VisStoryMaker: supporting non-expert analysts in visually exploring datasets and communicating insights with visual annotations and data stories

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Figure 1: VisStoryMaker's main user interface – A: dataset variables; B: variable mappings; C: current chart; D and D': related questions and recommended visualizations (partial view); E and E': related data facts and recommended visual annotations (partial view); F: visual annotations customization; G: entry point to data story module (StoryMaker).

Abstract

Due to data production and availability growth, professionals in several disciplines have been facing an increasing need to explore and understand data, obtain insights, and communicate them effectively. Many visualization systems have been developed commercially and within the research community to support non-expert analysts. We can consider at least three challenges these tools aim to face: support the selection of appropriate visualizations and decide on the visual mappings, extract and communicate factual information from the visualizations, and use visualizations in data-rich narratives. In response to these challenges, we developed VisStoryMaker, a visualization tool that supports both exploration and communication about data. To aid users in exploring and understanding data, VisStoryMaker recommends visualizations through system-generated questions and data facts. To support communicating about data, the system recommends visual annotations of data facts and provides a story-building module, allowing analysts to use the generated charts and facts as a blueprint for a data story. We have conducted empirical studies to compare VisStoryMaker's features

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with existing applications: chart recommendations with Voyager 2, storytelling construction with Flourish, and data facts and chart annotations with Tableau. Our findings indicate that the system-generated questions and data facts supported non-expert analysts in exploratory analysis. They perceived visual data facts annotations as useful and supported them in raising hypotheses about the data, understanding data, and leading to insights, thus enhancing data analysis. Participants perceived the visual annotations and StoryMaker as helpful in organizing the system-generated pieces of information and incorporating them into comprehensive narratives and presentations.

CCS Concepts

• Human-centered computing → Visualization; **Visualization systems and tools**.

Keywords

Visualization recommendations, Exploratory questions, Data facts, Visual annotations, Data story, Visual data exploration, Visual data communication

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1 Introduction

Due to the growth of data production and availability, professionals in several disciplines have been facing an increasing need to explore and understand data, obtain insights, and communicate them effectively. A growing number of visualization systems have been developed commercially and within the scientific community to support non-expert analysts.

We can highlight three of the challenges these tools face: supporting the selection of appropriate visualizations and deciding on the visual mappings [25], extracting and communicating factual information from the visualizations [6], and using visualizations in data-rich narratives [32, 62]. Moreover, visualization design by non-expert analysts and designers can be difficult and time-consuming [6].

Several researchers are currently investigating mechanisms for providing more accessible charts, for instance, through reader-friendly annotations [4, 26, 37, 48]. Another related field of inquiry has been the investigation of the potential benefits of integrating charts in data stories to support a structured interpretation and data-driven communication [21]. However, there are some limitations on tools for data story-building by non-expert analysts, such as the inclusion of further options to enrich the authoring process of data stories [21, 32, 62].

In this context, our main research question is: *How can we support non-expert analysts in data exploration and communication through visualization recommendations, visual annotations, and authoring data stories?* We then break down our main research question into four research sub-questions:

- SQ1 How can system-generated questions (and the corresponding visualization recommendations) support non-expert analysts in exploratory analysis?
- SQ2 How can system-generated data facts (and the corresponding visualization recommendations) support non-expert analysts in exploratory analysis?
- SQ3 How can system-generated visual annotations of data facts support non-expert analysts in data-driven communication?
- SQ4 How can mechanisms combining visualizations and data facts into a data story support non-expert analysts in data-driven communication?

To answer these questions, we performed the following steps. First, we conducted a systematic literature review to understand the state-of-the-art through exploratory research [38] (section 2). Then, we used this body of research from the literature review as input to develop a visualization system named VisStoryMaker (section 3). We have conducted three empirical studies to assess the perceived value of VisStoryMaker's features with existing systems: chart recommendations with Voyager 2; visual annotations of data facts, which is a textual description of the result of statistical functions [64], with Tableau Public; and storytelling authoring with Flourish (section 4).

Based on our findings, non-expert analysts felt that VisStoryMaker offers a useful and easy-to-use approach to both exploring and communicating data. By recommending data facts that may interest users, the system allows them to consider different avenues of investigation they may not have before. In terms of communicating through the use of visualization, VisStoryMaker allows them to structure the charts they build into a data story, allowing readers to follow their chain of thought as they observe each visualization.

Our findings indicate that system-generated questions and data facts aid non-expert analysts in *exploratory analysis*, thus enhancing visual analysis. Moreover, we found evidence that VisStoryMaker provides support to *visual data communication* since both data facts and annotated visualizations can be incorporated into data visualizations and data stories to convey reader-friendly charts to a wider audience (section 5 and section 6).

Therefore, our contributions include the design and implementation of a system that recommends data facts and visual representations based on an underlying conceptual model that takes into account dataset features, extending an existing visualization tool. In addition, we present the results from three separate empirical studies that explore the construction of charts in this system using recommended charts framed around analytical questions, the exploration of the data with the use of recommended data facts, and its communication via the creation of visual data annotations; and, in StoryMaker, data stories that combine all three elements: charts, visual annotations in charts, and data facts, in a hybrid visual and textual representation.

2 Related Work

Many works have been developed in the most diverse fields of data visualization. In the next subsections, we present some related work on visualization recommendations, visualization annotations, and narrative visualizations.

2.1 Visualization recommendation

Communicating data is the main purpose of visualizations [8, 51, 68]. This communication occurs through the visual channels that encode data. Those channels are visual components such as position, color, and size, to name a few [34, 48]. Choosing the mapping between data and visualization channels is still a significant challenge for designing visualizations [48, 57]. To support analysts in this challenge of choosing appropriate visualizations, several systems and approaches have been proposed [9, 11, 17, 24, 29, 40, 42, 44, 45, 47, 69].

The APT [44] is a seminal work on visualization recommendation that uses a set of primitive graphical languages and expressiveness and effectiveness criteria and proposes a compositional algebra to enumerate possible visualizations. Later, Mackinlay et al. [45] proposed the *'Show Me'* interface, incorporating a chart recommendation feature in Tableau [66] that automatically generates multiple visualizations.

The VizDeck tool [50] relies on a set of statistics about the data and automatically recommends a set of visualizations that are fetched by a search field through which the user can enter visualization types or attribute names by filtering the visualizations. Similarly, other data-driven visualization recommendation systems were also developed and could show how effective this recommending technique can be [13, 17, 28, 29, 42, 47].

Wongsuphasawat et al. [74] presented Voyager 2 as an evolution of Voyager [73]. Voyager 2 enables the union between manual and automatic chart specification, allowing users to specify visualizations by defining the mapping between variables and visual dimensions and presenting a set of visualizations suggested from the variables mapped by the user.

To enable a better understanding of the recommendations and favor the data exploration process, de Sousa and Barbosa [16] developed the ViSC tool, a visualization recommendation system to support chart construction for statistical data. ViSC uses an ontology that defines the task the user can perform on the data and maps it onto questions and visualizations that may be used to answer it.

