Understanding Narrative Linearity for Telling Expressive Time-Oriented Stories

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ABSTRACT

Creating expressive narrative visualization often requires choosing a well-planned narrative order that invites the audience in. The narrative can either follow the linear order of story events (chronology), or deviate from linearity (anachronies). While evidence exists that anachronies in novels and films can enhance story expressiveness, little is known about how they can be incorporated into narrative visualization. To bridge this gap, this work introduces the idea of narrative linearity to visualization and investigates how different narrative orders affect the expressiveness of time-oriented stories. First, we conducted preliminary interviews with seven experts to clarify the motivations and challenges of manipulating narrative linearity in time-oriented stories. Then, we analyzed a corpus of 80 time-oriented stories and identified six most salient patterns of narrative orders. Next, we conducted a crowdsourcing study with 221 participants. Results indicated that anachronies have the potential to make time-oriented stories more expressive without hindering comprehensibility.

KEYWORDS

Storytelling, Narrative Visualization, Narrative Order

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1 INTRODUCTION

As narrative visualization [60] has been gaining in popularity in recent years, creating more *expressive* data-driven stories has become a natural pursuit [7, 14, 37]. The narratives of visualization are comparable to the narratives of story forms such as novels and films, where a storyteller may present the story events in the order they occurred linearly (i.e., chronology) or deviate from linearity (i.e., anachronies [29]). Such manipulation of narrative linearity is viewed as a basic element and fundamental skill of storytelling [31] due to its ability to enhance engagement, create better user experience, convey ideas, or persuade [6, 55, 63]. There are also discussions about the importance of breaking the linearity in terms of attracting users' attention and increasing the perception of uniqueness [41, 43]. Given such benefits, narrative linearity has been widely practiced by data journalists, designers, and public speakers. For example, when delivering a presentation about the social progress of Sweden from 1709 to 2004 [27], Hans Rosling starts his narrative from 2004, then goes "300 years back into Swedish history", and explains the data chronologically (see Fig 1).

While prominent in the wild, few attempts have been made to examine narrative linearity. Prior research about expressive narrative visualization has focused on storytelling genres [5, 69], visual embellishment [8, 10–12, 16, 30], and narrative sequence [4, 33, 44]. For example, Amini et al. [4] investigated the structures of 50 data videos through the lens of initial, establisher, peak, and release. Hullman et al. [33] identified six sequencing choices (e.g., causal, spatial) that facilitate visualization transition. Although the aforementioned work has laid a solid foundation on understanding expressive storytelling, narrative linearity, as a critical component of narrative visualization, is largely overlooked. Missing such knowledge can pose difficulties for designing compelling narrative structures or generating expressive storylines for visualization genres [60] such as data videos and slideshows. On the other hand, while narratologists have conceptualized some basic techniques of ordering narratives (e.g., analepsis and prolepsis [29]), the choices of applying these techniques can be infinite [36]. Therefore, it is necessary to distill narrative order patterns that capture the regular modes of manipulating narrative linearity from data-driven stories, thus providing generalizable and repeatable solutions to ordering narratives. Given the above motivations, this work investigates narrative linearity in data-driven stories and examines whether different narrative order patterns help improve story expressiveness. We choose to study time-oriented stories specifically, given that such stories are a prominent type of narrative visualization [25, 34] whose narrative order can be precisely identified by examining the temporal positions of the narrative points.

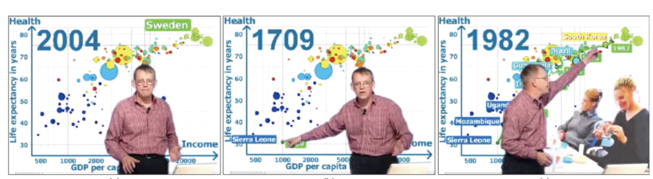

Figure 1: Hans Rosling's presentation about the social progress of Sweden [27]: (a) he first presents the data visualization of 2004 to the audience, then (b) goes back to 1709, and (c) shows how the visualization changes from 1709 to 2004 chronologically.

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The studies were carried out in three steps: First, we conducted preliminary interviews with seven experts from data journalism to understand the motivations and challenges of manipulating narrative linearity in time-oriented stories. Then, we manually collected a corpus of 80 time-oriented stories from online sources. By coding this corpus, we identified six salient narrative order patterns. Next, we conducted a crowdsourcing study with 221 participants to evaluate and compare the six patterns in terms of improving the expressiveness of time-oriented stories. Both quantitative and qualitative results suggested that anachronies have the potential to enhance story expressiveness while being equally comprehensible as chronological narratives. These results contribute to the knowledge around narrative visualization and introduce new solutions of expressiveness to data-driven storytelling.

