Where Are We So Far? Understanding Data Storytelling Tools from the Perspective of Human-AI Collaboration

HAOTIAN LI, The Hong Kong University of Science and Technology, China
YUN WANG, Microsoft Research Asia, China
HUAMIN QU, The Hong Kong University of Science and Technology, China

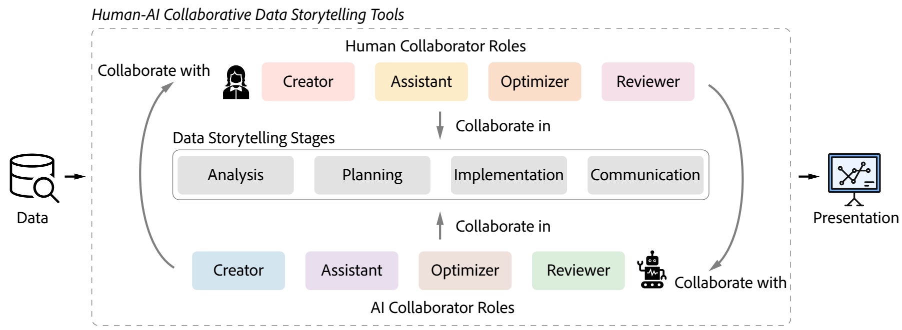

Fig. 1. This figure illustrates our framework of human-AI collaboration in data storytelling tools. It characterizes human-AI collaborative data storytelling tools from (1) the stages that they cover and (2) the roles of human and AI collaborators in these stages.

Data storytelling is powerful for communicating data insights, but it requires diverse skills and considerable effort from human creators. Recent research has widely explored the potential for artificial intelligence (AI) to support and augment humans in data storytelling. However, there lacks a systematic review to understand data storytelling tools from the perspective of human-AI collaboration, which hinders researchers from reflecting on the existing collaborative tool designs that promote humans' and AI's advantages and mitigate their shortcomings. This paper investigated existing tools with a framework from two perspectives: the stages in the storytelling workflow where a tool serves, including analysis, planning, implementation, and communication, and the roles of humans and AI in each stage, such as creators, assistants, optimizers, and reviewers. Through our analysis, we recognize the common collaboration patterns in existing tools, summarize lessons learned from these patterns, and further illustrate research opportunities for human-AI collaboration in data storytelling.

CCS Concepts: • **Human-centered computing** → **Visualization**.

Additional Key Words and Phrases: data storytelling, human-AI collaboration

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1 INTRODUCTION

The art of creating compelling data stories entails the integration of different aspects, such as data analysis, visualization, and presentation. However, these aspects pose significant demands for human creators, especially when they have to deal with large, complex, or dynamic data sets, manage a considerable number of data story elements, and produce visually appealing presentations. Moreover, crafting compelling visual data stories requires creativity, logical consideration, diverse skills from data analysis to graphic design, and a keen awareness of the audience and the context.

Researchers in the visualization (VIS) and the human-computer interaction (HCI) domains have proposed new data storytelling tools that integrate AI techniques, such as natural language processing and machine learning. These tools aim to enhance human-AI collaboration in data storytelling by leveraging the complementary strengths of humans and AI. For example, AI can assist humans in finding interesting data facts [125], organizing story pieces [98], generating visualizations [86], or providing feedback [33], while humans can provide domain knowledge, creativity, or emotional appeal. However, designing effective human-AI collaboration in data storytelling is not trivial, as it involves many challenges and trade-offs, such as balancing the control and autonomy of the human-AI system, and facilitating the communication and coordination between the two parties. While existing surveys (*e.g.*, [11, 90]) have collected a corpus of papers on data storytelling, they do not provide a holistic understanding of how humans and AI collaborate in data storytelling tools. To facilitate reflection on the current research progress and outlook on future opportunities, this paper aims to answer the research question: *How do humans and AI collaborate in the existing data storytelling tools?*

To answer the question, we first build a paper corpus about human-AI collaborative data storytelling tools from the VIS and HCI literature. Then the tools are coded based on our framework from two dimensions (see Figure 1). First, informed by the different characteristics of stages in the storytelling workflow, such as skill requirements [30] and storytellers' expectations [59], we identify *the detailed stages covered by tools*, including data analysis, data story planning, data story implementation, and data communication. Second, in each stage, the collaboration patterns are examined through *human and AI collaborators' roles*, namely creators, reviewers, optimizers, and assistants. The roles facilitate understanding how humans and AI contribute to the data storytelling stage by leveraging their advantages, which is an open challenge in achieving human-AI collaboration [10]. Combining the two perspectives, we can comprehensively understand the relationship between the stage features and the design of human-AI collaboration.

Our study results in an overview of the development of human-AI collaborative tools in data storytelling between 2010 and 2023. Human-AI collaborative data storytelling tools have received the most research interest since 2019, after the dominance of purely manual tools between 2016 and 2018. We also reflect on the similarities and differences in human-AI collaboration patterns at different stages. Based on these findings, we further discuss the implications for the design of data storytelling systems and the future of data storytelling practice and research.

We hope our review of the current state of the art in human-AI collaborative data storytelling will be a valuable resource for researchers and designers working on human-AI collaborative tools. We also hope this paper will highlight new directions for future research. The main contributions of this paper are as follows:

- We conduct the first survey to characterize the human-AI collaboration in data storytelling at a stage level by building a paper corpus of human-AI collaborative data storytelling tools from the VIS and HCI literature and coding them according to the stages of the data storytelling workflow and the roles of humans and AI.
- We report the findings from existing human-AI collaborative data storytelling tools and the design patterns of human-AI roles at different stages, identify the challenges and opportunities for the design of data storytelling systems, and further suggest future research directions from the perspective of human-AI collaboration.

2 RELATED WORK

This section introduces related work about data storytelling and human-AI collaboration in visualization.

2.1 Data Storytelling

Data stories often present a sequence of story pieces that are supported by data facts and are accompanied by data visualizations [57]. Data storytelling has been gaining growing interest from researchers following the seminal work by Segel and Heer [94], where they outlined the narrative visualization design space by reviewing existing examples. It is a powerful tool for communicating insights and knowledge from data in data science teams, across different teams in the organization, and to the general public. When creating and spreading data stories, diverse skills, including data analysis and visualization, are required in a pipeline with multiple tasks, such as planning data stories and presenting them to audiences [20, 30]. To build the theory of data storytelling and enhance the practices, researchers have investigated data storytelling from multiple perspectives, including understanding real-world data stories (*e.g.*, [103]), framing design spaces and guidelines (*e.g.*, [44]), and developing data storytelling tools (*e.g.*, [47]).

To organize and review the progress of research in data storytelling, several surveys have been conducted in the past years. Tong *et al.* [114] reviewed data storytelling from who, how, and why data stories are authored and spread. Their characterization of data storytelling tools is limited to the structure of data stories, *i.e.*, linear, parallel, or user-directed data stories. Zhao and Elmqvist [141] summarized the format of data stories from six perspectives, including audience, data, media, *etc.* They do not explicitly provide a taxonomy for data storytelling tools. Ren *et al.* [90] investigated data storytelling tools leveraging narratology. They categorize existing data storytelling tools by whether the authors of data stories introduce their own opinions and whether the audience decides the sequence of the story.

Since data storytelling often requires various skills and enormous effort from the authors [57], applying AI in data storytelling tools to eliminate these needs has attracted researchers' attention. To cope with the trend, a recent survey by Chen *et al.* [11] classified data storytelling tools according to whether the tool leverages AI to generate data stories or support data story authoring besides data story characteristics (*i.e.*, genre, interactivity, and structure). Though they also attempt to characterize AI usage in tools, their taxonomy over-simplifies the categorization of AI-powered tools by dividing them into two types: AI-supported and AI-generator tools. According to a previous interview study [59], data workers have various needs in different stages of data storytelling and require AI collaborators to perform multiple roles in collaboration. Such observation reflects the need to understand a *fine-grained collaboration pattern* between AI and humans *in different stages* (*e.g.*, planning and communicating the data story) of the data storytelling workflow, which is failed to be accommodated by Chen *et al.* [11]. In this paper, we review the existing human-AI collaborative data storytelling tools from the roles of humans and AI in different stages and identify potential future research opportunities.

2.2 Human-AI Collaboration in Visualization Research

Considering the pros and cons of humans and AI systems, there is a growing trend of investigating how to achieve collaboration between humans and AI in different tasks rather than replacing humans with AI [54, 117]. In the field of visualization research, human-AI collaboration has been investigated in the following three perspectives [121].

First, AI can collaborate with humans in creating and understanding visualizations (AI4VIS). Typical tasks in this line of research include visualization recommendation [42, 67] and retrieval [60, 136]. Under this category, two surveys [120, 132] were conducted to provide an overview of AI and machine learning (ML) techniques used for related tasks. Besides, Zhu *et al.* [143] and Qin *et al.* [87] reviewed the automatic visualization recommendation techniques.

