (Koytek et al. 2018) (Fig. 5f). Furthermore, the simultaneous reading of multiple visualizations is significantly aided with the `lay out` (Romat et al. 2019b) and `reorder` (Kim et al. 2018), as they help users visualize the data from various angles.

Evaluation. In two papers, the evaluation was not reported (Browne et al. 2011; Saket et al. 2017). One paper reports participants' answers to the questions on the final visualization; participants did not interact with the tool (Kim et al. 2018). In the remaining ten papers, three common goals of the evaluation were, a) significance of the specific interactions in the requirements of the analysis (5/10), b) usage pattern of the tool for high-level tasks (3/10), and c) significance of the tool in the analysis (4/10). Researchers (Lam et al. 2011; Amar and Stasko 2004; Patterson et al. 2014; Pike et al. 2009) have suggested measures for evaluations to assess users' cognitive experience. The measures, such as the number of insights discovered, how well answered questions, the number of queries users take-on before answering the questions, the accuracy of performed tasks, and logging data, are suitable for goals and have been used in evaluations.

The significance of the tool in the analysis and its usage pattern is commonly assessed by free exploration (e.g., Wongsuphasawat et al. (2017); Yalcin et al. (2018); Zgraggen et al. (2014); Willett et al. (2011)). High-level tasks, e.g., "*search states where tobacco and alcohol use was correlated to accidents and overdoses*" (Romat et al. 2019b; Yoghourdjian et al. 2018) are used to identify the impact of multiple interaction technique(s) on sense-making (e.g., Romat et al. (2019b); Heer et al. (2007)) and analysis (e.g., Willett et al. (2011); Koytek et al. (2018)). Irrespective of the approach, logging of users' actions, screen capturing, video recording, and anecdotal notes are commonly used for the data collection. The results show how much each interaction technique is used in the analysis, users' satisfaction with interactions, types of queries/questions/hypothesis that users generate to understand the data, and how users use the tool. User feedback (Fig. 6) also indicates the aspects that can facilitate or hinder the analysis process. Users' preference for the starting suggestive views relates to their cognitive activities (see Table 1)—they focus on the overview before moving to in-depth insight. Moreover, since prior knowledge helps develop the mental model, starting views are valued, enhancing the mental model.

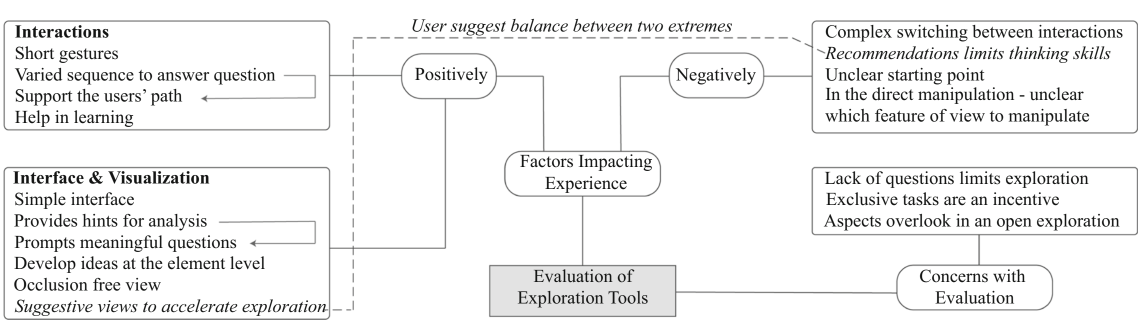

Fig. 6 A thematic network of users comments on tools for exploration of visualizations

Simultaneously, users have shown concern about the evaluation process. The concerns and limitations could have a considerable impact on the strength of evaluations. Open exploration provides knowledge about how much users learn about data, and evaluators should try to uncover the reasons behind unexplored information. However, sometimes users do not get too much involved in the dataset, or unnecessarily repeat some steps [Shu et al. (2020) to appear], impacting the results. If users are asked to perform the low-level tasks, e.g., find a specific pattern, it will enhance their engagement. More importantly, evaluators can observe the speed, accuracy, and users' engagement with the interactions that help understand the data and making sense of it. Though, with logging, researchers have shown users' comfort with interaction techniques (Romat et al. 2019b). It is equally important to identify how much each interaction contributes to learning about the data. A combination of open exploration and exclusive task-based studies would be beneficial for a thorough analysis. Collaborative studies, where, in a group, few users create questions and respondent(s) execute interaction technique(s) for answers (Koytek et al. 2018), can be a worthy approach for the evaluations.