More recently, the VisMaker tool [41] was developed, presenting an interface to build data visualizations and proposing a question-oriented visualization recommendation approach, where the system generates some questions combining the different variables, integrating the proposals from [16, 74]. The VisMaker system [41] was perceived by non-expert analysts as a tool that can facilitate the understanding of the recommendations and support them in raising hypotheses about the data, enriching the data exploration process. However, VisMaker does not provide a mechanism for visual annotations or authoring data stories. We propose VisStoryMaker to enhance VisMaker in order to address these other issues.

2.2 Visualization annotations

According to Munzner [48], annotations refer to adding one or more visual or textual elements to visualizations. Annotations are useful for describing facts or highlighting something to pay attention to in visualizations [35].

Some work has been developed to enable and even automate the creation of annotated visualizations, facilitating this process for less experienced users. Kong and Agrawala [36] presented a clear definition and a taxonomy of graphical overlays. They defined graphical overlays as visual elements added in a base visualization to facilitate graph comprehension. The Contextifier system produces annotated line charts for financial time series [31]. It automatically creates a line graph and chooses textual annotations based on the content of a given news article.

Part of the process of annotating visualizations is related to data fact computing. Srinivasan et al. [64] mapped the analytic tasks proposed by Amar et al. [1] onto a set of variable types and data facts, presenting a prototype software tool, Voder, which is a visualization recommender tool that investigates the use of system-generated data facts as interactive widgets to aid human perception.

Regarding chart annotations, Ren et al. [53] sought to characterize a design space informed by a survey of 106 annotated charts published by six prominent new graphics desks. Using this design space, they designed and developed ChartAccent, a tool that allows people to quickly and easily augment charts via a palette of annotation interactions that generate manual and data-driven annotations.

Also, looking at annotations, Hullman and Diakopoulos [30] consider them one of the four editorial layers in data storytelling, alongside the data, visual representation, and interactivity layers. While there are certainly some tools and techniques that address these other layers, they argued that support for the annotation layer was underdeveloped.

2.3 Narrative visualizations

A narrative can be defined as an ordered sequence of steps; each step can contain words, images, visualizations, video, or any combination of these [37]. Storytelling has been used in many areas like education, media and entertainment. Even though it has been developed in various areas for years, it is still a relatively new topic in data visualization [67]. Still, several works argue that narrative elements can be added to visualizations to facilitate the communication of a message [22, 37, 46, 55, 58, 60, 63, 67].

Much research has been conducted to understand and formalize storytelling elements. According to Polti [52], there are 36 dramatic situations that can occur in a story. Campbell [7] discussed the *"hero's journey"*, a structure widely used for storytelling which consists of 12 stages. However, each genre and medium will require specific storytelling strategies.

As the need to present a complex dataset in an effective, more understandable, and engaging way for different audiences is a challenge, using narratives to help make sense of visualizations has become a trend [2]. According to Gershon and Page [23], stories communicate information in a psychologically efficient format, in the same way that visualizations do; however, visualizations differ from other narratives due to the complexity of the content that needs to be communicated [72].

The expression "narrative visualization" was used by Segel and Heer [63] to refer to visualizations that incorporate data stories in their design to guide the public in correctly interpreting data visualizations. They categorized seven genres of narrative visualizations: magazine style, annotated chart, partitioned poster, flow chart, comic book, slide presentation, and film/video/animation. Each genre can be combined with interactivity and messages to produce different experiences for both the author and the reader.

Lee et al. [39] described the process of creating a story with data visualizations, detailing the activities, artifacts, and roles involved in the process. It comprises three main components: exploring data, creating a story, and telling it.

According to Dove and Jones [18], data stories use interactive exploratory techniques to improve the communication of ideas and promote insights. There is great potential in narrative visualizations (or data stories), supporting different communication purposes in various contexts, for example, in the scientific domain [43]. However, there is a need to develop and improve visual analysis tools that support the construction of data stories [19, 60]. In this context, some tools, such as Tableau[1] and Flourish,[2] have been developed with features to help users to create data stories.

In this paper, we explore how recommendations of visualizations and data facts, as well as annotations of data facts in visualizations, can support non-expert analysts. We present the VisStoryMaker tool and its proof-of-concept model associating visualizations, data facts, annotations, and its data story builder features that aim to help with the challenges of selecting appropriate visualizations and deciding on the visual mappings, extracting and communicating factual information from the visualizations, and using visualizations in data-rich narratives.

3 VisStoryMaker

In response to the aforementioned challenges, we developed VisStoryMaker, a mixed-initiative [27] visualization tool that supports both exploration and communication about data. VisStoryMaker builds onVisMaker [41], which recommended data visualizations through system-generated questions. We made substantial changes and extensions to VisMaker to include mechanisms (i) for recommending data facts; (ii) for recommending and allowing the customization of visual annotations, and (iii) for creating data stories combining all three elements: visualizations, data facts, and visual annotations, as well as any additional text the user may find necessary for composing a coherent narrative.

Figure 1 shows VisStoryMaker's user interface. To guide our system's information architecture and interaction design, we considered lessons learned from former visualization systems and expert feedback. After loading a dataset, VisStoryMaker presents in panel (A) (Figure 1) the list of variables in the dataset and their respective data types: quantitative (Q), nominal (N), ordinal (O), and temporal (T). The system infers the variable data types when the dataset is uploaded, but users can change the data type in this panel (for instance, changing from quantitative to ordinal, if that is the case). The current list of supported visual dimensions is presented in panel (B): X axis, Y axis, color, shape, and size, which can be used to specify the main chart in panel (C) by using the Vega-Lite visualization grammar [61].

[1] https://www.tableau.com/
[2] https://flourish.studio/

To aid users in exploring and understanding data, VisStoryMaker recommends visualizations through system-generated questions (D) and data facts (E). The interaction between these features is detailed in section 3.1. To support communicating data, the system recommends visual annotations of data facts and provides a story-building module, allowing analysts to use the selected generated charts and data facts as a blueprint for a data story. The annotation feature is presented in detail in section 3.2, and the data stories creation feature is presented in section 3.3.

3.1 Navigating through visualization recommendations based on system-generated questions and data facts

VisStoryMaker displays two tab panels below the main chart panel. These tabs, identified as panels (D) and (E) in Figure 1, contain a list of questions and data facts, respectively.

The Questions tab (D) was first implemented in VisMaker. The VisMaker's recommender engine generates a list of questions and data visualizations by adding new variables to users' variables selection, as illustrated in Figure 2. In this approach, VisMaker computes new combinations of variables, mixing the user-chosen variables with the other unselected variables, identical to the Voyager recommendation engine [73]. However, what differs in our approach is the strategy to group these combinations into analysis questions and corresponding visualization recommendations. We refer the reader to Lima and Barbosa [41] for additional details.