Second, visualization can serve as a tool to monitor, understand, and steer AI systems (VIS4AI) for better collaboration between humans and AI. For example, the What-If Tool [129] and RuleMatrix [78] apply visualizations to explain AI behaviors. GAM Changer [127] allows users to edit machine learning models with visualization interfaces. There have been multiple papers to investigate the progress of this line of research, such as the latest ones by Subramonyam and Hullman [106] and by Wang *et al.* [119]. Lastly, visual analytics systems can serve as an interface for human-AI collaborative data analysis and decision making. Researchers have explored human-AI collaboration in visual analytics systems for various domains, including urban analytics [69], sports [105], and education [61]. Besides the reviews of visual analytics for different domains (*e.g.*, urban [32] and education [53]), a recent paper by Domova and Vrotsou [29] outlined the usage of AI in these systems based on the visual analytics pipeline.

Among all three perspectives, our paper is the closest to AI4VIS research since human-AI collaborative data storytelling tools are also partially powered by its advances. For example, DataShot [125] and Notable [62] leverage the visualization recommendation algorithms in prior research [28, 110]. However, previous surveys about AI4VIS [120, 132] focus on how the AI techniques were applied in visualization-related tasks, including data storytelling, but do not specifically investigate how humans work with AI in data storytelling tools. To fill the gap, our study focuses on the collaboration between humans and AI without emphasizing the techniques used in AI.

3 METHODOLOGY

This section introduces our research methodology, including how we collected and coded the corpus of tools.

3.1 Paper Collection

To collect papers about human-AI collaborative data storytelling tools, we started our search with the data storytelling tool papers covered in the latest surveys [11, 90]. Since the two surveys only covered papers up to August 2022, we further augmented the corpus by searching recent relevant venues up to June 2023, including ACM CHI, UIST, IUI, IEEE TVCG, IEEE VIS, PacificVis, and EuroVis (papers are published in Computer Graphics Forum), with the keywords "narrative visualization" and "data storytelling" following a keyword-based paper searching strategy [76]. Then two leading co-authors read and examined the corpus of papers individually to keep the papers describing human-AI collaborative tools for data storytelling. We also enriched the corpus by checking the papers that cited these papers or are used as references by them in the corpus. The conflicts in paper selection were resolved through multiple discussions between the two co-authors. In the end, we collected 60 papers for further investigation in the paper. Figure 2 shows an overview of the papers. It reveals that research in data storytelling tools receives growing interest from both the VIS and the HCI communities.

When deriving the corpus of papers, we have several criteria for the papers to be included in our corpus. First, *the paper should mainly serve the purpose of data storytelling with information visualizations.* When surveying related research, we noticed that several previous studies applied narrative visualization-related techniques for data analytics, such as VisInReport [95] and NetworkNarratives [64]. Though they applied narrative techniques, they are not designed for telling data stories and are therefore not included in our corpus. We also did not consider interactive chart recommendation tools (*e.g.*, Voyager2 [131]) or chart authoring tools (*e.g.*, Charticulator [89]) that are not specifically designed for data storytelling. Data storytelling tools for scientific visualizations are also excluded (*e.g.*, AniViz [1], Molecumentary [52], and ScrollyVis [79]). Second, *the paper should describe a tool for data storytelling.* To align with the main purpose of this paper, *i.e.*, understanding the collaboration between human and AI in tools, the scope of papers is limited to data storytelling tools rather than design spaces (*e.g.*, narrative structure based on Freytag's Pyramid [135]) or grammars (*e.g.*,

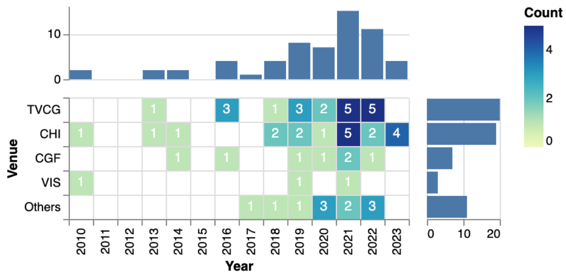

Fig. 2. This figure shows an overview of our collected papers in venues and years. The venues with less than three papers are merged to "Others."

Animated Vega-Lite [144]). To determine whether AI is applied in the tool, we followed a previous survey about AI for visualization [132] and research in human-AI collaboration [45, 59] to adopt an inclusive definition of AI, where heuristics-based, ML-based, and deep learning (DL)-based AI are all included.

3.2 Paper Coding

Considering the goal of this paper, *i.e.*, understanding how existing tools facilitate the collaboration between humans and AI in the data storytelling workflow, we decided to code the collaboration pattern in each step of the workflow. To achieve this goal, we first surveyed existing research about data storytelling workflow [20, 24, 57] and human-AI collaboration patterns in data storytelling [59]. Then we derived the preliminary framework for coding papers from previous studies. Based on the preliminary framework, two co-authors coded all papers in the corpus individually, leveraging both papers and related presentation or demo videos if provided. The two authors met weekly to discuss and fine-tune the framework and coding criteria. Finally, the papers with conflicting labels were discussed to reach an agreement. In the following sections, we introduced the framework (Section 4) and summarized the coded tools (Section 5). We also provide an interactive browser of the coded tools at https://human-ai-universe.github.io/data-storytelling.

4 FRAMEWORK

This section introduces the framework for characterizing the collected human-AI collaborative data storytelling tools. A previous study [59] investigated data workers' preferred AI collaborators through an interview study. The results reveal that data workers prefer to have different types of AI collaborators, including creators, assistants, optimizers, and reviewers, in different stages of the data storytelling workflow. For example, AI assistants were preferred when planning data stories, such as collecting data insights, while AI creators were appreciated for making data stories, such as authoring story pieces. However, the prior surveys on storytelling tools [11, 90] do not investigate the collaboration between humans and AI at the stage level, which makes it impossible to compare the existing tools with users' expectations and identify potential future research opportunities. To fill the gap, this paper aims to characterize the collaboration pattern in different stages. Furthermore, the roles of human and AI collaborators can reflect how to leverage their pros and mitigate their cons in each stage, which is considered a challenge for designing a human-AI collaborative experience [10]. As a result, our framework consists of two dimensions: (1) what *stages* in the data storytelling workflow a tool serves (Section 4.1); and (2) what *the roles of human and AI collaborators* are in each stage (Section 4.2).

4.1 Stages in the Data Storytelling Workflow

The first perspective of our framework is the tools' coverage of stages in the storytelling workflow. To derive the categorization of stages, we first surveyed how previous research defined stages in data storytelling workflow. The practical workflow of data storytelling has been discussed in multiple previous papers (*e.g.*, [20, 24, 57, 59]). These papers have proposed different ways of defining stages in data storytelling workflow. We adopted the most widely recognized data storytelling workflow [57] as the preliminary version of stages in our framework, where they split the entire workflow into three stages: *"explore data"*, *"make a story"*, and *"tell a story"*. Furthermore, in the "tell a story" stage, there are two sub-stages, *"build presentation"* by authors, and *"share a story"* with audiences. When reading the papers, we noticed that most tools aim to automate the sub-stage of building presentations but do not explicitly facilitate the communication of data stories with audiences. For example, DataShot [125] produces data posters and NB2Slides [142] creates slides. However, they do not facilitate the communication of these data stories. On the other hand, some research solely provides human-AI collaborative ways for sharing data stories, such as SketchStory [56] and the interactive data story presentation approach by Hall *et al.* [37]. Furthermore, the potential difference between stakeholders in these two stages is mentioned by Lee *et al.* [57] and Chevalier *et al.* [20]. The presentations are often built by editors, while the stories are shared among presenters and audiences. Therefore, we decided to consider the two sub-stages in the "tell a story" stage as two individual stages when coding the tools.

To avoid confusion and make the names of stages simpler, inspired by Li *et al.* [59], the four stages in our framework are named as *analysis*, *planning*, *implementation*, and *communication*, which corresponds to "explore data", "make a story", "build presentation", and "share a story" [20, 57], respectively. In the *analysis* stage, the users of tools often explore data to identify insights, such as the trend of data, and may summarize knowledge from the insights. With the insights and knowledge from data, users need to *plan* how the story will be told. When planning the data story, they often determine the core message, prepare the outline, and sequence the data insights collected from the analysis. Users next *implement* data stories following their plans, such as authoring charts, writing texts, integrating story pieces, and styling the data stories. Finally, the data stories are *communicated* with the audiences on different occasions, such as team meetings or formal presentations.

With the definition above, we coded all tools in our corpus. Notably, some tools may not only serve for one stage. For example, Calliope [98] first computes the data insights, then organizes the sequence of insights, and finally creates a scrollytelling story or a poster. According to our criteria, it covers three stages, analysis, planning, and implementation. Furthermore, some tools may not complete all tasks in one stage, such as InfoColorizer [138]. It is limited to suggesting color usage in the implementation stage. Since we only code tools at the stage level, InfoColorizer is coded as a tool applied in the implementation stage. Another point that requires attention is that the implementation and communication stages may not be entirely distinguishable for some genres of data stories, such as data videos and articles. Unlike some genres of data stories (*e.g.*, presentation slides), data videos and articles are created to be consumed by the audiences asynchronously. Therefore, after creating them in the implementation stage, they can be spread directly for communication without the necessity of an additional stage where they are explicitly presented to the audiences. To handle the case, we only coded the tools with a clear purpose for presenting data stories as serving the communication stage, such as SketchStory [56]. In other words, we do not consider the tools for creating data videos or articles as covering the communication stage.