4.4 Presentation

The presentation tool facilitates users in the communication of their data. While realizing narratives as a powerful and engaging means of communication (Wang et al. 2019; Cao et al. 2020, Tang et al. 2020)—the tool helps users to deliver thought-provoking sequences (Wang et al. 2019; Zhao et al. 2015; Amini et al. 2017). Compelling but simple, an important aspect of the presentations, also remained in focus. Primarily, tools support few interactions and simple workflow so that users with diverse levels of expertise can quickly craft the visualizations. Presentations can be template-based or user-defined.

4.4.1 Template-based presentations

Users quickly `generate` visualizations by loading the data (Mackinlay et al. 2007; Viegas et al. 2007; Wang et al. 2018b; Amini et al. 2017; Zhu et al. 2020). Primarily, they select the visualization (Viegas et al. 2007) or choose a template (Amini et al. 2017; Mackinlay et al. 2007) (Fig. 8a). In either of the cases, data is automatically presented in the selected format. The approach is useful to overcome the barriers that users feel in the visual encodings. Simultaneously, tools provide menus to alter representations. Through a few clicks, users can `bind` the visual elements to the data attributes (Wang et al. 2018b; Amini et al. 2017) and `manipulate` the visual appearance (Amini et al. 2017). Users can add annotations (Zhao et al. 2015) and infographics (Wang et al. 2018b; Amini et al. 2017) (Fig. 8b) in the representations `composed` of existing images/representations. `Lay out` finalizes the narrative presentations (Amini et al. 2017). Narratives with the linear (Zhao et al. 2015; Amini et al. 2017) or hierarchical (Wang et al. 2019) (Fig. 8c) slide shows can be generated through direct manipulation. Layout, embellishment, annotations all contribute to grasping the meaningful linkage between multiple views.

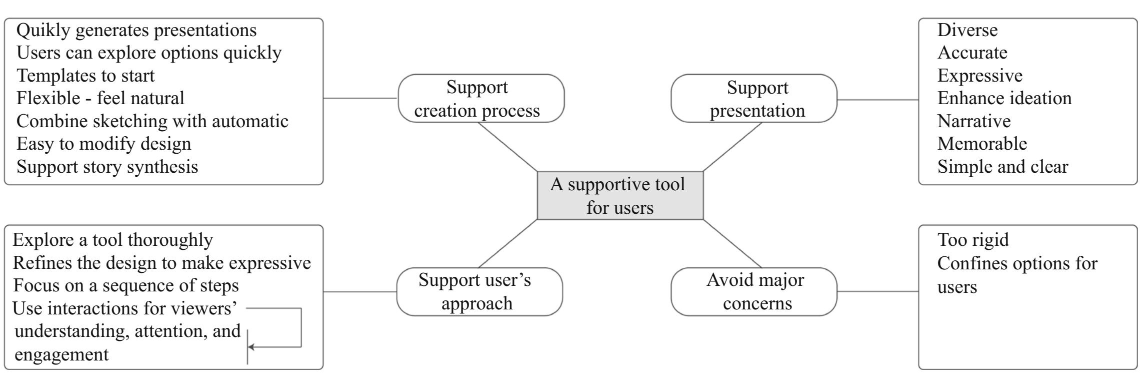

Fig. 7 A thematic network of users comments on tools for creating visualizations for presentations

4.4.2 User-defined presentations

Users can also develop highly customized presentations of their data. The SketchStory (Lee et al. 2013) provides considerable flexibility to users in presenting their thoughts (Fig. 8d). They can `create` infographics and interactively explore the data (Lee et al. 2013). Thus the tool combines the presentation with expressiveness and exploration. In the tool, simple gestures lead to a considerable transformation in the visualization(s).