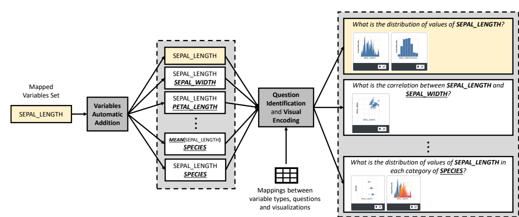

Figure 2: The VisMaker's recommender engine proposed in Lima and Barbosa [41]

The navigation tab Data Facts (E) was inspired by the design of the *related views* [74]. Each data fact is accompanied by a set of chart thumbnail recommendations and a visual cue preview (E'), as illustrated in Figure 3.

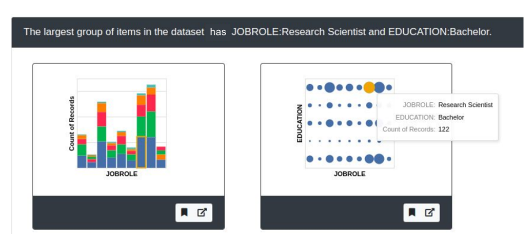

Figure 3: An instance of a system-generated data fact, visualization thumbnail recommendations, and data details on mouse hover.

Table 1 characterizes our conceptual framework for visually representing data facts in visualizations. Some charts treat ordinal data (O) in the same way as nominal data (N). In this case, we use the representations {N,O} to reference either kind of variable.

Figure 4 illustrates the rationale of this conceptual framework underlying the VisStoryMaker system. At first, the model maps user-selected data types (*e.g.*, quantitative, nominal) with possible tasks that could be performed from Amar et al.'s taxonomy [1] – *e.g.*, compute a derived value, find extremum, find anomalies. We decided to use the low-level taxonomy proposed by Amar et al. [1] as a starting point to generate data facts based on the work of Rodrigues et al. [56], who reviewed several visualization tasks taxonomies. Due to the similarity between low-level tasks and data facts, we associated one or more task(s) to substantiate data facts. As defined earlier, a data fact is a textual description of the output of one or more statistical functions. Table 2 presents an initial set of heuristics combining *<task, statistical function>* currently available in VisStoryMaker. We drew on former systems as inspiration to produce the textual descriptions [13, 64]. All data facts come with recommended visualizations grounded on graphical perception studies considering tasks [33, 49, 57, 59]. Finally, for each recommended graph, the model presents options of visual annotation cues to highlight data facts in the visualization, based mainly on Kong and Agrawala's taxonomy [36] of overlays and the information visualization literature [6, 35, 48].

This framework powers the core engine of the VisStoryMaker tool to generate data facts, recommend visualizations, and visual annotation cues. We marked with an asterisk (*) the default visual annotation for each data fact in Table 1. Note that we defined 'color' as the default option for most data facts because it is a common design choice to highlight selected items by changing their color [48, p.252].

We designed our proof-of-concept model (Table 1) to be extensible, *i.e.*, although it is not an exhaustive listing of all possible data facts and visual representations, it can be augmented as needed.

3.2 Annotating visualizations based on system-generated data facts

VisStoryMaker exposes the user-chosen data facts (F) located next to the main chart, as shown in Figure 5. The system allows the users to choose and customize the color of the preferred visual representations of data facts through checkboxes and a color picker. In addition to the user-chosen data facts, VisStoryMaker also presents a couple of additional data facts that could be added to the working visualization, as the item with light shade in Figure 5.

3.3 Supporting the authoring of data stories

VisStoryMaker contains a module for authoring data stories with visualizations, identified in Figure 1 as panel (G). This part of the system is shown in Figure 6. At the top, we have the general information fields about the story created: title, subtitle, date, data source name and link (if any), author name, and notes. Each data story can contain several cards, each card with one visualization. In the figure, we currently have only one card added, with the preview on the left and the *DataStory* field on the right. The user can change the *layout* of each *card*, open the view in the main VisStoryMaker window, and delete the *card*. The user can customize the text field format: font size and type, colors, alignments, etc., and add other resources: image, video, links, codes, etc. In this way, the user can manipulate the elements to make the story more attractive or to highlight points in the text. At the bottom, the user can add *tags* associated with the *data story* created.

The *Statistics* field presents some statistics and data facts about the selected visualization. If the user finds some important statistic for their story, they can select the text and copy it to the *DataStory* field. Also, it is possible to change the *layout* of the *card* in the leftmost option located at the bottom of the *card*, adjusting the size of the visualization and its position in the story.

The created data stories are presented at the end in PDF format, following the magazine style. This genre is more author-oriented, as it depends greatly on the message you want to convey and does not include interactivity. We chose to initially implement the magazine genre in VisStoryMaker because the author-oriented approach is better when the goal is efficient communication and data storytelling [63]. Moreover, we made this module extensible to include other genre types, to further explore a balance between the approaches identified by Segel and Heer [63].

4 Studies

We conducted three studies to evaluate VisStoryMaker, to assess its support for: (Study 1) data exploration through the questions and visualization recommendations, compared with Voyager 2's recommendations; (Study 2) communication of insights through data stories, compared with Flourish; and (Study 3) both data exploration and communication of insights through the questions, data facts (3a), and visual annotations (3b), compared with Tableau. For all studies, we collected both quantitative and qualitative data, following a mixed-methods approach.

In Study 1, because our goal was to assess the contribution of the recommended questions to visual exploration tasks, we compared VisStoryMaker with Voyager 2 because of the similarity between the Voyager 2 charts recommendation feature and the VisStoryMaker question-oriented recommendation feature (in terms of the combination of variables). In Study 2, because our goal was to assess StoryMaker, the story-building module of VisStoryMaker, we picked Flourish due to its popularity for authoring data stories among journalists [65]. In Study 3, because our goal was to assess the recommended data facts and visual data annotations, we chose Tableau because it is a state-of-the-art tool for visualization construction that does not require programming skills (as opposed to other popular tools, such as Power BI) and allows non-expert analysts to incorporate visual annotations on data visualizations.

4.1 Studies Setup

Each study involved two sets of tasks, one with VisStoryMaker and one with the tool for comparison (either Voyager 2, Flourish, or Tableau, depending on the study). We varied the order in which participants used the tools, the datasets, and the tasks they performed to avoid learning effects and differences in the data and the tasks interfering with the results. Therefore, all studies comprised four groups of participants (Table 3). Participants of all studies reported

Table 1: Model of data facts, visualizations, and visual annotations cues.