4.2 Roles of Human and AI Collaborators

As discussed at the start of this section, we further coded how humans and AI collaborate in different stages after figuring out how tools cover different stages in the storytelling workflow. Specifically, inspired by prior research in collaboration among humans [71, 84], we assigned roles for human and AI collaborators in each stage covered by a data storytelling tool. Taking Erato [109] as an example, it facilitates the analysis, planning, and implementation stages. In the analysis stage, humans explore the dataset with the assistance of AI. AI suggests potential interesting data facts during exploration. Then we coded the analysis stage of Erato as having humans as creators and AI as an assistant. With roles like creator and assistant, we can investigate how the existing tools distribute work among collaborators and leverage their advantages. This section introduces how the roles are defined and applied to our corpus of papers.

We started our coding with the collaboration patterns between humans and AI in the data storytelling context by Li *et al.* [59] since it is the only previous research on the topic. However, they focus on defining the roles of AI collaborators since their purpose is to learn what assistance by AI is desired by users. In our work, we extended their definition from AI to both AI and humans, where we had four types of AI or human collaborators: *creator*, *assistant*, *optimizer*, and *reviewer*. For clarity and simplicity, we use "human-" or "AI-" prefixes before the roles, such as human-creator and AI-assistant, to indicate the collaborator's identity and role in one stage.

In a stage of the data storytelling workflow, an AI-creator or human-creator finishes most of the work from scratch and takes the highest level of control of the stage. For example, in DataShot [125], data analysis is fully completed by AI. Then we considered AI as the creator of data analysis in DataShot. Differently, NB2Slides [142] asks humans to complete the data analysis without AI's intervention. As a result, we coded the analysis stage of NB2Slides as human-creator. Unlike creators, human-assistants and AI-assistants often work with creators together when authoring the data story. They can reduce the workload of creating content in data stories or compensate for creators' inability. As a result, they have a lower level of control. An example of AI-assistants can be Chartreuse [25]. In the implementation stage, AI in Chartreuse extracts reusable templates from existing infographics to simplify creating new ones. We provide a detailed discussion about assistants in Section 6.2.

Optimizers and *reviewers* mostly perform after creators and assistants take action. AI-optimizers and human-optimizers automatically improve the entire or part of the data stories. Different from assistants, they do not participate in the creation process and, therefore, do not share the workload with creators directly. They repeat the work that creators and assistants have finished to improve the quality. For example, Notable [62] allows human-optimizers to edit the AI-created sequence of data insights. At last, AI-reviewers and human-reviewers assess the created content in data stories and provide the results or suggestions for creators to improve the data story. Compared to optimizers, they do not take any actions to improve the data story but only provide feedback. An example of AI-reviewer is the approach proposed by Fan *et al.* [31], where AI assesses the line charts in data stories and annotates the potential deceptive issues.

We have additional considerations when coding the tools following the definition of collaborator roles. First, we avoided assigning the creator role to both human and AI collaborators in the same stage. Its rationale is that we prefer to clearly distinguish whether AI or humans take control of the stage and bear more workload through the roles of creators and assistants. Second, when a type of stakeholder takes multiple roles in one stage, we only code the primary role. We have such consideration to simplify the coding process and the summary of common collaboration patterns. For example, in the implementation stage of Infomages [22], after users create charts and AI merges the chart with an image, users can review the distortion of the new charts and ask AI to optimize them. In this case, humans serve as

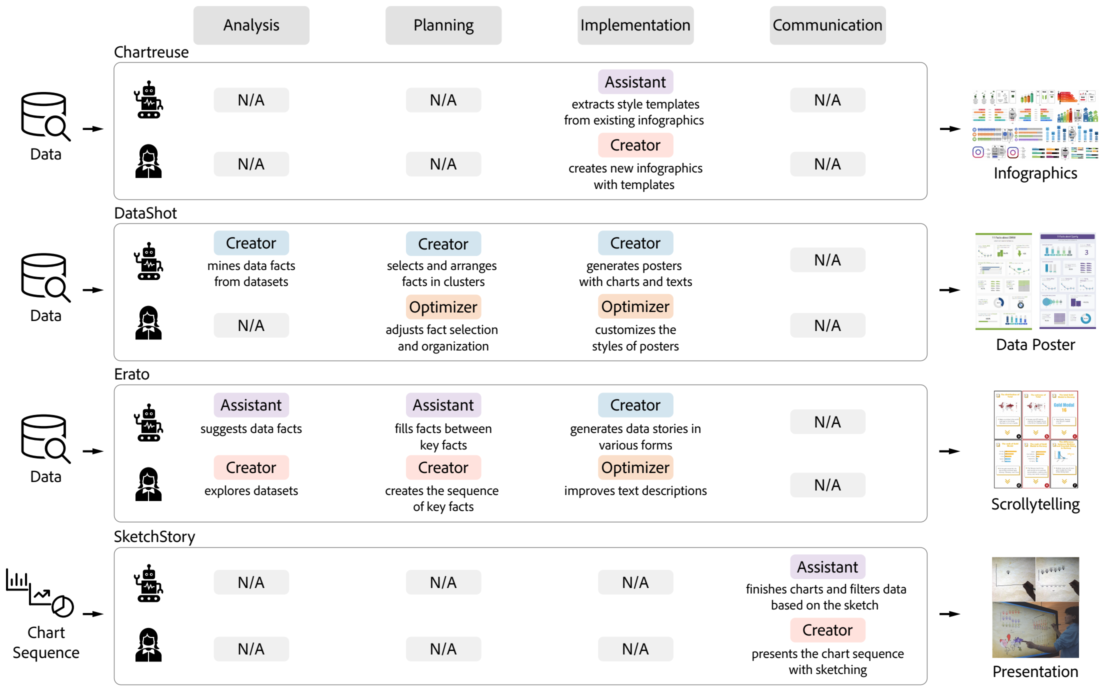

Fig. 3. This figure demonstrates four example tools, including Chartreuse [25], DataShot [125], Erato [109], and SketchStory [56], assessed by our framework.

creators and reviewers, while AI is an assistant and optimizer. However, following the consideration, we only keep human-creator and AI-assistant since the review and optimization tasks are auxiliary and optional.

Figure 3 explains how we coded tools according to our framework by showing four tools. The complete results of our coded human-AI collaboration patterns in different stages are available in Table 1.

5 OBSERVATIONS OF TOOLS AND STAGES

This section introduces our findings regarding tools and stages. To provide an overview of our reviewed tools, Figure 4 shows the development of data storytelling tools. The chart reflects that the research of data storytelling is gaining increasing interest. Furthermore, we notice that the purely manual tools have the highest proportion between 2016 and 2018. Since 2019, human-AI collaborative tools have gained increasing interest from researchers.

5.1 Tools

In Table 1, according to the covered stages, we find four groups of tools and separate them with horizontal lines in Table 1. This section introduces them from top to bottom.

The first group of 27 tools focuses on the implementation stage. In the implementation stage, tool users build data stories with the data analysis results and story plans in the previous stages. They may create story pieces (*e.g.*, charts and text), add animations, and arrange the layout of visual elements. According to a previous interview [59], the implementation stage is the most desired stage where users would like to receive assistance from AI.

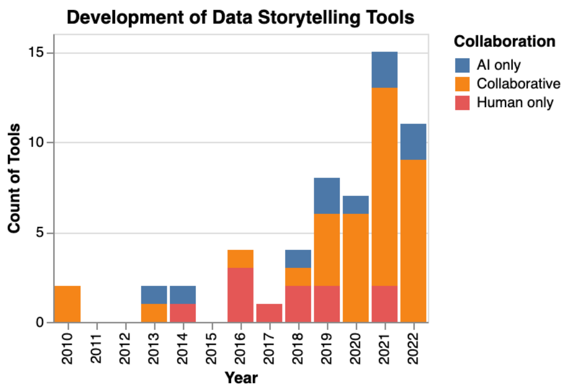

Fig. 4. This figure shows the development of data storytelling tools between 2010 and 2022 with the number of tools and collaboration between humans and AI. The year 2023 is excluded since we only collect tools up to June 2023.

Most of the early storytelling tools rely on human-creators' effort in implementation. Data-Driven Guides (DDG) [49] and DataInk [133] present standalone tools for users to encode data with manually designed visual elements in infographics through direct manipulation. To reduce the effort of designing visual elements, DataQuilt [139] introduces an AI-assistant to extract glyphs from images with computer vision approaches. Chartreuse [25] and Vistylist [99] further extend it to extracting templates (*e.g.*, glyphs and colors) from existing infographics for styling human-created ones. Another usage of AI-assistants is to suggest colors, as Yuan *et al.* [138] and Liu *et al.* [70] do. To further eliminate the need to create charts, Text-to-Viz [26] and Retrieve-then-Adapt [86] explore AI-creators that generate infographics with users' natural language input, such as "40 percent of USA freshwater is for agriculture". Chen *et al.* [15] proposes a deep learning-based approach to extract templates from timeline infographics and use the templates to extend them with new data. The path of these tools demonstrates a trend of *developing tools with higher AI automation*.