Evaluation. In two papers (Mackinlay et al. 2007; Viegas et al. 2007), a formal user study was not conducted, and in one paper, users commented on the visualizations as viewers (Zhao et al. 2015). In the remaining four, we found three common goals of the evaluations, a) usefulness and usability of the tool (3/4), b) users' authoring experience (2/4), and c) the quality of presentations (4/4). Visualization experts (Lam et al. 2011) have also emphasized evaluating the effectiveness of presentations in the communication of ideas.

Generally, the new tool is compared with the existing, for the ease (Wang et al. 2018b; Amini et al. 2017) and the quality of presentations (Wang et al. 2018b; Zhao et al. 2015; Amini et al. 2017; Lee et al. 2013). The findings that show users prefer the tools that allow them to generate accurate and expressive representations of their data quickly. Furthermore, the automatic tools that are flexible in the creation process are preferred over the manual drawing tools (Wang et al. 2018b; Lee et al. 2013). Users focus more on specific views. Users' preference for informative yet simple representations and biased attitude relates to their cognitive activities (see Table 1). We provide a summary of user feedback in Fig. 7.

In the comparison-based study, users provide comprehensive comments on interactions and representations. Additionally, a clear demarcation between the different phases of development, and a set of questions on which users talk after creating presentations, lead to meaningful feedback (Wang et al. 2019). However, the results could be biased due to the difference in the major goals of the tools compared (Wang et al. 2019). The findings can also be insignificant if users achieve the same results from compared tools (Amini et al. 2017). Furthermore, user feedback is not always conducive. Users do not discuss every feature, specifically, those who have no idea of the core concepts of data visualization (Wang et al. 2019). The well-designed tasks can help users realize the importance of those features which they may overlook otherwise (Lee et al. 2013). They can tell users clearly what can or cannot be done, and consequently, they can provide a better assessment of users' experience.

4.5 Extraction

Users apply the extraction on the exiting images or the text. When the image or text is loaded, the system automatically `extracts` the underlying data. Users can then `refine` the extracted data (Jung et al. 2017). By `binding` the extracted data to the visual mark, users can create various representations of the extracted