Types	Task	Visualization	Example Data Fact	Annotations
Q	Derived Value	Histogram	`var0` has mean of `val_mean`.	*Color line, Label
	Find extremum	Dot	`val_max` is the highest element for `var0`.	*Fill color, Stroke
	Characterize distribution	Histogram, Strip	Half of values of `var0` are in the range $Q1$ - $Q3$. (Q_1 and Q_3 stand for *first quartile* and *third quartile*, respectively.)	*Fill color, Stroke
	Find Anomalies	Box	`var0` seems to have `amount_outlier` outliers.	*Fill color, Stroke
{N,O}	Find Extremum	Bar chart	`category0_label` has the highest number of occurrences	*Fill color, Stroke, Text Highlight
	Characterize distribution	Bar chart	Number of items in `category0_label` is X times the number of items in `category1_label`.	*Fill color, Stroke, Text Highlight
T	Compute Derived Value	Line	The mean number of occurrences of `var_0` is `mean_occ`.	*Point, Line, Label
$Q \times Q$	Correlation	Scatter	There are an apparent strong positive correlation between `var0` and `var1`, with coefficient $r = 0.75$.	*Regression line, Label
$Q \times$ {N,O}	Characterize Distribution (+Derived Value)	Bar	Average `var0` of `category0_label` is X times `category1_label`.	*Fill color, Stroke, Text highlight
	Find Extremum (+Derived Value)	Bar	`categoryMax_label` has highest average value for `var0`.	*Fill color, Stroke, Text highlight
	Find Extremum	Strip, scatter	`var1` has item `categoryMin_label` with lowest value for `var0`.	*Fill color, Stroke
$Q \times T$	Compute Derived Value	Line, Area	`var0` has mean of `val_mean` in this period.	*Color mean line, point, label
{N,O}× {N,O}	Find Extremum	Stacked Bar, Scatter + Size	The largest group of items in the dataset have `var0`: `category0_label` and `var1`: `category1_label`.	*Fill color, Stroke, Text Highlight
	Characterize Distribution (+Find Extremum)	Stacked Bar, Scatterplot + Size	`category1_label` has most number of items. Most items in `category1_label` belong to `category2_label` for `var1`.	*Fill color, Stroke and Text Highlight

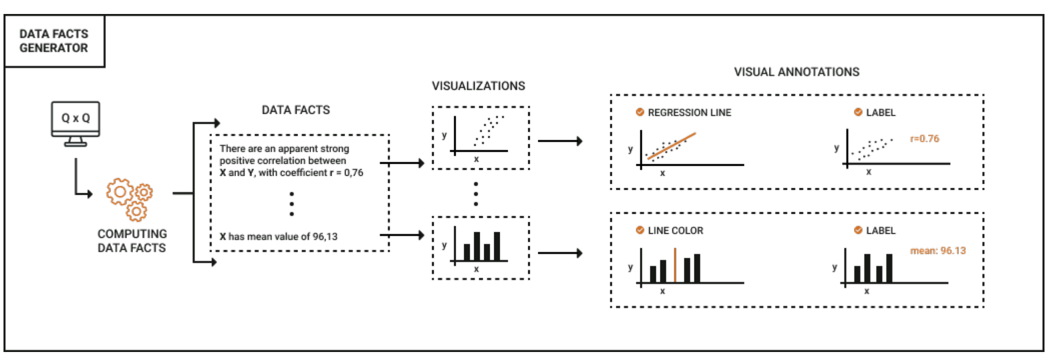

Figure 4: Illustration of our model's operation for visually annotating data facts in visualizations

that they had no previous acquaintance with the datasets used in the studies.

We conducted each session individually, synchronously, and remotely, via Zoom. Participation in the study was voluntary, and

Table 2: Tasks and statistical functions currently available in VisStoryMaker.

Task	Statistical function
Find Extremum	Minimum Maximum
Derived Value	Average Median
Find anomalies[1]	data point $\leq Q_1 - 1.5 \times IQR$ data point $\geq Q_3 + 1.5 \times IQR$
Correlation[2]	$r > 0.7$, strong positive correlation $r < -0.7$, strong negative correlation $r > 0.5$, moderate positive correlation $r < -0.5$, moderate negative correlation
Characterize distribution (relative values)[3]	$categoryMaxValue \geq \kappa \times categoryMinValue$ (category pair with largest difference)
Characterize distribution (common range of values)	Half of values are in the range Q1-Q3

[1] Q_1, Q_3, IQR stands for *first quartile*, *third quartile* and *interquartile range*, respectively.
[2] r is the Pearson's correlation coefficient.
[3] κ is the proportion between $categoryMaxValue$, $categoryMinValue$.

Table 3: Participant groups according to datasets and tools.

	Group	Dataset 1	Tool 1	Dataset 2	Tool 2
Study 1	1	capes-rj	VisStoryMaker	weather	Voyager 2
	2	weather	VisStoryMaker	capes-rj	Voyager 2
	3	capes-rj	Voyager 2	weather	VisStoryMaker
	4	weather	Voyager 2	capes-rj	VisStoryMaker
Study 2	1	students performance	VisStoryMaker	medical costs	Flourish
	2	medical costs	VisStoryMaker	students performance	Flourish
	3	students performance	Flourish	medical costs	VisStoryMaker
	4	medical costs	Flourish	students performance	VisStoryMaker
Study 3	1	employee performance	VisStoryMaker	covid vaccination	Tableau
	2	covid vaccination	VisStoryMaker	employee performance	Tableau
	3	employee performance	Tableau	covid vaccination	VisStoryMaker
	4	covid vaccination	Tableau	employee performance	VisStoryMaker

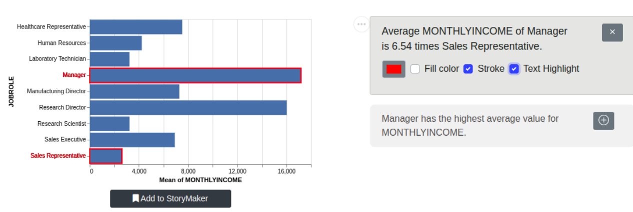

Figure 5: Customizing visual annotations of data facts in visualizations in VisStoryMaker.

because of our country's regulations, the participants were not financially compensated. We used a convenience sample [10] due to the institutional proximity with individuals with the desired profiles. The participants in all studies were not experts in data visualization. All studies were submitted and approved by the Research Ethics Committee of Pontifical Catholic University of Rio de Janeiro, protocol 97/2020. We explained the study procedures to all participants, who signed an informed consent form agreeing with the study procedures and conditions.

In Study 1, we recruited 24 participants: 16 for the question-answering task and 8 different participants for the data exploration task. All of them self-reported as having at least a basic level of knowledge of chart interpretation. This study used the datasets *capes-rj* and *weather*. *Capes-rj* comprises 7 variables and 4,993 records from postgraduate programs distributed in different cities in the state of Rio de Janeiro over time; and *weather* comprises 7 variables and 2,922 meteorological records in the cities from New York and Seattle, in the United States.

In Study 2, we recruited 12 participants: 8 with a background in Computer Science and 4 in Journalism. Most of them self-reported as skillful in building and comprehending charts, but not at an expert level. However, the participants stated that they were not

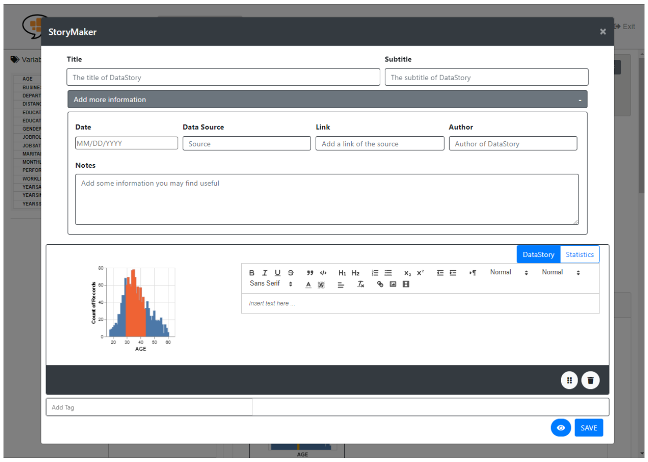

Figure 6: VisStoryMaker's StoryMaker (marked as (G) in Figure 1)

acquainted with tools to author data stories with visualizations. The datasets used in this study on *medical costs* and *students performance*; the first one has 1,338 records and 7 variables of people's medical costs and other information, and the second one has 1,000 records and 8 variables containing personal data about students who took a test or exam.