Besides infographics, we notice several tools are designed for creating annotated charts. ChartAccent [88] provides a GUI tool for creating annotations on SVG-based charts. Click2Annotate [13] and Touch2Annotate [14] allow users to select their interested area and then generate visual highlights and related text descriptions following pre-defined templates. Since the AI-creators fill the templates automatically, they may not fully understand users' intent. Therefore, they allow human-optimizers to adjust the content, including the data findings and text descriptions. These three tools facilitate data story authors' creation of annotated charts. Contextifier [43] and NewsViews [34] generate annotated charts according to data articles to help readers understand them. The generation process does not involve humans. Comparing these tools, we have another observation about human-AI collaboration in these data storytelling tools: *the design of collaboration patterns depends on the usage scenario of the tool*. When authoring data stories, the authors should be allowed to express their intent in data stories. As a result, multiple tools allow human-optimizers to revise the content produced by AI-creators as an approach to take control of data stories. Besides the tools mentioned above, other authoring tools also verifies our finding. For example, Text-to-Viz [26] and Infographics Wizard [116] allow users to customize the design of generated infographics. The collaboration pattern can be different when developing tools for data story consumers, like data article readers. These tools often do not need to consider consumers' intent. Instead, they illustrate existing data stories. Therefore, readers do not collaborate with AI in these tools.

Table 1. This table introduces our reviewed tools in detail. We coded them with the framework in Section 4. For simplicity, we shorten the names of collaborators: A-C : AI-creator, A-A : AI-assistant, A-O : AI-optimizer, A-R : AI-reviewer; H-C : Human-creator, H-A : Human-assistant, H-O : Human-optimizer, H-R : Human-reviewer. Based on the stages, the tools can be roughly divided into four groups with horizontal lines.

Year	Tool	Analysis	Planning	Implementation	Communication
2016	Data-Driven Guides [49]	N/A	N/A	H-C	N/A
2017	ChartAccent [88]	N/A	N/A	H-C	N/A
2018	DataInk [133]	N/A	N/A	H-C	N/A
2019	Timeline Storyteller [7]	N/A	N/A	H-C	N/A
2020	Infomages [22]	N/A	N/A	H-C A-A	N/A
2020	DataQuilt [139]	N/A	N/A	H-C A-A	N/A
2021	Chartreuse [25]	N/A	N/A	H-C A-A	N/A
2021	InfoColorizer [138]	N/A	N/A	H-C A-A	N/A
2021	CAST [35]	N/A	N/A	H-C A-A	N/A
2022	Vistylist [99]	N/A	N/A	H-C A-A	N/A
2013	Contextifier [43]	N/A	N/A	A-C	N/A
2014	NewsViews [34]	N/A	N/A	A-C	N/A
2018	Metoyer *et al.* [77]	N/A	N/A	A-C	N/A
2019	Chen *et al.* [15]	N/A	N/A	A-C	N/A
2020	Retrieve-then-Adapt [86]	N/A	N/A	A-C	N/A
2021	AutoClips [97]	N/A	N/A	A-C	N/A
2021	Datamations [85]	N/A	N/A	A-C	N/A
2019	DataSelfie [48]	N/A	N/A	A-C H-A	N/A
2010	Click2Annotate [13]	N/A	N/A	A-C H-O	N/A
2010	Touch2Annotate [14]	N/A	N/A	A-C H-O	N/A
2018	Voder [104]	N/A	N/A	A-C H-O	N/A
2019	Text-to-Viz [26]	N/A	N/A	A-C H-O	N/A
2021	InfoMotion [123]	N/A	N/A	A-C H-O	N/A
2022	Infographics Wizard [116]	N/A	N/A	A-C H-O	N/A
2019	Fu *et al.* [33]	N/A	N/A	A-R	N/A
2022	Fan *et al.* [31]	N/A	N/A	A-R	N/A
2022	Liu *et al.* [70]	N/A	N/A	A-A	N/A
2014	Ellipsis [92]	N/A	H-C	H-C	N/A
2016	DataClips [3]	N/A	H-C	H-C	N/A
2021	Idyll Studio [23]	N/A	H-C	H-C	N/A
2021	VizFlow [107]	N/A	H-C	H-C A-A	N/A
2021	Kori [23]	N/A	H-C	H-C A-A	N/A
2021	Data Animator [112]	N/A	H-C	H-C A-A	N/A
2023	GeoCamera [65]	N/A	H-C	H-C A-A	N/A
2021	VisCommentator [17]	N/A	H-C	A-C H-O	N/A
2022	SmartShots [111]	N/A	H-C	A-C H-O	N/A
2022	Sporthesia [16]	N/A	H-C	A-C H-O	N/A
2023	DataParticles [9]	N/A	H-C	A-C H-O	N/A
2021	Gemini² [50]	N/A	H-C A-A	H-C A-A	N/A
2020	Gravity [80]	N/A	H-C A-O	H-C	H-C
2022	Gravity++ [81]	N/A	H-C A-O	H-C	N/A
2021	ChartStory [140]	N/A	A-C H-O	A-C H-O	N/A
2016	CLUE [36]	H-C	H-C	H-C	H-C
2019	InsideInsights [75]	H-C	H-C	H-C	N/A
2021	Toonnote [46]	H-C	H-C	H-C	N/A
2018	InfoNice [126]	H-C	N/A	H-C	N/A
2023	Slide4N [118]	H-C	H-C A-A	A-C H-O	N/A
2022	NB2Slides [142]	H-C	A-C	A-C H-O	N/A
2019	DataToon [47]	H-C A-A	H-C	H-C A-A	N/A
2022	Erato [109]	H-C A-A	H-C A-A	A-C H-O	N/A
2023	Notable [62]	H-C A-A	A-C H-O	A-C H-O	N/A
2020	Brexble [21]	A-C	N/A	A-C H-A	N/A
2019	DataShot [125]	A-C	A-C H-O	A-C H-O	N/A
2016	TSI [8]	A-C H-A	A-C	A-C	N/A
2020	Calliope [98]	A-C H-O	A-C H-O	A-C	N/A
2020	data2video [73]	A-C H-O	A-C H-O	A-C H-A	N/A
2021	Lu *et al.* [72]	A-C H-O	A-C H-O	A-C H-O	N/A
2022	Roslingifier [100]	A-C H-O	A-C H-O	A-C H-O	N/A
2013	SketchStory [56]	N/A	N/A	N/A	H-C A-A
2022	Hall *et al.* [37]	N/A	N/A	N/A	H-C A-A

Despite AI-assistants and AI-creators, applying AI-reviewers to review created charts for data storytelling has also been explored previously. Fu *et al.* [33] explore applying computer vision models to assess the aesthetics and memorability of infographics. The vision models can rank the input visualizations or output the scores regarding aesthetics and memorability. Fan *et al.* [31] propose an approach to assess the deception in line charts with heuristics-based approaches. Once any deceptive design is detected, they will generate both the misleading and the correct charts with warning information as an annotation on the original chart.

All tools discussed above are designed for static charts. Informed by the advantages of animations, such as enhancing audiences' engagement [19], four tools transform static charts into animated ones [35, 85, 97, 123]. CAST [35] provides a GUI tool for specifying animation in charts with AI-assistants. InfoMotion [123] automatically animates infographics and involves human-optimizers to further optimize the animation.

In the first group, most of the tools are designed for individual story pieces. Therefore, they do not necessarily provide functions for users to organize the story pieces. For data stories with multiple pieces, such as data articles and data videos, creators often plan them ahead of implementation, according to Lee *et al.* [57]. **The second group of 15 tools integrates the planning and implementation stages for data storytelling.**

In this cluster, most of the tools facilitate data video creation. In the planning stage, they commonly ask human-creator to specify the sequence of keyframes in data videos [3, 9, 65, 111, 112] or pick key events in sports videos to add overlay visualizations [16, 17]. Gemini[2] is the only tool that applies AI-assistants in the planning stage. It generates intermediate charts between the start and end charts in an animated transition using GraphScape [51] to minimize the cognitive load to understand the animation. In the implementation stage, AI-assistants and AI-creators are frequently applied to eliminate humans' workload. For example, Data Animator [112] assists in matching visual elements between keyframes. DataParticles [9] parses the narration of data stories and then generates animation to illustrate the derivation of related data findings. Besides automatic parsing, it allows human-optimizers to modify the animation manually, including the data and animation effect.

Besides, Idyll Studio [23], Kori [55], and VizFlow [107] are designed to accommodate data article authoring. In Idyll Studio, human-creators write texts to organize all story pieces and prepare interactive charts in articles. Compared to Idyll Studio, Kori and VizFlow enhance text-chart linking in the implementation stage with AI-assistants. VizFlow suggests potential visual elements to be annotated, such as sectors in pie and bar charts. Kori matches text with Vega-Lite [93] specification and automatically adds visual embellishments on charts. Gravity [80] and its successor, Gravity++ [81], are designed for authoring presentation slides. They adopt AI-optimizers to optimize the human-created story piece sequence with GraphScape [51].

ChartStory [140] is the only tool in this cluster to apply AI-creators in the planning stage. The AI-creator in ChartStory organizes all story pieces into data comics with a minimum spanning tree. Compared to AI-creators in the implementation stage, the less frequent usage of AI-creators in the planning stage aligns with the results in a previous interview [59], where data workers do not prefer AI to automate the planning stage. A potential explanation for this phenomenon is that the way of planning data stories is directly related to the authors' intent. Therefore, *humans would like to take more control in the planning stage*. Furthermore, planning data stories often *requires understanding and designing narrative structures*, such as "Martini Glass Structure" and "Drill-Down Story" [94], which is challenging for AI [135]. Another potential reason from the technical side is *the challenge for AI-creators to understand humans' intent and data findings*. Humans' intent and findings in the data analysis may not be expressed in a standardized way [4]. For example, data findings can be expressed with arbitrary charts or texts. It leads to the difficulties of AI's understanding. Therefore, designing AI-creators in the planning stage can be hard.