2 BACKGROUND AND RELATED WORK

This section provides the background knowledge about narrative linearity and related work in the visualization community, including narrative visualization and time-oriented storytelling.

2.1 Narrative Linearity and Anachronies

Every story has two orders: the natural order of the story (which is always chronological) and the order in which it is narrated [29]. When told chronologically, a story's narrative order is equal to its natural order. When storytellers distort the events in the story out of their linear order, the discrepancies between the two orders are called anachronies [6]. In literary narratives, for example, frequently adopted anachronies include retrograde (reverse chronology), zigzag (alternating between the past and present), analepsis (flashback), prolepsis (flashforward), syllepsis (grouped or parallel time), and achrony (ambiguous time), as summarized by narratologist Genette [29]. Garcia Landa [28] further pointed out that a narrative either looks to the future, following the logic of succession, or towards some point in the past, following the logic of retrieval. Thus, any narrative order is a result of applying and combining such basic motions of time. As an exceptional skill of human beings, manipulating narrative linearity has been extensively applied in various storytelling forms, such as novels, films, and speeches [6, 59]. For example, fairy tales often begin with a flashback (e.g., "once upon a time") which brings the readers back to a faraway wonderland. By breaking the linearity of a story, a storyteller can emphasize or de-emphasize certain story points, and trigger emotional responses or aesthetic feelings from the audience [18, 55, 63]. Also, anachronies are found to be a useful vehicle that cues attention and forces the audience to read more intensively, thus contributing to a concentrated reading experience [6].

While narrative linearity has been discussed in humanities for a long time, how it could be incorporated into visualization remains unclear. On the one hand, telling data-driven stories usually asks for a clear and quick presentation of narrative points to the target audience [24] (which can be different from the common goals of novels or films), thus requiring the narrative orders to be concise, efficient, while not being too artistic. On the other hand, storytellers or computer systems seek for handy patterns that capture the regular manipulation of narrative linearity. Therefore, we propose that a set of narrative order patterns that can be compatibly applied to data-driven stories is desired.

2.2 Narrative Visualization

Recent years have witnessed a growing interest in narrative visualization [60]. To facilitate storytelling, one thread of the research focuses on how data can be *shown*. Relevant topics include the styles and aesthetics of visual representations [17, 46], and graphical elements in visualization such as color [7], layout [5, 14, 61], and embellishment [8, 10–12, 16, 30]. Another thread, on the other hand, looks into how data can be *told* through narratives. For example, Hullman and Diakopolous [32] proposed a taxonomy of rhetorical techniques used in narrative visualization, such as provenance rhetoric and linguistic-based rhetoric. McKenna et al. [44] identified seven flow-factors that shape data story reading experiences, such as level of control, story progression, and navigation feedback. Amini et al. [4] studied the narrative structure of 50 data videos by decomposing the videos into initial, establisher, peak, and release, inspired by cinematography. Hullman et al. [33] examined sequential ordering in narrative visualization and identified six types of between-visualization transitions, including dialogue, temporal, causal, granularity, comparison, and spatial transitions. They also found that global constraints such as parallelism help make a narrative structure more effective.

While the above research has shed light on understanding narrative techniques and structures, narrative linearity, as an indispensable part of narrative visualization, is under-explored. This work, to the best of our knowledge, is the first to conduct a systematic investigation of narrative linearity in time-oriented stories. We hope this work will inspire the design and development of future tools for creating expressive narrative visualization.

2.3 Time-Oriented Storytelling

Time-oriented stories use temporal data to present changes, arguments, or ideas [3, 14, 62]. Time is a central thread that ties everything together in the human history of visual storytelling, starting from caveman paintings and Egyptian hieroglyphs to picture books and comic strips [3]. For data visualization, *change over time* is among the seven main types of data-driven stories [25, 34] and has been examined by many researchers. For example, Brehmer et al. [14] proposed a design space for timelines that highlights design expressiveness. Their design space consists of three dimensions derived from the analysis of 263 timelines, including representation (e.g., linear, circular, spiral), scale (e.g., chronological, logarithmic), and layout (e.g., unified, segmented). Di et al. [23] further evaluated the effectiveness of linear, circular, and spiral timeline representations as to visualize recurrent, non-recurrent, and mixed events sequences. Bach et al. [5] proposed a set of design guidelines to tell stories about dynamic networks with data comics where temporal flows are represented in juxtaposed panels.