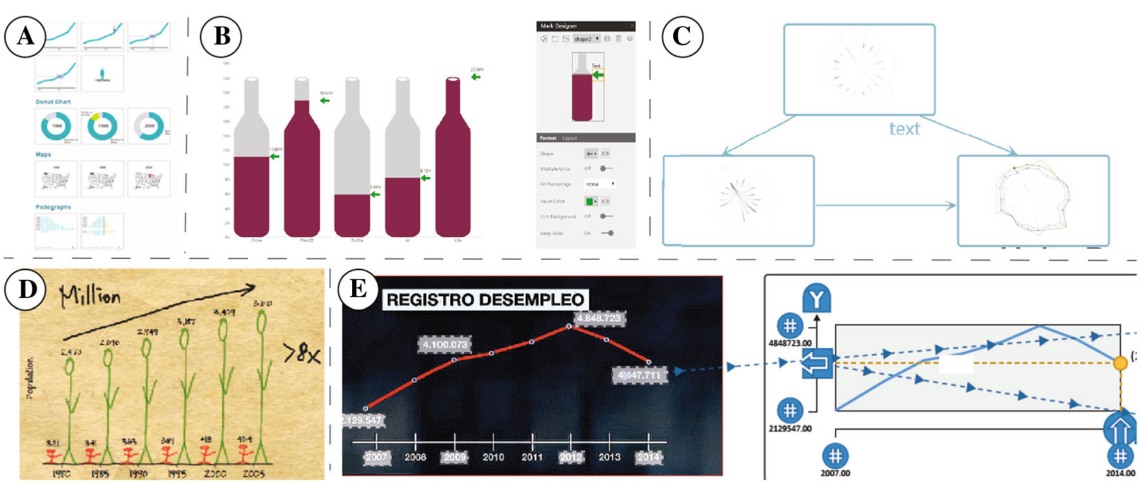

Fig. 8 In the presentation tool, users select the template (**a** (Amini et al. 2017)) and modify the view (**b** (Wang et al. 2018b)) through menus. They define the layout (**c** (Wang et al. 2019)) and design (**d** (Lee et al. 2013)) through direct manipulation. In extraction, users extract from the images to create visualizations (**e** (Nacenta and Méndez 2017)

data. They can also apply the functions that reveal the information, which is not evident in the parent visual representation (Nacenta and Méndez 2017) (Fig. 8e).

Evaluation. Researchers suggested measuring the accuracy of contents extracted from the visualization, the number of elements extracted, and the time for extraction (Patterson et al. 2014). The metrics are suitable for the users' cognitive-activity (see Table 1)-based evaluation. Chartsense (Jung et al. 2017) has reported the evaluation. However, the system automatically extracts the data. In the iVolver (Nacenta and Méndez 2017), the extraction approach can be traced to the users' mental model, but no evaluation of the tool is available. Researchers (Méndez et al. 2017) have evaluated the tool through comparison-based studies. However, it was process-based evaluation—interaction techniques were not assessed.

5 Discussion

In this section, we have summarized the salient take-away points of the review, as suggestions for designing interactions and conducting evaluations. We have also discussed the future of the DVAT from the perspective of technology and user expertise

5.1 Designing effective interactions

For providing users a good experience with a tool, the foremost requirement is to understand users and the context in which they will use the tool. Users' feedback had informed us that they appreciated those tools, which attracted their attention to the essential interaction techniques. The well-designed tool minimizes the chances of inattentional blindness and overlooking key functionalities. It causes a minimum deviation of users from the interaction techniques that are relevant to fulfill their requirements. Here we summarized some key points that can significantly contribute to designing the effective interaction techniques of the DVAT. We cannot present an exhaustive list of points that ensure those interactions, which can make users feel overwhelmingly satisfied. In fact, the concept of a good design is domain-specific. We elaborate on the points which would have greater leverage on usability and intuitiveness of the interaction techniques. In addition, developers/evaluators can empirically verify them.

1. *Meaningful Gestures* Humans expect a reason for the difference or similarity between the features supported by a tool. The different interaction techniques with no noticeable difference in their gestures create interference and decrease performance (Patterson et al. 2014). Likewise, multiple gestures of an interaction technique that lead to similar changes in a representation confuse users. Users may feel not using the technique completely. Interactions should have appropriate gestures, and there should be an obvious difference in the results achieved from them.
2. *Acceptable Transformations* Users show concern with the transformations that occur in visualizations on the application of the interaction techniques. The transformation that causes distractive changes confuses users (Tory and Moller 2004). Distraction can be due to a sudden unclear change in the view [Shu et al. (2020) to appear], or part of the view that becomes hidden with the techniques, like zoom or details-on-demand. The impact of issues on users' experience must be addressed. Simultaneously, users' feedback shows they like a few interactions in achieving the desired results. Developers of the tool should strive to provide a balance between two extremes—providing transformations balanced with the users' mental models.
3. *Interactions Access Affordances* Users are sometimes not able to identify the interaction techniques supported by the tool. The tool's features, if not explicitly presented, cause considerable load on the working memory. Consequently, users' cognitive efforts are spent on the understanding of tools rather than attempting tasks (Crapo et al. 2000). Users focus on the primary functionality. Therefore, developers should make an effort to present the most prominent interactions as a focus. The journey towards the goal should take simple and easy steps. Previous work shows that users have a positive experience if the information is in the form of chunks (Crapo et al. 2000). The concept has the potential to apply in the integration of interaction techniques in a tool.
4. *Interactions Usage Affordances* Better user experience can be defined as the one that lasts for moments or retains the in user memory. Just creating memorable interactions should not be the design objective. The outstanding approach is to make complex things possible, as well as convenient. A major step towards the right interactions is a review of the effectiveness and limitations of the gestures of the existing interaction techniques.