In Study 3, we recruited 28 participants between 18 and 54 years of age. All participants self-reported as non-experts with visualization tools – *i.e.*, intermediate-level or novice users. Intermediate-level users felt well-equipped to build basic charts [20] with visualization tools or to perform data analysis with a visualization library. Of the eight novice users, four disclosed they had a brief acquaintance with Power BI[3] or Tableau,[4] and the other four expressed no prior experience with visualization tools. The datasets used in this study were *covid vaccination*, composed of 11 variables and 3,388 records about daily vaccinations records of some Latin American countries, and *employee performance*, with 16 columns and 1,470 rows of synthetic data about the performance of employees from a fictitious company.

4.2 Studies Procedures

Before each study session, we collected the participant's consent to record the screen and audio for later review. Once they approved, we gathered some profile and background information for our analysis. We piloted each study to consolidate the procedures.

The study sessions lasted 60-90 minutes. In each study, we first gave a brief training on the interface and a few features of the first tool (∼ 5 min), using a different dataset from the ones used in the study tasks. We allowed participants to watch the training video more than once. Next, we gave participants the first dataset according to the study scenario they belonged to (Table 3). We provided a dataset summary document describing the attributes and their corresponding data types. None of the participants were familiar with any of the datasets and with the VisStoryMaker tool.

[3]https://www.microsoft.com/pt-br/power-platform/products/power-bi
[4]https://www.tableau.com/pt-br/community/public

For each tool, we asked participants to perform a guided question-answering task (without a time limit) and an unguided task to explore the tool aspects relevant to each study (with a 30-minute time limit).

In Study 1, participants were instructed to explore the dataset for a maximum of 30 minutes, building data visualizations that they found interesting about the given dataset, and using the visualization recommendations to improve their exploration process.

In Study 2, the question-answering task and the exploration task were performed in the same session. Another difference is that the goal for the users was to create two stories for a newspaper. For each story, they had to answer two basic questions about the dataset. To answer these questions, participants had to create visualizations and write a story based on them.

In the guided task of Study 3, we instructed the participants to construct a visualization. Then, we asked them to use the tool to provide answers to closed-ended questions, like: *"What is the value of the mean for the variable you chose?"*, *"How would you highlight the mean value in the visualization you've built?"*, *"Can you customize the visual representation of the average you made? If so, which one?"*. We aimed to ensure the participants interacted with the visual annotation feature at least once for later evaluation. With respect to the unguided part, the task was fairly open-ended: we asked participants to explore the dataset using the tool to show their findings as a presentation.

An experimenter observed each session and took notes. We encouraged the participants to 'think aloud' while interacting with the tools [38].

After performing each task, the participants completed a questionnaire regarding the tool they had just used. We designed the questionnaires to assess the participants' perceived ease of use and perceived usefulness, grounded in the Technology Acceptance Model (TAM), which is a suitable theoretical tool to measure the perceptions of use by individuals [15]. Participants used a 7-point Likert scale to answer each question (where 1 was totally disagree and 7 was totally agree), providing some quantitative evidence of the similarities and differences between the tools.

After the participants concluded the tasks, we briefly interviewed them. We asked them general questions about their experience using each tool and asked for feedback on specific features of VisStoryMaker, according to each study (∼ 5min). We recorded and transcribed the interviews and analyzed the data using typical qualitative research techniques, such as thematic analysis [5].

5 Quantitative analysis

This section presents a quantitative analysis of the data collected in studies 1 and 3. Study 2 did not present any significant findings so, for brevity, its quantitative analysis is not included here.

5.1 Evaluating VisStoryMaker's support to data exploration and understanding through questions and data facts related to visualization recommendations

We compared VisStoryMaker with Voyager 2 for the **question-answering task** along the dimensions of ease of use, usefulness, attitude, and self-efficacy. A Wilcoxon matched-pairs test is a non-parametric hypothesis test method for comparing two paired samples. In this study, we compared the perceptions of use of each tool, captured through 7-point Likert-scale scores [70]. The p-value obtained ($p < .05$) showed that there was a statistically significant difference between VisStoryMaker and Voyager 2 in ease of use, attitude, and self-efficacy, all in favor of VisStoryMaker (Table 4).

In the question-answering task, we also evaluated the correctness of both the visualization and the answer to the question. All combinations occurred with both systems: (i) correct visualizations and answers; (ii) correct visualizations but incorrect answers; (iii) incorrect visualizations but correct answers; and (iv) incorrect visualizations and answers. In particular, Voyager 2 presented a problem of scale in one of the tasks, resulting in a correct visualization but whose scale made it very difficult to compare the values, leading many participants to incorrect answers.

Regarding the **data exploration task**, eight participants were asked to explore the data and generate useful visualizations. They had 30 minutes to complete the task. The same questionnaire was applied as in the question-answering task, but, this time, the only significant difference occurred in the statement "I think the tool (VisStoryMaker) is easy to use" ($p - value = 0.033$), related to the *ease of use* dimension. The median score was 6.5 for VisStoryMaker and 5.0 for Voyager 2.

In general, participants were able to complete most tasks using both tools. Both tools facilitated the construction of statistical data visualizations, especially when participants had a question in mind.

5.2 Evaluating VisStoryMaker's support to the communication of insights through visual annotations

We compared VisStoryMaker's visual annotation mechanism to Tableau Public's. To check whether the differences were statistically significant, we computed the non-parametric Wilcoxon matched-pairs test [70]. Table 5 presents the results for each item. We highlighted the statistically significant results in boldface.

Regarding the task of **visually annotating data facts** in charts, the perceived usefulness and ease of use by non-expert analysts of VisStoryMaker's visual annotation approach scored significantly higher than Tableau Public's. For each statistically significant result, we investigated whether there was practical difference, as well, by calculating the effect size as the matched pairs rank-biserial correlation [14]. According to Bartz [3, p. 184], the results that we obtained for effect size suggest strong or very strong practical significance, as shown in the final column of Table 5.

6 Qualitative analysis

This section presents a qualitative analysis of the data concerning VisStoryMaker's support to data exploration and understanding through questions and data facts, its support to the communication of insights through data stories, and its support to the communication of insights through visual annotations.