While the above studies all examined time-oriented stories from the perspective of visual design, little is known about how to tell expressive stories about time through ordering narratives. By analyzing a corpus of 80 time-oriented stories through the lens of narrative linearity, this work contributes to the knowledge around time-oriented storytelling.

3 PRELIMINARY STUDY

To gain more insights into storytellers' practice of manipulating narrative linearity in time-oriented stories, we conducted semi-structured interviews with seven professionals from data journalism. We were interested in: (i) the motivations for manipulating narrative linearity in time-oriented stories, and (ii) the challenges of designing narrative orders.

3.1 Interview Process

We invited seven professionals via posting advertisements on social media platforms and word of mouth, including four data editors (E1, E2, E3, E4 with two years, three years, one year's, and five years experience in news agencies), one visual designer (E5 with five years experience in designing visualization), and two video producers (E6, E7 with two years and one year's experience in data videos). The interviews were conducted online via meeting software that enables screen sharing. We first introduced our research topic and the core concepts (i.e., narrative linearity, chronology, anachronies, time-oriented stories) to the participants, showed them examples of time-oriented stories, and then asked them a set of interview questions. Example questions include, "how do you understand the functions of manipulating narrative linearity?", "have you ever applied this storytelling technique in your practice?", and "did you meet any problems or challenges?". Overall, each interview lasted approximately one hour.

3.2 Analysis and Results

To analyze the interview transcriptions, we followed the thematic analysis process proposed by Braun and Clarke [13]. The data were sectioned and coded in terms of our two research questions. Two researchers first read through all the transcriptions independently, familiarized themselves with the data, and noted items of potential interest. They then analyzed the transcriptions, generating codes until reaching a saturation point. Afterward, they met and compared their codes. Similar codes were clustered and organized into potential themes, while mismatches were adjusted or dropped. They refined the codes and themes until achieving a 100% agreement. The researchers met for three sessions in total before reaching the final themes. Our findings are summarized in Table 1.

Motivations	**Mentioned By**
1. Cater to Communicative Intents	E1, E2, E3, E5, E6, E7
2. Manage the Flow of Attention and Emotion	E1, E4, E5, E6, E7
3. Hook the Audience Quickly	E1, E3, E5, E6, E7
4. Consolidate the Memory	E1, E3, E4
5. Create Novelty	E2, E5, E6
6. Adapt to Conventional Thinking	E2, E6
Challenges	**Mentioned By**
1. Balance Expressiveness and Comprehensibility	E1, E2, E4, E6, E7
2. Save Time for Authoring	E1, E5

Table 1: The results of preliminary interviews, summarized by the themes mentioned by the participants.

3.2.1 *Motivations.*

Six themes emerged as the motivators of manipulating narrative linearity in time-oriented stories.

Cater to Communicative Intents Six out of seven participants mentioned that manipulating narrative linearity is a common way to facilitate the presentation of main ideas, arguments, or values. For example, E1 said that "*the narrative order should ultimately serve data communication; when you order the story content, it's like finding the best path leading to your telling goal*". Similarly, E2 said that "*some data are more important than others in terms of expressing the main idea, and that's why we have to reorganize them; otherwise, you are just showing people a neutral sequence of facts.*" More specifically, common communicative intents of time-oriented stories include explaining reasons or causes (e.g., "*people need to look back to the history to understand how did we get here*" (E5)), presenting differences (e.g., "*jumping between time can quickly reveal how things change during a period, which also implies how serious a problem is*" (E2)), or highlighting consequences (e.g., "*I use chronological telling sometimes to push people to think about the results*" (E6)).

Manage the Flow of Attention and Emotion Five participants agreed that stories need dramatic development or variance in the telling flow to attract the audience. As said by E6, "*ordering a story is about manipulating reading experience, and there should be a set-up, peak, conflict, and resolution; you should prevent making your audience sleepy but it is also unwise to excite them too much.*" E1 also acknowledged that "*a well-designed narrative order means a good telling rhythm; a completely linear narrative is usually not enough for activating the audience*". E5 complemented that "*if people are emotionally aroused, they will invest more attention in reading the content, especially when the story is long.*"

Hook the Audience Quickly Another theme mentioned by five participants is efficiency-driven. E6, as a content producer, agreed that user behavior is an important driver of manipulating narrative linearity: "*people are impatient to wait if you keep telling things pointlessly; to attract them, I often change the order of story pieces and present the most eye-grabbing fact as soon as the story begins.*" E7 recalled his experience in data videos and commented that "*normally if you can't interest the audience in 5 seconds, they will leave, so don't hesitate to show your coolest part in the beginning.*"