According to Lee *et al.* [57] and Chevaliar *et al.* [20], authors need to iterate between analysis and the other stages in the data storytelling workflow. To facilitate such back and forth between stages, **the next group of 16 tools extends their covered stages to the analysis stage**.

In this group, early tools mainly attempt to integrate the functionalities from analysis to implementation in the same tool without any AI support. They save human-creators' efforts of transferring data and charts between analysis and other stages. For example, CLUE [36] integrates the data story authoring and presentation modules with visual analytics tools. In this way, the explored charts can be annotated and then reused for presentation easily. Built in Power BI, InfoNice [126] provides a convenient approach to customize statistical charts. Similar to DDG [49] and DataInk [133], InfoNice is for individual chart authoring. As a result, it does not support the planning stage.

Considering the long workflow of data storytelling, automatic end-to-end approaches were proposed to generate stories from data with AI-creators. Early approaches are limited to generating data stories for temporal data, such as TSI [8] and data2video [73]. A noteworthy characteristic of data2video is that it asks human-assistants to annotate charts in data stories. Besides annotation, another example task of human-assistants is writing narrations for generated data stories [21]. Inspired by data fact mining algorithms [28, 110], a series of data story generation approaches was proposed to handle general tabular data. They leverage the definition of data facts, usually including data attributes, data subspace, data pattern type, data pattern focus, and data pattern interestingness, to standardize the representation of data findings. *The unified representation tackles the technical challenge of communicating data findings with AI and thus facilitates the usage of* AI-creators *in the first three stages of data storytelling*. For example, DataShot [125] first mines all potentially interesting data facts. Then it organizes data facts with the same focus or in the same subspace into multiple posters. The charts and text descriptions are also generated accordingly. Shi *et al.* [98] and Lu *et al.* [72] follow a similar pipeline to generate slides or scrollytelling stories. Since these tools generate complete data stories automatically, they often allow human-optimizers to optimize the output with user interfaces.

Though saving manual effort, an outstanding drawback of these end-to-end approaches is neglecting humans' intent in data analysis and follow-up communication. To handle the challenge, the most recent studies, Erato [109] and Notable [62] enhances humans' control in the analysis and planning stages with different strategies. The strategy of Erato [109] is to let human-creators explore, select, and order the key data facts in data stories in the analysis and planning stages. Then AI-assistant can complete the sequence with additional data facts to make the story more coherent and smooth. The final data story is built on the sequence of data facts by an AI-creator. It allows humans to control the directions of data stories by assigning anchor points. Notable allows human-creators to conduct data analysis in computational notebooks and applies an AI-assistant to illustrate potentially interesting data facts for users' selection. Then AI-assistant plans the sequence of data facts and generates corresponding slides for communicating the data stories. In this way, users can control the direction of data stories by determining what data facts will be included. From the tools introduced above, we observe a path of developing data storytelling tools for stages from analysis to implementation. *The tools have evolved from fully human-creator tools, through fully AI-creator tools, and to mix-initiative tools with both AI-creators and human-creators recently.*

Another trend in this cluster is *developing AI-powered data storytelling tools in widely applied computational notebooks.* Notebooks provide a platform for users to analyze their data iteratively and swiftly. One of its drawbacks is being messy for information seeking and organization [38]. ToonNote [46] proposes hiding code and presenting charts in notebooks as data comics to help readers focus on the analytical results. Moreover, several studies leverage AI to reduce the workload of organizing notebooks into data stories for presentation. The AI-creators in NB2Slides [142]

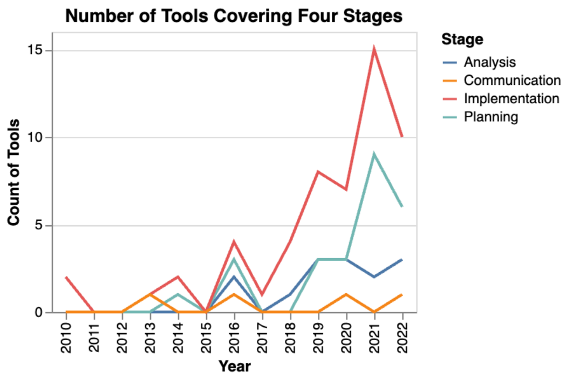

Fig. 5. This figure shows the number of data storytelling tools covering four stages between 2010 and 2022.

and Slide4N [118] generate presentation slides by understanding code and documentation in notebooks. Notable [62] facilitates producing data stories along with exploration with AI's support.

The last group of two tools applies AI-assistants in the communication stage solely. With a set of charts as input, SketchStory [56] allows users to present a data story more engagingly with free-form sketching. It recognizes users' sketches to auto-complete charts and filter data in charts. Hall *et al.* [37] supports mid-air gestures to help present charts in virtual meetings. They utilize AI to recognize users' gestures and then update the chart, such as highlighting data elements or zooming in to a subset of data.

5.2 Stages

The previous section illustrates an overview of surveyed tools in four clusters. This section takes one step further to examine how the four stages, analysis, planning, implementation, and communication, are covered by those tools. Figure 5 presents the tools' coverage of four stages over the years. The implementation and planning stages have always been the researchers' focus. The analysis and communication stages are not supported in most tools.

According to Table 1, the **analysis** stage is covered by 16 among 60 tools in our corpus, in other words, 26.7% of all tools. Such results support the interview results by Li *et al.* [62], where data workers need to switch between tools for communicating data findings. One potential reason for not supporting analysis in data storytelling tools is that building a fully functional data analysis module in data storytelling tools can involve great engineering effort and require users to adapt to a new environment. To mitigate the gap between analysis and other stages, a potential opportunity is to integrate data storytelling tools with widely adopted data analysis platforms, such as BI tools [126] and computational notebooks [46, 62, 118, 142].

Around half of our reviewed tools (29 out of 60) cover the **planning** stage. Different from the analysis stage, we notice the main reason whether a tool covers the planning stage is closely connected to its output format. When the tool's output involves multiple visualizations, such as data videos and articles, it needs to support the organization of these visualizations and, therefore, has a module to cover the planning stage. Some examples include DataClips [3], Idyll Studio [23], and Data Animator [112].

The **implementation** stage is covered by almost all tools (58 out of 60), which may indicate that how to facilitate implementation is the problem that receives the most attention in human-AI collaborative data storytelling. From

Figure 6, we find that the tools in the implementation stage are from building individual story pieces, such as single infographics, to more complex data story genres with multiple charts, *e.g.*, data videos. The chart also demonstrates that animated charts have gained growing interest since 2020. Moreover, tools for animated multiple charts experienced an explosion in 2021.

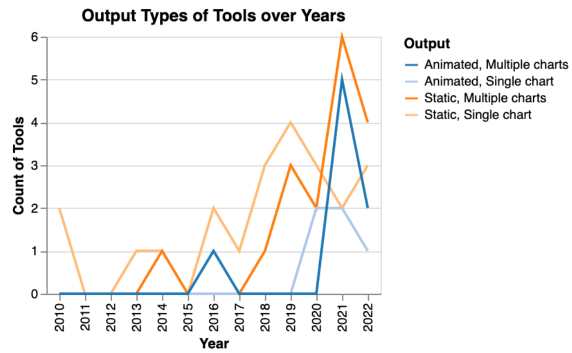

Fig. 6. The figure shows the output of tools that cover the implementation stage between 2010 and 2022. The color hue encodes whether the output is animated or static. The color saturation represents whether the output includes single or multiple charts. The paper by Fu *et al.* [33] is excluded since it outputs the scores and ranks of visualization memorability and aesthetics.

We notice that the **communication** stage is under-explored in the workflow of data storytelling. Only four tools cover this stage. One potential reason is that many data story genres do not have an explicit communication stage, as discussed in Section 4.1. Such genres include data videos and data comics. However, a previous study reveals that slides are the most popular format of data stories [44]. It was also reflected in an interview with data workers [59]. Slides often require humans to present them for communication purposes. Exploring how to facilitate the presentation beyond existing research can be interesting. Another reason is that multiple data storytelling tools do not target drafting complete data stories. For example, Text-to-Viz [26] and InfoMotion [123] facilitate the creation of static and animated infographics. Their created infographics may be used as part of a data story, such as presentation slides. Notable [62] purposefully allows users to further edit the generated slides with their familiar tools, such as PowerPoint. Therefore, the communication stage is beyond their scope.

6 LESSONS LEARNT ABOUT HUMAN-AI COLLABORATION PATTERNS

This section reflects how previous research applies human-AI collaboration in data storytelling tools. Figure 7 summarizes the human-AI collaboration patterns in four stages.

6.1 In individual stages

We first focus on the lessons we learned from human-AI collaboration in individual stages.

Analysis. We realize that data fact recommendation algorithms [28, 110] are frequently used as AI-creators or AI-assistants in the analysis stage (*e.g.*, DataShot [125], Erato [109]). Their advantages include mining various data findings in tabular data automatically and providing a unified representation of data findings among humans and AI [39]. One potential drawback is that they oversimplify the insights in data analysis, such as neglecting domain knowledge [5]. We hope that there can be more research to further push the frontier of data analysis by AI-creators.