6.1 Evaluating VisStoryMaker's support to data exploration and understanding through questions and data facts related to visualization recommendations

Comments on the ease of use of VisStoryMaker appeared in participants' responses in the interview. Nine out of 16 participants in Study 1 remarked that the VisStoryMaker's questions, coupled with the visualization recommendations, helped them reach their goals, and two participants emphasized that the questions helped them understand the meaning of the recommended charts more easily. In contrast, seven participants criticized Voyager's user interface, stating that the amount of information presented proved to be a little confusing and ended up hindering them.

The visualization and question recommendation system that was implemented in the exploratory side of VisStoryMaker was also the topic of great discussion in Study 2, with 10 out of 12 participants explicitly mentioning it with a positive valence. This is exemplified in the following statement: "*It (VisStoryMaker) makes it more accessible, [...] you keep selecting the variables you want, and it shows you the possibilities in terms of how you want to tell your story.*" – P04, Study 2.

When examining the role of data facts in supporting data exploration in Study 3, several participants (10 out of 28) thought that ***the data facts in VisStoryMaker aided them in exploring the data*** In particular, they argued that the data facts supported them in accelerating exploration, understanding information, hypothesizing about the data, and getting insights about the data: "*the data facts could help me to hypothesize or get some insights when analyzing the data.*" – P07, Study 3; "*the tool presented me with several statistics ... this information could lead me to have insights into data.*" – P18, Study 3; and "*these facts and questions helped me formulate insights*" – P02, Study 3.

The non-expert analysts reported that the available facts were common information they typically look for when visualizing data. They perceived the data facts as helpful for *hypothesizing* and could lead to *insights* from data, thus *enhancing data analysis*. Users perceived VisStoryMaker's recommended visualizations as helpful in suggesting visual representations to communicate numbers to a broader audience.

6.2 Evaluating VisStoryMaker's support to the communication of insights through data stories

In general, participants (8 out of 12) in Study 2 found ***VisStoryMaker's data story creation mechanisms easier*** than Flourish's: "*The order of [VisStoryMaker's data story] creation and organization is much better, as well as the fact that it puts everything in a single document [...] The organization of the workflow is better in VisStoryMaker.*" – P03, Study 2.

Six participants ***did not like Flourish's workflow*** to build the data story with multiple visualizations: "*One thing I didn't like was the need to go back and forth to create new visualizations*" – P06, Study 2; "*I think this issue of going back and forth in creating visualizations [...] it is a more annoying process.*" – P03, Study 2.

Table 4: Results of Wilcoxon matched-pairs test (Study 1), showing median scores for each tool and the p-value of the difference.

Question	VisStoryMaker	Voyager 2	p-value
I think the tool is easy to use [ease of use]	**6**	5.5	**0.005** **
Learning how to use the tool was easy for me [ease of use]	**7**	5.5	**0.002** **
It is easy to become skillful using the tool [ease of use]	**7**	6	**0.013** *
Using the tool to explore datasets is a good idea [attitude]	**7**	6	**0.023** *
I felt confident using the tool [self-efficacy]	**7**	5	**0.038** *

$N = 16$, * $p < .05$, ** $p < .01$, two-tailed

Table 5: Results of Wilcoxon matched-pairs test (Study 3)

Question	VisStoryMaker	TP	p-value	effect size
Q01 - Overall, the tool is easy to use	6.0	5.0	**0.00006** ***	0.9 very strong
Q02 - It is simple to use tool	6.0	4.5	**0.00004** ***	0.94 very strong
Q03 - The tool made it easy for me to visually annotate data facts in charts	7.0	5.0	**0.00335** **	0.74 strong
Q04 - The tool's feature of highlighting data facts on charts is useful	7.0	6.0	**0.00394** **	0.82 very strong
Q05 - The different options for visually representing data facts on charts in the tool are useful	7.0	6.0	0.06177	-
Q06 - The personalization options for visual annotations are useful in the tool	7.0	6.0	0.05576	-
Q07 - Using the tool to explore data is a good idea	7.0	6.5	**0.01902** *	0.68 strong
Q08 - Using the tool to communicate insights from data is a good idea	7.0	6.0	0.08909	-
Q09 - The tool's interface is pleasant	6.0	5.0	**0.00720** **	0.61 strong
Q10 - I enjoyed using the tool's interface	6.0	5.0	**0.00170** **	0.75 strong
Q11 - Using the tool's interface required mental effort	2.0	4.0	**0.00033** ***	0.9 very strong
Q12 - Interacting with the tool was frustrating	1.0	2.0	**0.00091** ***	0.91 very strong
Q13 - Overall, I am satisfied with the tool	6.5	5.0	**0.00078** ***	0.85 very strong

VisStoryMaker = VisStoryMaker median score, TP = Tableau Public median score.

$N = 28$, * $p < .05$, ** $p < .01$, *** $p < .001$, two-tailed

The diversity and quality of Flourish's chart types were emphatically mentioned by 4 out of 12 participants, such as in the following statements: "*The charts are beautiful. I found that there were many options for visualization, and they were all already there.*" – P03, Study 2, and "*Flourish seems to have a set of charts that is bigger and different. It is quite rich, with the potential to create various charts, which I found nice.*" – P04, Study 2.

During these sessions, more than half of the participants struggled to find the right fields to insert information in Flourish, while none showcased a similar difficulty in VisStoryMaker. A noteworthy comment that encapsulates this was: "*I liked this part [in VisStoryMaker] a lot as well, of the window for Title and Subtitle already there. I do not have to think about it or search where to input it.*" – P04, Study 2.

In terms of narrative visualizations, five participants ***preferred the slide format in Flourish***, in which the narrative visualization is presented at the end, with statements such as: "*I think I was a little more impressed with Flourish's format that created a presentation.*" – P03, Study 2. However, they also cited the potential of having both formats (slide and magazine): "*If it is something I must do in the computer, the slide would catch my attention, but if it is something that I need to create as a report and print, then it would be the magazine format. I would have both in an ideal world.*" – P03, Study 2.

At the end of the interviews, we asked participants for any final comments. From those, we highlight the following two:

"*I would say that my first impression of these two tools [VisStoryMaker and Flourish] is that they are very intuitive and seem to be better for creating a story when I do not know exactly what I want, what chart to use, etc. The alternative would be to use Python, in which you must first think of the chart, even though you have greater control over it. I thought that these two tools are more interesting, because they are faster and also allow you to explore different visualizations, even before you think about what you actually want to do. That is* *why I found VisStoryMaker more interesting than Flourish, although I would use both.*" – P11, Study 2.

"*These tools [VisStoryMaker and Flourish] would be great in the hands of journalists. At the same time that Flourish is very good, this interactivity for a journalist that may not know much about data and is trying to improve a visualization of a story can be difficult, with VisStoryMaker making it more practical, easier for the journalist.*" – P12, Study 2.

A clear limitation of Study 2 was the small number of participants (12), which made a robust statistical analysis difficult. New studies are needed to cover a broader set of participants. Another limitation was that the study was not focused on constructing visualizations. As participants were able to ask for help to construct the visualizations to answer the questions, said assistance may have interfered with the data stories they were building.