Consolidate the Memory Three participants mentioned that manipulating narrative linearity can help strengthen memory. For example, E1 said that "*I usually use a flashback to reinforce the story content in case people's memory fades with time*". E4 said that "*revisiting the beginning of a story can remind people of where they come from and how they get here; many movies adopt this method in their endings to shape a feeling of completion.*"

Create Novelty Three participants mentioned that nonlinear narrative orders may bring about a sense of novelty. For example, when watching a story sample, E5 commented that "*in this case, if you show me the human history from the big bang all the way till now, I would say the narrative order is acceptable, but too normal since it is everywhere*". E6 agreed that "*a novel telling sequence is felt more fun and interesting; it may even help build a personal narrative style and make the stories distinctive.*"

Adapt to Conventional Thinking The last theme is about human habits. While all participants agreed that chronology is the most conventional way of telling time-oriented stories, E2 and E6 complemented that some anachronies also adapt to conventional thinking: *"chronology is a natural way of human thinking...but not the only one...it is also natural for people to know results first, and then figure out why"* (E2), "*people like to first look back to the past and then look forward to the future*" (E6).

3.2.2 Challenges. Two themes emerged as the challenges for manipulating narrative linearity.

Balance Expressiveness and Comprehensibility Five participants mentioned that there is a tension between adding expressiveness to narrative orders and making the data understandable: "*data is very factual, or even boring, so you have to use some unexpected ordering to give it the drama it lacks; however, you don't want the drama to obstruct the data interpretation*" (E4), "*finding a balance between presenting the data clearly and interestingly is not easy*" (E7), "*sometimes you adopt a fancy telling method but find that your audience just does not understand it*" (E6).

Save Time for Authoring E1 and E5 commented that there are no established principles or guidelines for quickly designing narrative orders for time-oriented stories: "*concepts such as chronology and reverse chronology are well-known, but transforming such basic ideas to concrete narrative sequences still requires careful design*" (E1). Thus, editing narrative linearity largely relies on storytellers' domain knowledge and personal experiences with data: "*If there was a tool, I wish it could recommend ordering templates for me based on the dataset I have*" (E5).

In summary, we found that manipulating narrative linearity is common in practice and may benefit time-oriented storytelling from various aspects. However, more knowledge around the methods and the consequences of manipulating narrative linearity is desired. Thus, this work focuses on finding *what* narrative order patterns are frequently applied in time-oriented stories and *how* these patterns influence user engagement. The participants' feedback also guided us to choose measurements (e.g., attention, memory) when evaluating the narrative order patterns in Section 5.

4 NARRATIVE LINEARITY ANALYSIS

In this section, we describe our methodology of collecting and analyzing a corpus of 80 time-oriented stories and report six narrative order patterns identified from the analysis.

4.1 Methodology

Our methodology of analyzing narrative linearity consisted of two procedures. First, we manually collected a corpus of 80 time-oriented stories from online sources. Then, we coded the stories to identify salient narrative order patterns.

4.1.1 Data Collection. To gather time-oriented stories of high quality, we started by searching for the corpora collected by previous studies about narrative visualization [4, 33]. Then, we referred to well-known news media (e.g., The Economist, BBC), organizations (e.g., Nature, NASA), and events (e.g., TED talks) to find additional samples. We also searched keywords such as "timeline", "history visualization", "trend visualization" on Youtube.com and Vimeo.com to collect stories from popular channels. In accordance with [4], a story was identified as qualified if it met three criteria: (i) it presents messages or arguments mainly supported by temporal data; (ii) it includes at least one data visualization; and (iii) it follows a non-ambiguous narrative sequence (e.g., with self-running playback, "Next" or "Continue" buttons, or a linear scroll path). As a result, 80 time-oriented stories were compiled, including 62 data videos, seven slideshows, six live presentations, and five web pages (see the full list in the supplemental file). Statistics showed that the stories were created between 2007 and 2020.

4.1.2 Analysis. We coded the narrative orders of the stories from two aspects using the method of close reading [15]: (i) how the narratives flow in order, and (ii) the underlying logic of the order. For (i), our coding process was inspired by Genette [29] who used visual symbols to code narrative points as well as their temporal positions in a story. For example, Genette used code "A2[B1]C2[D1(E2)F1(G2) H1]I2" to show the narrative points (A-I), their natural order (1-2), and between-point transition types (brackets for flashbacks and parentheses for flashforwards). Similarly, when coding stories, we first marked the temporal positions of narrative points. Then, we linked up the positions using solid or dashed arrows where solid arrows denote chronology or reverse chronology, and dashed arrows represent flashforwards or flashbacks. For example, the story of Fig 1 starts its narrative from 2004, then flashbacks to 1709, and continues chronologically until 2004. Thus, the order of this story was coded as 2004⇢1709→2004.