Planning. In the planning stage, we recognize that almost all AI-creators focus on planning the data story leveraging the data relationships between story pieces, such as placing data facts in the same subspace together [98, 125] or selecting important events in time series data [8, 100]. They often apply heuristics-based approaches to search for an optimal organization of story pieces based on various criteria, such as consistency [44, 51] and logical coherence [130] among multiple story pieces and the interestingness of individual story pieces [28, 110]. However, in practice, it may not be sufficient to rely on the data relationships when authoring data stories [62]. It is essential to consider the context, users' preferences, and other semantic information when planning the data story [135]. Towards this end, NB2Slides [142] summarizes the typical templates for communication between data scientists, but using fixed templates limits its flexibility. The other approach to mitigate the problem is to leverage human-optimizers to further customize the data story outline. In the future, it is possible to explore how to ask human-assistants to provide background information, such as the target audiences or data analysis project information [59], for AI-creators to plan the data story in a context-aware manner.

On the other hand, when human-creators plan the story manually in the rest of the tools, their context and target can be considered sufficiently but the workload is high. To reduce users' burden, AI-optimizers and AI-assistants are applied by multiple tools, including Gravity [80] and Gemini[2] [50]. However, similar to previously discussed AI-creators, most of these AI-optimizers and AI-assistants still rely on data relationships between story pieces. It is possible that such AI can complement users' planning since it is expected to explore the potential organization of stories based on data relationships more thoroughly and quickly. At the same time, there is also a risk of breaking users' logical flows of data stories. We argue that future research should examine the issue and take action to mitigate the potential problems, such as restricting AI's optimization on users' outlines.

Implementation. Implementation is the stage that involves the highest proportion of AI in the three stages other than communication. We exclude the communication stage from the comparison here due to the small sample size. About 77.6% (45 out of 58) of all tools introduce different forms of AI collaborators in the implementation stage. For comparison, the analysis and the planning stages have 62.5% (10 out of 16) and 48.3% (14 out of 29) tools that apply AI. This result aligns with users' expectations to reduce workload in the implementation stage [59]. They hoped AI could automatically generate charts or styling data stories. Furthermore, in the analysis and the planning stages, the proportion of sole AI-creators without human collaborators (analysis: 2 out of 16, 12.5%; planning: 2 out of 29, 6.9%) is smaller than that in the implementation stage (9 out of 58, 15.5%). This trend indicates that AI-creators are believed to address tasks in the implementation stage without human intervention, while the tasks in the analysis and the planning stages rely more on human intelligence.

Communication. In our corpus, merely four tools cover the communication stage. Besides two tools with human-creators, the other two incorporate AI-assistant for enhancing the presentation with rich interactions, including sketching [56] and gesture [37]. According to a previous study, the usage of AI in communication among humans may lead to some concerns [59]. The data workers believed that AI may have a negative effect on building relationships between presenters and audiences. That might explain why AI-creators are rarely researched. More future research is desired to understand the perception of AI when communicating data stories. Furthermore, we would like to encourage future investigations in diverse usages of AI. For example, we may introduce AI-reviewers to assess humans' performance in communicating data stories. Though previous research has explored visual analytics for improving presentation skills [122] and guidelines for presenting visualizations [134], we have not noticed any tools for assessing or improving skills for communicating data stories.

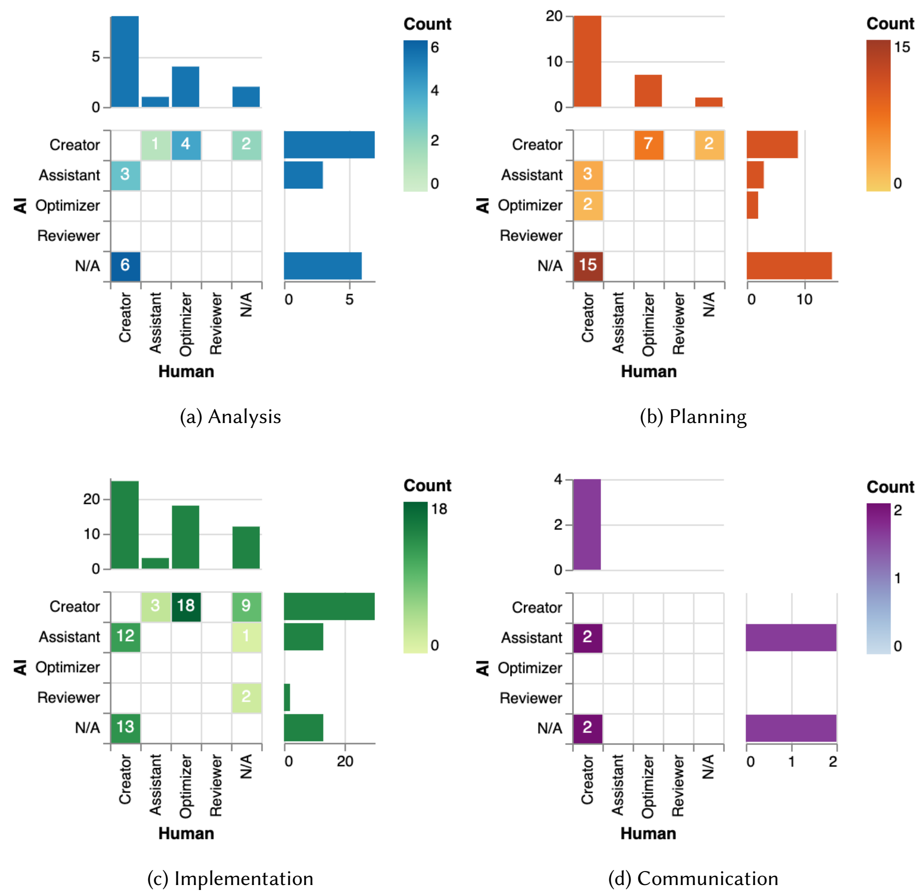

Fig. 7. This figure shows human-AI collaboration patterns in the analysis, planning, implementation, and communication stages. In all four charts, the horizontal axes represent humans' roles, and the vertical axes encode AI's roles. The colors in each chart show the frequency of collaboration patterns among all tools.

6.2 Across all stages

Figure 7 shows an imbalanced distribution of the frequencies of human-AI collaboration patterns. Several patterns have been frequently applied, while the others are rarely explored. Therefore, we believe it is essential to blur the boundary of different stages and examine representative patterns across stages for insights into design strategies of human-AI collaboration in storytelling tools.

What are the most common human-AI collaboration patterns? To identify the most common collaboration patterns, we first exclude the patterns where only humans or AI perform in individual stages due to the lack of collaboration. Among the remaining 58 collaboration cases, we notice that the most frequent collaboration patterns where humans and AI work together are human-creators + AI-assistants[1] (20 times) and AI-creators + human-optimizers (29 times). We consider that both collaboration patterns have their pros and cons.

[1]We use the plus sign "+" to represent the collaboration between two roles in one stage for simplicity.

When human-creators take control of one stage, they are able to perform more free-form actions following their ideas. For example, they can select any code in notebooks to organize the data story [118] or pick desired glyphs for infographics in the implementation stage [139]. One predictable cost of the control is more manual effort from human-creators. Besides, the requirement for AI-assistant is also higher since they need to understand the humans' input and then take corresponding actions. For example, Vistylist [99] leverages multiple deep learning-based vision models to extract infographic styles, such as fonts, colors, and icons. To mitigate the problem, one common strategy in prototype tools is to limit human-creators' input, such as limiting chart types [25, 107], restricting the input formats [62, 109].

When AI takes the creator role, humans' efforts can be significantly eliminated initially. However, the flexibility of results is greatly limited by the design of AI. For example, as previously mentioned, DataShot [125] can only produce simple data facts pre-defined by tool developers. Text-to-Viz [26] is limited to generating proportion-related charts. Another issue is that AI-creators can hardly consistently achieve satisfactory performance. It may take considerable effort to optimize AI's output.

Considering their pros and cons, there can be a trade-off in selecting the two collaboration patterns when designing AI-powered data storytelling tools. The selection may depend on multiple factors, including the usage scenario, user preference, and the performance of AI-creators. We hope that future research can further investigate the problem and propose potential guidelines for selecting different patterns.

While these two patterns have pros and cons, one common characteristic of them is that humans have sufficient agency in the overall data story creation process. When humans serve as creators, they can directly decide how the story is told. If humans are optimizers, it is possible for them to modify stories directly when AI-creators' stories are beyond their expectations. Such observation indicates that the tool designers often follow the common principle of enabling humans' control over AI-powered tools [2, 40].

What do assistants frequently perform? In the previous discussion, we noticed AI-assistants commonly team up with human-creators. Following prior research [59], assistants are defined as collaborators who take supplementary tasks for leading creators during story creation. Compared to other roles, they have a broad spectrum of usage. In this section, we examine the usage of AI-assistants and human-assistants for a clear understanding of the assistant role.

The first type of assistant performs individual tasks that creators delegate to them. When collaborating with these AI-assistants, human-creators can focus on the main tasks and save efforts in these auxiliary tasks. For example, human-creators can create charts and ask AI-assistants to add styles to them [25, 99]. When human-creators specify keyframes in animations, AI-assistants can automatically create transitions between them [50, 65]. Similarly, human-assistants write text descriptions for charts created by AI-creators [21] or add annotations [73]. Furthermore, the human-assistant in TSI provides key parameters for the AI-creator since AI cannot determine them by itself [8].