On the points mentioned above, users' feedback provides worthy guidance. Simultaneously, the visualization designers should not merely rely upon the users' preferences. Particularly speaking, users' subjective preference is not always a reliable indicator. Instead, designers should focus on the requirements which ensure that the tool supports the users' objectively satisfying performance Elting and her colleagues' (Elting et al. 1999) work is an example. The participants preferred a numerical table more than all other options as a display format. Nevertheless, it produced a lower level of the decision-making accuracy relative to the icon display, which was disliked by a quarter of the participants but produced the highest accuracy. In fact, users elaborate on their experience and preferences on a broad scale. They talk about the final goals they achieve from the tool. However, their performance and satisfaction are based on every aspect. Thus, both their subjective preferences and the objective assessment of what they should achieve needs to be considered in crafting useful tools.

5.2 Guidelines for evaluations

The challenging aspect of a tool's development is the evaluation of interactions. In an evaluation, the strength of goal, assessment method, and analysis, results in the insights that not merely provide a thorough judgment of interactions, they provide novel ideas. All evaluations that we reviewed, with different goals and assessment methods, lead to varying types of information. Users' responses were more open and sometimes complex, requiring considerable wisdom to extract valuable information. In general, the content of evaluations shows that researchers were able to gather information on varied aspects despite some weaknesses. For example, how was users' experience with the tool, whether they could learn the tool easily, what were their practices, did their practices change with the increase in their experience, and how effective the tool was compared to its competitors? Here we summarize some general guidelines for evaluations that can help to attain worthy findings. The suggestions have a high probability of being adopted already or discussed in the literature. We aim to cover the points defining how to assess the efficacy of the interaction design in the context of human cognition.

1. *Understand the Coherence between Cognition and Interactions* Through direct interaction, in which users present their experience and domain knowledge, evaluators can determine the relationship between the task and cognitive capabilities. Evaluators can also capture the users' mental-model through a think-aloud session in which users are working on a problem, and through the post-session interview (Klein and Hoffman 2008). In the think-aloud session, experts describe the reasons for using interactions or for adopting a particular sequence.
2. *Identify the Coherence of Interactions with the Mental Model*. The significant coherence between the interactive process and users' mental-model can be observed through their feedback. Specifically, experts can provide detailed comments on the closeness of the interactive process with their beliefs. Evaluators can also judge which alternative problems users would be able to solve with the process they followed in a specific problem. The approach is related to users' cognitive activities (Crapo et al. 2000; Kim et al. 2017b) (see Table 1).
3. *Cognitively Satisfying Interactions* There are three suggestions. First, users should focus on a particular mental model in the completion of tasks. Simultaneously, the evaluator should observe the users. The approach could provide a good judgment of the interactions, specifically if the process is rigid. Second, the evaluation can be conducted in the light of the cognitive activities. Consider an example, in the exploration process, users retrieve cues from one visualization and use them in others (Patterson et al. 2014). Evaluate whether users have gathered up useful cues. Third, interactions with the predictable sequence and clear cause-effect relationships are effective (Lam 2008). Determine whether users can establish this relationship and identify whether there is coherence between users' thoughts and the actual sequence.
4. *Iterative Evaluations to Enhance Cognitive Support* It is hard to attain good cognitive support from the interactions in the first step. The developer may need to follow a redesign process for the iterative refinement of interactions. Zacks et al. (Zacks and Tversky 2003) suggested the redesign process. First, design interactions based on users' cognitive abilities and then refine them by repeated cognitive-based evaluations.
5. *Iterative Evaluations for Thoughtful Feedback*. In any case above, better observation could be captured over a more extended period than with the single session. The evaluator could allow users to reflect upon long-term learning, which is developed when their familiarity grows with the interactions. The

long-term sessions can establish a scenario in which users re-evaluate the older experience in light of the new knowledge.