For (ii), we coded a story's ordering logic by first identifying the transition words used in its audio or textual narrative that sew up story segments. Then, we synthesized the transition words into a *story spine* [2], which shows the archetypal structure of the story. For example, *From white supremacy to Barack Obama: The history of the Democratic Party* [68] starts its narrative from the current state of the Democratic Party in the US. Then, as the audio narration says, "to understand how the party shifts through history, you have to go back", the timeline flashbacks to 1820 and the storyteller starts to explain the evolution of the party chronologically. Thus, the story spine of this story was coded as "Now...To understand how, you have to go back...In the beginning...Then...Then...Finally...". For stories that did not use clear transition words in their narratives, we consulted two experts we interviewed in Section 3 about how to interpret the narrative order logically and derived the story spines by cross-checking their answers. We also marked all data points used as the key joints in the story spines as well as any contextual information that helped explain why these data points were thought more special than others.

Two researchers coded 16 (20%) samples independently and refined the codes until they had reached a 100% consensus. The lead researcher then completed the coding on the remaining samples. After the coding process, we found that many time-oriented stories have shared narrative orders. By visualizing the codes using the diagram in Fig 2, we finally distilled and named six narrative order patterns which have occurred more than once in our corpus.

4.2 Narrative Order Patterns

The statistics show that 37 out of the 80 time-oriented stories in our corpus are told with chronology, and 43 stories use anachronies.

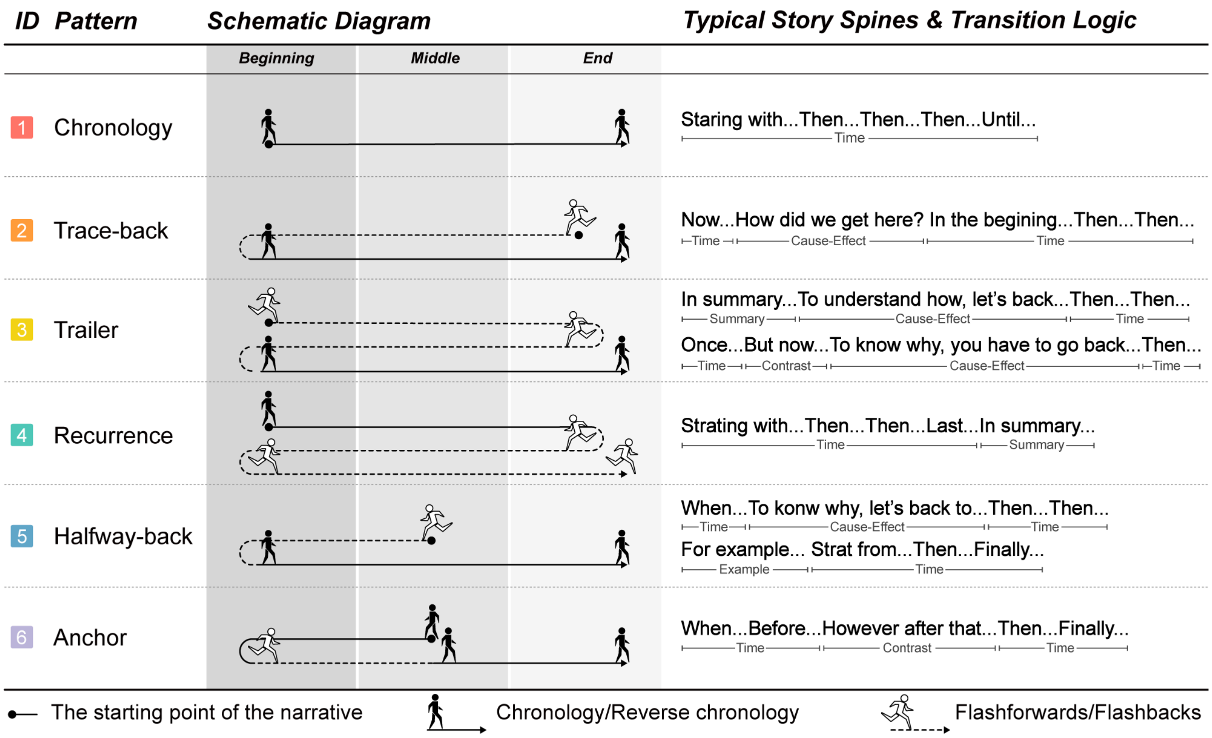

Figure 2: Six narrative order patterns. The schematic diagrams show how the narratives flow in relation to the natural order of the story, and the story spines indicate the underlying logic of the narrative orders.