Another type of assistant provides suggestions for a task that creators work on. For example, in the analysis stage, AI-assistants recommend interesting data facts [62, 109]. In the planning stage, they can fill story pieces into human-creators' sequences to make them more coherent [50, 109]. AI-assistants in Data Animator [112] and CAST [35] provide assistance in matching visual elements between keyframes or grouping similar visual elements for applying similar transitions, respectively.

An additional finding is that most AI-assistants are used for style-related tasks in the implementation stage, including adding animation and suggesting colors. A potential explanation is that styling data stories can be a complicated task with multiple factors to be considered, such as color, icon, *etc.* AI can eliminate users' workload in handling styles.

What and why do some roles lack investigation in previous research? We have discussed the common human-AI collaboration patterns previously. Now we introduce some rarely explored collaboration patterns.

As introduced before, the two most common collaboration patterns are human-creators + AI-assistants and AI-creators + human-optimizers. However, it is interesting that these roles are seldom swapped between humans and AI, *i.e.*, human-creators + AI-optimizers and AI-creators + human-assistants. Among them, human-creators + AI-optimizers occurs less frequently only in two serial tools [80, 81]. Furthermore, AI-optimizers are desired by some users according to previous research [59]. Therefore, our discussion starts with why AI-optimizers may not be widely applied in existing data storytelling tools. When AI-optimizers collaborates with human-creators, AI-optimizers act after humans' creation. Therefore, if humans and AI have different ways of understanding the same data story, one potential problem of letting AI optimize human-creators' design is to change humans' purposeful design along an undesired direction. For example, AI-optimizers may improve the story organization using data relationships while ignoring humans' original logic flow (see Section 6.1). What may make it even worse is an observation that there is a lack of effective communication channels between humans and AI [59]. It may increase the risk of misunderstanding between AI and humans.

Based on these observations, we have several suggestions for applying AI-optimizers with human-creators in data storytelling tools. First, when applying AI-optimizers, it is critical to design appropriate strategies to incorporate humans' opinions for their control of stories. For example, AI-optimizers should try to follow humans' designs and sync with humans before making uncertain decisions. Furthermore, considering the potential mistakes made by AI-optimizers, the tools should also allow humans' further modification. Second, the usage of AI-optimizers may depend on the tasks in the data storytelling workflow. In our opinion, it might not be ideal to apply AI-optimizers for stages where understanding data story background may affect the results considerably, such as organizing the story. On the other hand, AI-optimizers have some opportunities to perform background-agnostic tasks, such as optimizing the layout or color usage. Finally, a potential alternative to AI-optimizers can be AI-reviewers. AI-reviewers can provide feedback on humans' designs but do not directly modify them. In this way, humans can learn AI's suggestions and take action while considering their needs sufficiently.

In our corpus, the usage of AI-reviewers is limited to two tools [31, 33] that review individual charts' visual appearance and potential misinformation in the execution stage. We suspect that the reasons why AI-reviewers are not frequently explored correspond to the characteristics of data stories. First, data stories often involve multiple channels, including visualizations, animations, and narrations. To comprehensively evaluate them, it is essential to understand all channels and the interplay between them [18, 124], which poses the challenges of considering multi-modal inputs to AI systems. Second, data stories serve as a medium for communication between authors and audiences. Therefore, when reviewing data stories, a challenge is to consider audiences' preferences and the information gap between authors and audiences [41, 74]. To address the challenge, recent large language models (LLMs) demonstrate their potential. Previous research [83] reveals that LLMs can play different roles in conversations. They may be extended to provide feedback from various audiences' perspectives for data stories.

Another role we would like to discuss is human-reviewer. According to the definition, human-reviewers provide suggestions to AI-creators about their created content. Then AI-creators may update the content accordingly and ask for further human reviews. Compared to human-optimizers, it allows users to provide feedback rather than considering and implementing solutions directly. Such workflow requires AI to have the ability to understand humans' feedback and perform corresponding actions iteratively, which may be beyond AI's ability in existing tools. According to our observation, existing tools often apply AI to conduct given one-shot tasks, such as recommending potential animation [35] or identifying data facts [125]. These AI approaches are specialized at one assigned task and lack the ability to handle users' reviews. Another reason is that human-optimizers can be more efficient than human-reviewers when handling minor tasks to be revised. For example, a common task in designing infographics is to arrange the positions of the visual elements. When AI moves a visual element to an undesired position, it might be more convenient and predictable to directly manipulate its position rather than providing feedback to AI for adjustment, as indicated by a prior discussion [102].

7 SUGGESTIONS AND OPPORTUNITIES IN HUMAN-AI COLLABORATIVE DATA STORYTELLING

In Section 4, we introduce a framework to characterize data storytelling tools from the perspective of human-AI collaboration. We first demonstrate how the framework can be applied to compare and group existing human-AI collaborative storytelling tools and discuss their development in Section 5. Section 6 further illustrates their design patterns. This section proposes the research opportunities revealed by analyzing existing studies with the framework.

Investigate the strategies to maximize automation and agency in data storytelling tools comprehensively. Heer pointed out that the ultimate goal of designing human-AI collaborative tools is maximizing AI automation and human agency concurrently [39]. We notice an interesting trend toward this goal when analyzing the tools in our corpus. Figure 4 reveals that the development of data storytelling tools experiences two apparent phases. Between 2016 and 2018, most tools were manually authoring tools where human-creators take the entire control of storytelling. Since 2019, human-AI collaborative tools have occupied the largest proportion among all tools and shown an increasing trend, while the number of purely automatic tools has been relatively low and stable over the years. As the trend indicates, researchers have widely investigated human-AI collaborative ways to automate data storytelling with consideration of humans' control. This aligns with the creative component of authoring data stories well [113], which can make designing compelling data stories an open-ended task. Therefore, it is hard to define a clear goal for AI to accomplish automatically. The creation of data stories still heavily relies on humans' experience and judgment. As a result, it is crucial to respect humans' control over the entire data storytelling workflow while attempting to improve the automation level.

In Section 6.2, we mentioned that existing work often uses two collaboration patterns to guarantee humans' control when collaborating with AI in single stages, including asking humans to author the content with AI assistance (human-creators + AI-assistants) or allowing humans to optimize AI-created content (AI-creators + human-optimizers). However, the two aforementioned collaboration patterns have not been systematically investigated in existing tools to decide their performance in maximizing agency and automation. We believe future research should take one step further to carefully examine and compare these frequent human-AI collaboration patterns from multiple angles, such as users' perceptions and preferences for these patterns under different scenarios. Ultimately, these results can be transformed into design guidelines for future tool developers' references. Moreover, along with the development of AI, other currently under-explored human-AI collaboration patterns revealed by our review (see Section 6.2) can also be investigated for ensuring humans' control and improving automation. For example, human-reviewers can provide feedback for AI output and save the effort of direct modification as human-optimizers do. AI-optimizers can automatically improve humans' created content with extensive consideration of their intent.

Beyond individual stages, a more interesting observation is about the tools that cover the analysis, planning, and implementation stages experienced three phases (see Section 5.1). The earliest tools aim to bridge the analysis and follow-up stages to reduce efforts for transferring analytical results instead of automating data storytelling directly [36, 75]. They are still manual storytelling tools. Later, in the second phase, researchers propose tools to generate complete data stories from datasets directly, such as DataShot [125] and Calliope [98]. Though they allow manual optimization, humans' intent is not considered in the initial story generation. More recently, the development of these tools reached the third phase, where humans can control data story content and structure in the analysis and planning stages, and AI takes over the implementation stage [62, 109, 118]. We realized that following the trend, tools have been closer to the expectation of tool users, where the planning stage is not preferred to be fully automated [59], demonstrating the development of understanding data storytellers in our community. Furthermore, the observation reveals a potential strategy to maximize automation and agency in human-AI collaborative tools. When the workflow involves multiple stages, like data storytelling, it is possible to adopt different collaboration patterns in different stages according to the stage characteristics. In this way, though not maximizing the automation and agency in a specific step, they can be maximized in the entire workflow. More research should be conducted to investigate the design strategy. For example, the relationship between collaboration patterns and stage nature is worth more investigation.

We hope our research community can continue the investigation and innovation of maximizing agency and automation in data storytelling. We also believe the lessons from developing human-AI collaborative data storytelling tools can potentially inspire other related fields and contribute to the future symbiosis of humans and machines [66].

Embrace the recent advances in AI systems. The past year has witnessed the emergence of powerful generative AI systems, including LLMs (*e.g.*, GPT-3.5[2], GPT-4 [82] and Llama2 [115]) and image generative models (*e.g.*, Midjourney[3] and Stable Diffusion [91]). Their appearance can boost human-AI collaboration in data storytelling tools. The most straightforward approach to leverage them is to finish generative tasks with better performance. For example, recent tools[4] use GPT-3.5 to create text for charts [68, 108, 137] instead of using template-based methods [62, 98]. Generating infographics from data with LLM was also explored [27]. Besides performance, another outstanding advantage of using them in data storytelling is the low requirement for training data. Lu *et al.* [72] indicated that there were no existing corpora of data stories, which resulted in the challenges of training machine learning models. Recent LLMs show great power in zero-shot or one-shot learning tasks [128], which releases the requirement of large-scale training datasets and demonstrates their potential for generative tasks in data storytelling.