The following paragraphs contain the main positive and negative aspects highlighted by participants. These are split between the two tools, Flourish, and the two main sets of features in VisStoryMaker, those with an exploratory focus and those with a communicative focus. We have separated our analysis of VisStoryMaker's features since, even though we sought to look at only the communicative aspects of the tool, the exploratory features were also mentioned.

Regarding the positive aspects, Flourish was noted for having more customizable and interactive visualizations and a greater variety of chart types. VisStoryMaker was generally considered easier to use, with its exploratory features being lauded for its recommendation of visualizations and related questions, the possibility of altering variable types, and applying aggregation functions to the data. In terms of its communicative component, it was complimented for its presentation of basic statistics about the underlying data, the ease with which participants could find information fields, and its workflow for creating narrative visualizations.

Concerning the negative aspects, Flourish was critiqued for its workflow, lack of functionality for manipulating the data, lack of graph recommendations, and difficulty identifying the right information fields for data input. VisStoryMaker was generally criticized for its lack of interactive features, with its exploratory component lacking the customization of charts, its little variety of chart types, and the lack of visibility as to which filters were active on the underlying data. Regarding its communicative side, participants complained about PDF being its sole export format and lacking variety in data store formats.

The interview data revealed that most participants considered the communicative part of VisStoryMaker to provide greater support for constructing data stories, mainly because of the recommender system at its core. As such, users did not have to think too much about which charts would be best for the type of question whose answer they wanted to represent. Furthermore, some participants stated that VisStoryMaker was simpler and more practical, while Flourish's interface was more complex, which could also be observed in the questionnaire data.

However, Flourish still possesses more storytelling functionalities not present in VisStoryMaker, and participants reported that. For example, some participants mentioned that its visualizations were prettier and, more crucially, were customizable and more interactive. They also mentioned ***VisStoryMaker features that were not available in Flourish***, such as the alteration of variable types, the application of functions in a few variables, and the presentation of statistical data in the visualizations saved by the tool, allowing for the construction of other visualizations and a deeper analysis of the data.

Some participants struggled to figure out how to insert information in Flourish (title, subtitle, etc.). In VisStoryMaker, they specifically mentioned how easy these fields were to find and engage with.

During the interviews, we noticed that Flourish's slide presentation style drew greater attention from some participants than the magazine style. One of the negative aspects of VisStoryMaker was its sole reliance on PDF as an export format. Another negative point in VisStoryMaker was the lack of visualization customization options (such as changing chart colour, editing axis names, including other filters in the visualizations, and using different layouts and sizes, among others).

Flourish presents a greater variety of visualizations, with participants seeming to appreciate viewing all of the available options that the tool provides.

Another aspect pointed out by participants was that ***VisStoryMaker's workflow was superior*** since it allowed users to load their desired dataset, create and save visualizations from the main panel, access the StoryMaker when desired, and easily return to building visualization in the main dashboard. In Flourish, users must choose their desired template before loading their dataset. In the story construction area, if the user wishes to insert a new visualization, they must repeat the entire process of constructing visualizations.

In regard to missing functionalities, participants saw a great deal of complementary features when comparing both tools. There were some features from Flourish that VisStoryMaker might benefit from having, and vice versa.

6.3 Evaluating VisStoryMaker's support to the communication of insights through visual annotations

Twenty-three (82%) participants in Study 3 considered that VisStoryMaker's features did indeed support them in communicating insights. Participants described some usage scenarios we had not anticipated. For instance, a journalist could incorporate the generated facts into news reporting: "*If I needed to write a journalistic article about a topic, with VisStoryMaker, I could have several ideas on how to organize them in a journalistic article...*" – P26, Study 3; Another participant, a tax auditor, also suggested using facts in creating reports to corroborate ideas: "*as part of my job, I tend to look for outliers. (..) These facts are a big deal for people who perform statistical and critical analysis. When you get statistical data, you can compare them with each other and come to a conclusion.*" – P28, Study 3. Therefore, participants not only recognized the benefits of visual annotations of data facts to communicating with data but also suggested other scenarios in which facts could be useful in their daily activities.

Regarding item Q03 (*The tool made it easy for me to visually annotate data facts in charts*), four participants pointed out that ***VisStoryMaker makes it easy and intuitive to highlight facts visually***. An intermediate-level participant said, "*In general, I found*

VisStoryMaker much easier to use than Tableau. Especially when it comes to adding visual annotations to the data" – P22, Study 3. To complement this, a novice participant cited what may have led to this point of view: "*VisStoryMaker gave me a lot of options, it already anticipates things that I might want to use, so it makes it easier to use because of that.*" – P19, Study 3. Concerning item Q15, a participant summarized the common opinion regarding this issue: "*Although Tableau provides more options for you to insert these visual annotations than VisStoryMaker, Tableau provides a more complicated way of annotating and customizing.*" – P22, Study 3.

Participants perceived our system as simple and easy to use (items Q01, Q09, Q10, and Q12). Novices and intermediate-level users felt that ***VisStoryMaker's visual annotations and data facts were useful and supported them in creating hypotheses, understanding data, leading to insights, creating reports or presentations, and exploring the data*** (items Q04 and Q07).

Two participants said they would use a combination of the two tools: "*I would use VisStoryMaker to explore, and if there were a visualization that I did not like, I would use Tableau.*" – P12, Study 3, and "*I think the best of both worlds would be to do a preliminary analysis using VisStoryMaker, and then I would use Tableau to generate charts to communicate to other people.*" – P17, Study 3.

We further inquired participants about their opinions of the catalog of data facts and visual annotations. They said the data facts were similar to the ones they would typically look for when analyzing data. They felt satisfied with the available facts and would not remove any because they considered it useful to have options for saving time, even the simplest ones (maximum, minimum).

A negative point identified through our study about the visual annotations was that ***including multiple visual data facts in the chart could cause visual clutter and distract readers from the data***, in line with Bateman et al. [4]. This opens up space for further studies to recommend more subtle visual annotation options.

In summary, as for *visual data communication*, participants thought ***VisStoryMaker's visual annotations of data facts could support them in generating ideas on organizing the information and incorporating them in journalistic articles, reports, presentations, and scientific papers***.

6.4 Thematic analysis of the data collected in Study 3

Thematic analysis is a consolidated method for analyzing qualitative data [5]. We used this method to closely examine the interview transcripts of Study 3 to identify common topics and ideas that came up repeatedly. In doing so, we were able to capture salient categories and identify relevant themes regarding participants' thoughts on VisStoryMaker and Tableau. We limit this analysis to Study 3 because it was the only study in which we collected rich interview data.

The analysis is structured around three main entities: the user, the system (VisStoryMaker or Tableau), and the data. The user engages with the system to explore the data or communicate facts and insights. All of the remaining categories refer to different aspects of this interaction. For example, its main product is a chart or a series of annotated charts and text composing a data story. Creating said charts can occur through accepting the system's recommendations or through manual construction.