The narratives of time-oriented stories can start at the beginning, middle, or end of the storylines. However, almost all narratives finish at the end of the storylines. We also identified five categories of transitions that connect story spines and imply the underlying logic of narrative orders: **Time** transitions such as "to begin with", "then", and "next" show the sequence of time. **Cause-Effect** transitions such as "to understand how" and "to know why" try to figure out the causes or consequences of something by a process of reason. **Contrast** transitions such as "however", "but", and "on the other hand" represent a logical turn revealing differences. **Summary** transitions such as "to summarize" and "in conclusion" signify an overview of a story. **Example** transitions such as "for example" and "for instance" are used to introduce typical cases. Below, we first introduce the six identified narrative order patterns and their underlying transition logic one by one, then discuss how we should apply the patterns to specific datasets.

4.2.1 Six Patterns. Fig 2 shows the six patterns we identified combined with typical story spines. The six patterns include chronology, trace-back, trailer, recurrence, halfway-back, and anchor.

1 **Chronology** Chronology arranges narrative points in their natural order of occurrence in time. The narrative starts from the beginning of the story and finishes at the end of the story without any deviations from the linear path. For example, *The True Timeline Behind The People vs. O.J. Simpson* [19] presents a sequence of events that happened during the O.J Simpson trial linearly, from the discovery of the victims to the verdict. As shown in Fig 2, chronology is a pattern constituted by *time* transitions only.

2 **Trace-back** Trace-back starts its narrative from the end of the story, then flashbacks to the beginning and continues chronologically until the end. For example, *A brief history of America and Cuba* [67] starts the story by talking about the latest news that America is opening up relations with Cuba. Then, "to understand just how big of a deal, where the hostility came from, and why it took so long to end", the storyteller brings the audience back to the 1850s and presents the historical events chronologically. As shown by the story spines, trace-back is a narrative order pattern that guides the audience to reason the *causes and effects*.

3 **Trailer** Trailer starts its narrative from the beginning of the story, then flashforwards to the end of the story, flashbacks to the beginning again, and continues chronologically until the end. In other words, this pattern exposes the story's ending quickly to the audience in the beginning. For example, in *7 Billion: How Did We Get So Big So Fast?* [52], the storyteller first shows how the world population accelerated from 1000 CE to 2011 CE using a swiftly growing bar chart. Then, he returns to 1000 CE and carefully explains how the growth occurred chronologically. Similar to trace-back, trailer is also a narrative order pattern that intentionally guides people to figure out *causes and effects*. But compared with trace-back, trailer has one more jump in the beginning. This jump can be interpreted as either a *summary* transition that foreshadows the progress of the whole story, or a *contrast* transition that emphasizes the difference between the starting point and ending.

4 **Recurrence** Recurrence first tells a story chronologically to its end, then flashbacks to the beginning and recaps the story again quickly. The feature of this pattern is that it repeats the already-told story at the end of the narrative. For example, when giving a presentation about world economic progress from 1810 to 2009, Hans Rosling [9] first gives a careful explanation of the animated bubble chart as to how it changes over time chronologically. Then, the chart flashbacks to 1810 and quickly replays again until 2009. Thus, logically speaking, recurrence is a narrative order pattern that uses a *summary* to tie the story together at the end.

5 **Halfway-back** Halfway-back starts its narrative from a middle point, then flashbacks and continues chronologically to the end. For example, *Humanity's cultural history captured in 5-minute film* [49] visualizes the immigration of notable people using a flow map. The storyteller starts the narrative by first showing the flow of Leonardo da Vinci who moved from Italy to France in 1500 CE; then the story flashbacks to 600 BCE and presents the accumulation of immigration flow chronologically. In this case, the storyteller chooses a middle point in the dataset as a typical *example* to introduce the visualization to the audience. Otherwise, similar to trace-back, the initial flashback in halfway-back can also be interpreted as a teaser that encourages reasoning *causes and effects*.

6 **Anchor** Anchor starts its narrative from a middle point; it first proceeds in reverse chronological order to the beginning of the story, then turns back and continues chronologically until the end of the story. For example, *Time: The History & Future of Everything* [1] explains the stretches of time by first talking about now, and then recounting historical events in a retrograde order (e.g., industrialization, the rise of civilization), all the way back to the birth of the universe. Next, the story flashforwards to now and the storyteller talks about what might happen in the future chronologically. From the perspective of transition logic, anchor is a narrative order built on *contrast*. It separates a story into two comparable chunks from its middle, first explaining one chunk, then transferring to the other chunk.