Other than generative tasks, these AI systems also enable a large space for imagining human-AI collaborative experiences. For example, Data Player animates charts based on understanding accompanying narrations with GPT-3.5 [96]. Besides, we mentioned another potential case of leveraging LLMs to review data stories from the perspectives of audiences with diverse backgrounds in Section 6.2. We also anticipate that LLMs' ability to have conversations with humans may also facilitate communication between human-reviewers and AI-creators.

Though these AI systems can bring advantages, the risk of applying them should also be aware, such as hallucination [58] and bias [63]. These potential problems further enhance the need for human-AI collaboration. For example, human-reviewers can check if the created data stories involve fake numbers and ask AI to correct them.

Extend human-AI collaboration to multiple human and AI collaborators. One observation we made during the research is that most of the surveyed storytelling tools are limited to the collaboration between one human and one AI system. However, previous research notices that the workflow of communicating data analytical results may involve several human collaborators [20, 57], such as data analysts, story editors, and presenters. To assist these human collaborators, different AI collaborators may also be required to facilitate their diverse backgrounds and requirements. As a result, it is possible for future storytelling tools to consider the collaboration among multiple stakeholders. The previous research in collaborative data communication also implies the need for such tools [6]. We anticipate that the appearance of these tools has the potential to further expand the collaboration patterns identified in our paper (see Table 1 and Figure 7). For example, we imagine that there might be a tool where AI-optimizers and human-optimizers can

[2]https://platform.openai.com/docs/models/gpt-3-5
[3]https://www.midjourney.com/
[4]These tools are not included in our corpus since they were not officially published before June 2023.

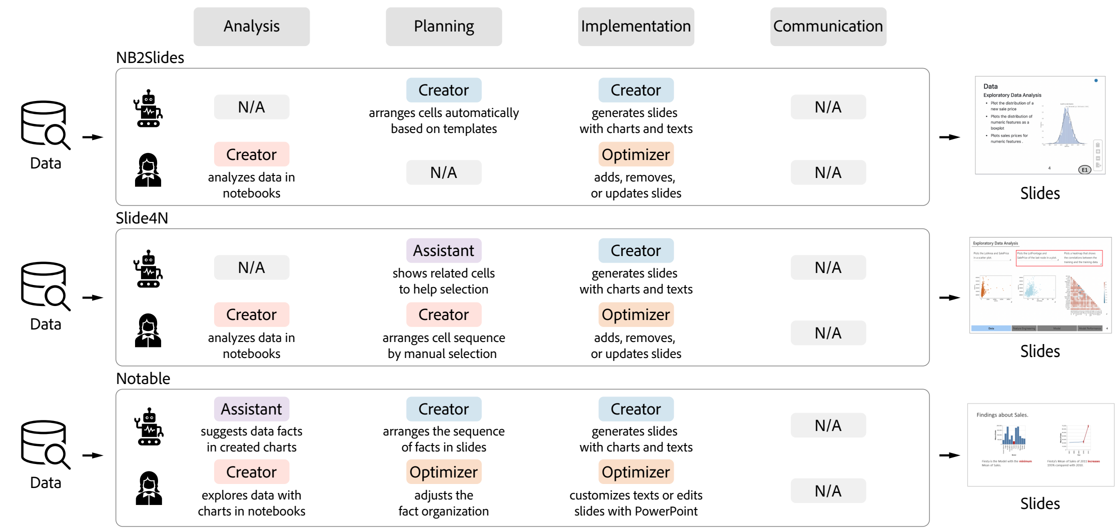

Fig. 8. This figure shows the usage of our framework to compare three recent slide creation tools in computational notebooks, *i.e.*, NB2Slides [142], Slide4N [118], and Notable [62]. With our framework, their difference in human-AI collaboration is straightforward.

collaborate to leverage their advantages in improving data stories created by other human-creators. Human-optimizers can focus on logical problems, while AI-optimizers improve styles.

Specify human-AI collaboration patterns explicitly with our framework of roles and stages. Many recent data storytelling tools consider collaboration strategies between humans and AI explicitly, such as Erato [109], Slide4N [118], and Notable [62]. However, their text description of human-AI collaboration strategies may not be straightforward enough for understanding and comparisons against other tools. We would like to encourage future research to apply our framework of roles and stages as an easy and standard way to express their strategies for human-AI collaboration. In this way, it will be easier to discriminate data storytelling tools from the angle of human-AI collaboration other than conventional dimensions, such as genres. For example, Slide4N [118] and NB2Slides [142] are two recent tools for generating slides from computational notebooks. As a later tool, Slide4N [118] argues that adopting a human-AI collaborative approach is one of its major differences from NB2Slides [142]. With our roles and stages, it is easy to notice that the difference between NB2Slides and Slide4N mainly lies in the planning stage, where Slide4N allows users to organize their story with AI assistance and NB2Slides entirely relies on AI (see Figure 8). We further compare them with Notable, another recent slide creation tool in notebooks, in Figure 8.

8 LIMITATIONS AND FUTURE WORK

This section discusses the limitations and future directions to continue our research.

8.1 Limitations

We notice two limitations in our research. First, *the granularity of stages can be more fine-grained.* In previous research [19, 57, 59], besides stages, they further identify the tasks in data storytelling workflow, such as styling data stories and answering audiences' questions. We did not code tools according to the human-AI collaboration patterns in these tasks since the tasks may be too detailed. If using tasks, the clusters of tools may be less noticeable. Furthermore, another concern is that some tasks may be mental tasks, such as connecting data findings logically [57]. It can be hard to decide if data storytelling tools take care of these tasks. Consequently, as a pioneer study towards human-AI collaboration in data storytelling, we provide an overview of these tools from a relatively high level, *i.e.*, stages. We sincerely hope future research can further extend ours to fine-grained patterns in different tasks with our roles of humans and AI.

Second, *our corpus of tools may not cover the latest data storytelling tools*. As Section 7 indicates, the recent advance of AI has the potential to push the frontier of human-AI collaborative data storytelling tools. Though our corpus of existing research tools may not cover the most recent ones due to the timing of the research, we believe our research can still be valuable to future tool designs with increasingly powerful AI systems. Our paper introduces a framework to characterize existing data storytelling tools and shows its application in comparing tools, understanding the footprints of the research community development, and identifying new research opportunities. Future designers and researchers can follow the framework to draw inspiration, assess their tools, and compare them with prior arts. We also plan to keep updating our online data storytelling tool browser at https://human-ai-universe.github.io/data-storytelling. It can serve as a sustainable source for the data storytelling community to reflect the progress of human-AI collaborative tools and ignite new ideas for more effective and efficient approaches.

8.2 Future work

We further propose two directions to continue our research. First, *more design choices in human-AI collaborative data storytelling tools can be explored*, such as the communication approaches between human and AI collaborators and the detailed AI techniques. Our paper outlines the humans' and AI's roles in human-AI collaborative data storytelling tools. We notice that there can be diverse communication methods between humans and AI, such as programming [50, 62], sketching [56], and gesture [37]. Considering the page limit, we cannot include a comprehensive investigation into the communication channels in the current paper and hope to continue the research in this direction. Furthermore, the detailed AI techniques may be worth more research. Since data storytelling tools often cover multiple stages, they can apply several AI techniques. A comprehensive review of AI algorithms for different stages and roles may provide a panorama of human-AI collaborative tool development from the technical perspective. Considering our focus on roles in collaboration, we decided to blur the difference between AI techniques and leave their survey as future work.

Second, *it is interesting to extend our research's scope from data storytelling tools to general visualization creation tools and creativity support tools*. As introduced in Section 3, we excluded the visualization creation tools that are not specifically designed for storytelling in the paper collection phase and constrained the scope for a more focused study. During our paper collection, we realized that existing visualization creation tools involve human-AI collaboration. For example, VizLinter [12] applies AI-reviewers to identify problems in charts. Voyager2 [131] leverages AI-assistants to recommend charts based on users' intent in visual data exploration. We hope to examine whether our framework of human and AI collaborators' roles can be applied to these visualization creation tools in the future. Furthermore, creativity plays an important role in authoring compelling data stories [113]. Therefore, data storytelling tools are closely related to the field of creativity support. We consider it interesting to extend our human-AI collaboration research to creativity support tools [101].

9 CONCLUSION

In this paper, we systematically investigate existing human-AI collaborative data storytelling tools from two perspectives: their covered stages and the roles of humans and AI in collaboration. Through reviewing these tools, we summarize findings and lessons learned, including the development of tools and the frequent human-AI collaboration patterns. Furthermore, we point out the opportunities in this line of research, such as exploring approaches to enhance automation and agency in these tools and extending existing work for collaboration among multiple humans and AI collaborators. In the future, we plan to keep track of the development of related tools and update our online browser of tools. We hope to extend our research to other factors in human-AI collaborative data storytelling, such as communication methods between collaborators and the technical details of AI systems. Moreover, the roles of humans and AI can be further studied and extended. It will also be interesting to explore if our framework can be applied to other human-AI collaborative tools, *e.g.*, visualization creation tools.

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