A few salient themes are worth discussing here. First, the presence of data facts and questions in VisStoryMaker may assist users in exploring the data by presenting additional avenues of investigation they might not have been aware of. Second, communicating the data can also benefit from data facts in VisStoryMaker – as data facts may add context to the narrative they are currently working on – and data questions, which may help make the story more coherent by allowing the users to structure it according to the questions it answers. Finally, the number of features in the tools can help make them more comprehensive but may also add complexity to the interactions, making them harder to engage, as was the case with Tableau.

One of the main goals that users engaging with VisStoryMaker and Tableau may have is to **explore the data** they are working with. During this process, they may **look for interesting data facts**, which are recommended to them in VisStoryMaker. Exploration within visualization tools usually occurs through creating and modifying various charts, using visual mappings to examine data attributes. In VisStoryMaker, in addition to having data facts suggested to them, users may also incorporate them as visual and textual annotations in the current graph, allowing them to better contextualize the data and insights. **Different data questions** in VisStoryMaker also allow users to change the current type of chart being visualized, focusing on different aspects of the data and allowing for other types of data facts to be uncovered. Through this **continuous process of visualizing the data in a specific chart type and then annotating it according to recommended data facts**, users can thoroughly explore a dataset and the insights that can be extracted from it.

Another reason why people may use tools like VisStoryMaker and Tableau is to **communicate** some aspects of the data in question. This entails creating the visualizations with the right visual mappings and tailoring them to the message they seek to provide. When multiple charts and texts are presented sequentially, communicating connected messages, they can be considered data stories. Both tools had specific features focused on authoring these stories, albeit with a few differences. While participants noted Tableau's comprehensiveness in terms of the various types of annotations and tailoring features that were available to them, they also saw **value in the suggestion of data facts and questions**. By having these, they felt more able to ensure that the set of visualizations communicates a coherent narrative.

For both **data exploration and insight communication** goals, users must engage with various interactions in VisStoryMaker and Tableau. Despite making them more comprehensive, **having more features may also increase complexity**. This is a point that participants often brought up during interviews regarding Tableau. Tableau, as an established and commercial visualization tool, has several features that are not available in VisStoryMaker. In some ways, this is positive since it gives users a wider range of functionalities to work with and allows them to achieve a broader set of goals. However, it also has a downside: as many participants stated, the large number of interactions available in Tableau confused them about how they should resolve the task at hand, given there were so many options. Since VisStoryMaker has fewer features, participants found it easier to achieve their desired goals since the required interactions seemed clearer to them. This is the constant balancing act that designers have to engage in wherein they need to find a set of features that can satisfy user needs without adding an excessive amount of complexity, which can actually work against user satisfaction.

By considering these themes derived from our qualitative analysis in conjunction with our quantitative data, we could address our research questions. Since they served to structure our studies, it is important to revisit them and consider what we found.

Regarding SQ1 (*How can system-generated questions (and the corresponding visualization recommendations) support non-expert analysts in exploratory analysis?*) and SQ2 (*How can system-generated data facts (and the corresponding visualization recommendations) support non-expert analysts in exploratory analysis?*), our findings indicate that the system-generated data facts and questions supported non-expert analysts in their exploratory analyses by accelerating their hypothesizing and leading to new insights about the data. This indicates that automatically highlighting new avenues of investigation may assist them in building new visualizations that present the data in different ways and reveal new information.

Regarding SQ3 (*How can system-generated visual annotations of data facts support non-expert analysts in data-driven communication?*) and SQ4 (*How can mechanisms combining visualizations and data facts into a data story support non-expert analysts in data-driven communication?*), participants stated that visual annotations aided them in understanding and communicating the data and that StoryMaker could be used to organize system-generated charts in comprehensive narratives. By being presented in conjunction with data facts and questions, the meaning behind what these charts communicate is emphasized. Having this in mind, participants appeared to give greater consideration to this communicative aspect of the charts and data stories they created.

6.5 Limitations

Our studies had some limitations worth discussing to better contextualize our findings' potential implications along three dimensions: evaluation, participants sample, and system functionalities.

Regarding the evaluation, in some of our studies, the interview questions may have been too general and made it difficult to differentiate between participants' views of specific system features and their overall opinion of VisStoryMaker and Tableau.

The participants sample followed a convenience strategy, recruiting institutional colleagues and their acquaintances. We also asked participants for recommendations of other candidates, in a snowballing approach. This limits the external validity and generalizability of the results.

Concerning the system functionalities chosen for the studies, we focused on a reduced set of features common to both systems. In doing so, we may have presented a biased view of Tableau since many of its features were not relevant to our studies' tasks. This raises questions about the fairness of the study design in comparing the tools.

Despite these limitations, we could still observe some of the implications of automatically recommending data facts and visualizations framed around questions. By using a convenience sample, our results were biased towards people with higher education, meaning that they may not apply to the overall public. However, since these groups are the ones that most engage with tools such as Tableau and other commercial visualization systems, our findings remain relevant.

7 Conclusion

In this paper, we presented VisStoryMaker, an extension of an existing visualization tool that supports both exploration and communication about data. VisStoryMaker recommends visualizations coupled with system-generated questions and data facts, assisting non-expert analysts in data exploration and understanding, specifically supporting hypothesizing and getting insights about the data. Besides assisting users in data exploration, VisStoryMaker recommends visual annotations of data facts and provides a story-building module, allowing analysts to use the generated charts and facts as a blueprint for a data story. As we have seen in our studies, non-expert analysts showed interest in these features, stating that they helped them organize their insights and structure them as cohesive data stories and presentations, thus supporting the construction of data-driven narratives.

To better understand how VisStoryMaker impacted these processes, we conducted a series of empirical studies comparing it to existing applications: chart recommendation features were compared with those in Voyager 2; story building with Flourish; and data facts and chart annotations with Tableau.

Future studies may allow us to better understand how people may use the system to support interactive storytelling. Using questions and data facts could be a first step towards that [54]. It is also worth investigating whether VisStoryMaker's features could be used to support collaborative storytelling [12, 71]. Looking forward, another promising avenue of investigation concerns the potential use of machine learning models to assist in the exploratory and communicative processes. For instance, can a conversational agent (*e.g.*, using a large language model – LLM) be efficiently used to automatically generate more sophisticated data facts based on user prompts? If so, how could we integrate this generated information to enrich the visual analysis and narrative? Several new research opportunities arise and can be explored on these topics.

This work focused on VisStoryMaker and the evidence gathered from three separate empirical studies that helped us better understand the potential impacts of its use. From our results, it appears that the suggestion of data questions assisted participants in their explorations of datasets, as it may lead to the exploration of new types of charts and facts, which in turn complement and may be visually annotated in these charts. In addition, the ability to structure their charts in a data story, considering the recommended data questions they may answer, facilitated their creation of data stories participants deemed coherent and thought communicated their desired messages. Although further investigation is welcome, including capturing data with other evaluation instruments (such as System Usability Scale, AttrakDiff, among others), our results show that VisStoryMaker's recommendations of charts and related questions, data facts, and visual annotation mechanism proved helpful to the users involved in our studies and established the contribution of our integrated solution.

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