What We Could Not Cover We also observed some narrative orders that only occurred once in our corpus; we report them here for future discussion: *Debt Rising in Europe* [66], for example, is a slideshow that shows the debt ratio of 2011 first, then goes back to 2005 and 2000 (i.e., following a reverse chronological order). *Time History of Atmospheric Carbon Dioxide* [21] tells a story about carbon dioxide concentrations throughout history by first presenting the data chronologically and then telling reverse chronologically. In addition, several nested narrative orders based on the six patterns were observed and are discussed in Section 6.

4.2.2 Applying the Patterns to Datasets. While chronology presents a time-oriented dataset by loyally following linearity, nonlinear patterns distort the linearity through deciding which data points should be prioritized and presented ahead of others. We found that two types of data are more likely to be prioritized and used as the key joints of story spines:

Statistically Important Time Some data points are important from the perspective of mathematics. Statistical importance can be subdivided into three categories. The first category is **extremes**, which is usually used in the starting phase of 2 trace-back and 3 trailer. For example, in *2017 was one of the hottest years ever* [48], the storyteller begins by showing that 2017 was extreme in temperature, then shows the process of the unprecedented global warming from the 1800s. **Turning points** and **benchmark values**, however, are usually used as the starters of 5 halfway-back and 6 anchor in order to facilitate comparison and build contrast. For example, *2060 and the world population pyramid* [26] starts its narrative from 1970, a time when the population distribution was most even; the storyteller uses this middle point to familiarize the audience with the pyramid visualization.

Semantically Important Time Alternatively, a data point may be prioritized because of its semantic meaning. For example, the data of **the present** is given priority in many time-oriented stories. Most samples using pattern 2 or 3 start their narratives by first emphasizing the current situation. Besides, **monumental/famous events** are also likely to be told first, especially in 5 halfway-back and 6 anchor. These findings are in line with prior knowledge that people tend to read data that they feel relatable or familiar with first [56]. Last, a temporal position can be semantically important because of **social conventions**. For example, 2000 is an important year because it represents a new century or era, which is a concept derived from our social life.

5 CROWDSOURCING EXPERIMENT

In this section, we evaluate the six identified narrative order patterns in terms of augmenting the expressiveness of time-oriented stories. As suggested by previous studies in HCI and multimedia [38, 65], story expressiveness is usually measured by learning outcome and user engagement level. Also, as our preliminary interviews show that there exists possible tension between story expressiveness and comprehensibility, we took it as another aspect of measurement. Thus, our hypotheses are as follows:

H1: We will observe substantial differences in the learning outcome between the six narrative order patterns.

H2: We will observe substantial differences in user engagement between the six narrative order patterns.

H3: We will observe substantial differences in the tension between expressiveness and comprehensibility between the six narrative order patterns.

5.1 Method

We recruited 221 participants from Prolific [39, 57], a crowdsourcing platform for academic research. Each participant viewed three time-oriented stories told with different narrative order patterns and answered a set of evaluation questions. The materials of this study are available at https://osf.io/eusjn/.

5.1.1 Stimuli. Each participant viewed three time-oriented stories, a number that enables efficient data collection while keeping the participants attentive [12, 69]. To prevent the participants from knowing the stories prior to the study, one author who majored in journalism and once worked as a data journalist created the three stories using fictitious data. As she created the stories, three criteria were considered: First, the stories should not require prior knowledge to understand. Second, sensitive or controversial topics (e.g., sex, race) that may stir up strong subjective feelings should be avoided. Third, the data visualization of the stories should be familiar to most people and does not hinder reading. We also referred to our curated corpus as well as previous studies [14, 23] to make sure that the fictitious stories we created were rooted in realistic contexts. For example, we found that time-oriented data is often used to explain the history of certain entities (e.g., a population, a person) or to reconstruct the procedures of happened events (e.g., an accident, a crime). Timelines are the most commonly used visualization in our corpus. We also noticed that both nominal and ordinal data can be used as narrative points in time-oriented stories. Also, following the finding in Section 4, we chose statistically or semantically important data points to be the starters when the narrative order patterns start from the middle. The initial version of the stories was sent to two of the professional data journalists we interviewed (Section 3) to cross-check that the quality of the fictitious stories is comparable to that of the stories in our corpus. We refined our stories according to the suggestions provided by the professionals, such as using neutral wording to avoid eliciting unnecessary emotions and adding more qualitative facts to make the stimuli more "storylike".