The points suggest that for crafting tools that could provide coherence between interaction techniques and cognitive activities, the developer should know human cognition. Section 4 covers the methods effective for evaluating interaction techniques based on human cognition. Broadly assuming the results from cognition-inspired evaluations, we can regard the interactions practically effective and cognitively satisfying if they can enable users to explore the data more thoughtfully. Additionally, if they can reduce the chances of trials and errors, increase users' efficiency with time, and enable them to share their experience.

5.3 Future of data visualization authoring tools

To stay with the leading trends of research, one needs to keep track of the trends and technologies that are continually changing the world of data visualization. In this way, the foremost necessity is enriching tools with the interactivity that corresponds to human factors. Human capabilities *(perceptual and cognitive skills plus multi-modality, e.g., visual, hearing, motor)* could provide many services beyond the limit of dimension restrictions in flat screens and commonly used interactive devices. The DVAT blend with natural human capabilities could facilitate users in accomplishing tasks on their devices. People make use of smart devices, watches, tiny screens, and wearables to visualize data. They want to access the data anytime and without being restricted to sit in front of the device and entirely focusing on one task. Enriching these devices with the authoring procedures that we accomplish on the conventional devices would considerably change the data visualization requirements. Moreover, the trend and advancement in AR/VR devices (Sicat et al. 2019; Chen et al. 2017, Ye et al. 2020 to appear) have made immersive visualization a focus of real-world applications. Thus, there are substantial prospects in excelling in these directions.

The discussion directs to an important aspect. For the advancement in the DVAT, developers need good skills to understand users and incorporate users' practices into the tool. Since the future of the DVAT depends on the level of natural experience users have with the tool, interaction techniques must be flexible enough to be tailored to the individual users' style and preferences. Along with the flexibility, the requirement of being easy to learn and use is uncompromisable. Users would not be willing to spend effort on the tool that is hard to learn, even if it can help create better representations. The prime focus of developers should not be to draw users' attention to the novel interactions. Instead, they should strive to craft tools that seem natural and predictable, more importantly, that boost users' cognitive capabilities.

6 Summary and conclusion

In this paper, we thoroughly studied the interaction techniques for five goals served by the DVAT. The review of interaction techniques has broad implications for the data visualization research. It contributes to knowing the interactions used in the exploration, ideation, and interpretation of visualizations. The details in the survey are also valuable in understanding the level of significance of each interaction for varied users' intent. Readers could also see how much each interaction contributes to the overall strength of an authoring tool. We also summarized the findings of the tools' evaluations. Summary highlights the strengths and weaknesses in the evaluations of interaction techniques. In addition, the analysis of users' feedback provides guidelines for the development of data visualization authoring tools that enhance users' cognitive satisfaction with the interaction techniques. Additionally, in the discussion, we compiled the thought-provoking ideas for broadening the accessibility and effectiveness of interactive tools.

Furthermore, going through the review, one can find that the contents related to Tables 1 and 2 suggest areas of further research. For instance, (1) establishing a clearer understanding of the experience users prefer to attain while using the tools, (2) how and when the tool can make the biggest contribution to the users' satisfaction with the authoring process and the results, and (3) how the tools for varied goals can be enhanced. Indeed, conceptualizing the DVAT as an engaging platform for users' interaction with visualizations and promoting high-level cognition emphasizes learning the characteristics of human cognition. However, this learning requires much research efforts beyond the suggestions given in this paper.

This review does not provide an exhaustive list of guidelines for creating the worthy tools for the varying goals. However, it highlights those points that provide a way to develop an observable link between the cognitive activities and interactive authoring. From a broader perspective, we believe that our review serves an important role in enhancing the articulation of the connections between information visualization and cognitive processes.

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