The three stories were: (i) The Life of Company X, which talked about the key events happened during the establishment and bankruptcy of a clothing company, (ii) The Population Change of Country Y, which showed how the population of a country grew over the years, (iii) One Day of Z, which described how a crime occurred. We split each story into 12 separate sentences (i.e., narrative points). The 12 narrative points together constitute a complete plot. We kept visual compositions such as color, font size, and label placement identical for each story. We then conducted a pilot study with 10 participants to assess our stimuli. In the pilot study, we tested stories with 6, 9, 12, and 15 narrative points, respectively. We excluded 6 and 9 since they could be easily remembered by the participants [45] and could not differentiate user performance very well, given that one of the goals of our study was to examine which narrative order patterns may lead to better memory. We also excluded 15 because its information was overwhelming as reported by some participants. Thus, we decided that a story with 12 narrative points should be of a proper length for study. In addition, we asked the participants to rank the three stories (12-narrative-point version) in terms of complexity. While we tried to make the stories equally complex, participants' opinions varied. The authors then held a discussion to assess how the story complexity would affect study results. We thought that the focus of our study was to compare the six narrative order patterns within each story so that the difference between the stories will not significantly influence the main body of the study. However, when presenting the three stories to the participants, the order of the stories should be counterbalanced to minimize confounding effects. Last, we found that all participants could understand timeline visualization very well without any prior training.

5.1.2 Measurements. We assessed the expressiveness of narrative orders from three aspects: (i) what the participants learned from the stories, (ii) the engagement level of the participants, and (iii) the tension between expressiveness and comprehensibility. For (i), we measured the participants' immediate recall after viewing each story. For (ii), since engagement is rich in meaning [42, 44, 58], we ignored aesthetic and interactive engagement [42, 47] and only

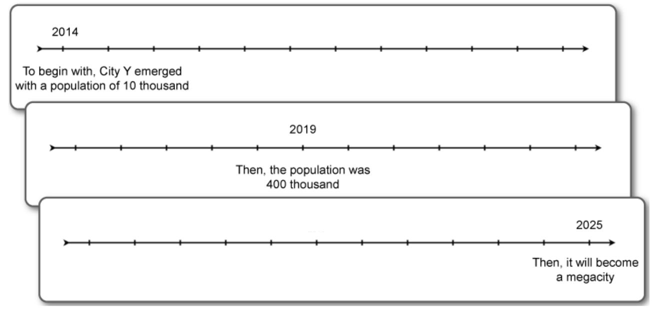

Figure 3: Screenshots of the study. Animation was used to present narrative points one by one according to the narrative order pattern they were assigned to.

focused on *narrative engagement*, which measures how people immerse in a storytelling process. Based on existing measurement frameworks [53, 54, 70], we assessed narrative engagement by measuring focused attention, enjoyment, affective arousal, interest, felt involvement, motivation, challenge, and likability using 7-point Likert scales. For (iii), we asked the participants to score the expressiveness and comprehensibility of a story on a grid inspired by Kennedy and Hill [35]. The X-axis of the grid represented the scale of expressiveness (-3 to 3) and the Y-axis represented the scale of comprehensibility (-3 to 3). We also collected qualitative feedback from the participants explaining their ratings.

5.1.3 Participants. We conducted a power analysis before the study using PASS software [51] to estimate an appropriate sample size based on the pilot study data. Simulations indicated that about 220 participants were needed to achieve an α level of 0.05 and a power of 0.8 when using a Kruskal-Wallis test. Therefore, we recruited 221 participants from Prolific (104 female, 116 male, 1 non-binary) who speak English as their first language. Their ages ranged from 18 to 76 (M = 34.09, SD = 11.71). Participants were paid $8 per hour. Very supportive participants were paid up to a $1 bonus. Each participant spent 27 minutes on average completing the study.

5.1.4 Procedure. The participants started by reading about the overall structure of the study. The study consisted of three sessions: the story reading session, the question session, and the survey session. The reading session and question session were repeated for each story. Each participant read all three time-oriented stories, one was told chronologically and the other two stories were told with two narrative order patterns randomly chosen from the five nonlinear patterns. In other words, each participant assessed three out of six narrative order patterns while one was chronology. The order of the stories and the patterns were counterbalanced.

In the story reading session, once the participant clicked "start", the story began to play. The order of the 12 narrative points in the story was reorganized according to the narrative order pattern they assigned to. The narrative points were presented one by one using animation (see Fig 3). Each narrative point was shown for four seconds, then faded out while the next point faded in. The participants were allowed to replay the story in case they missed any content. After reading, the participant then clicked a "next" button to enter the question session.

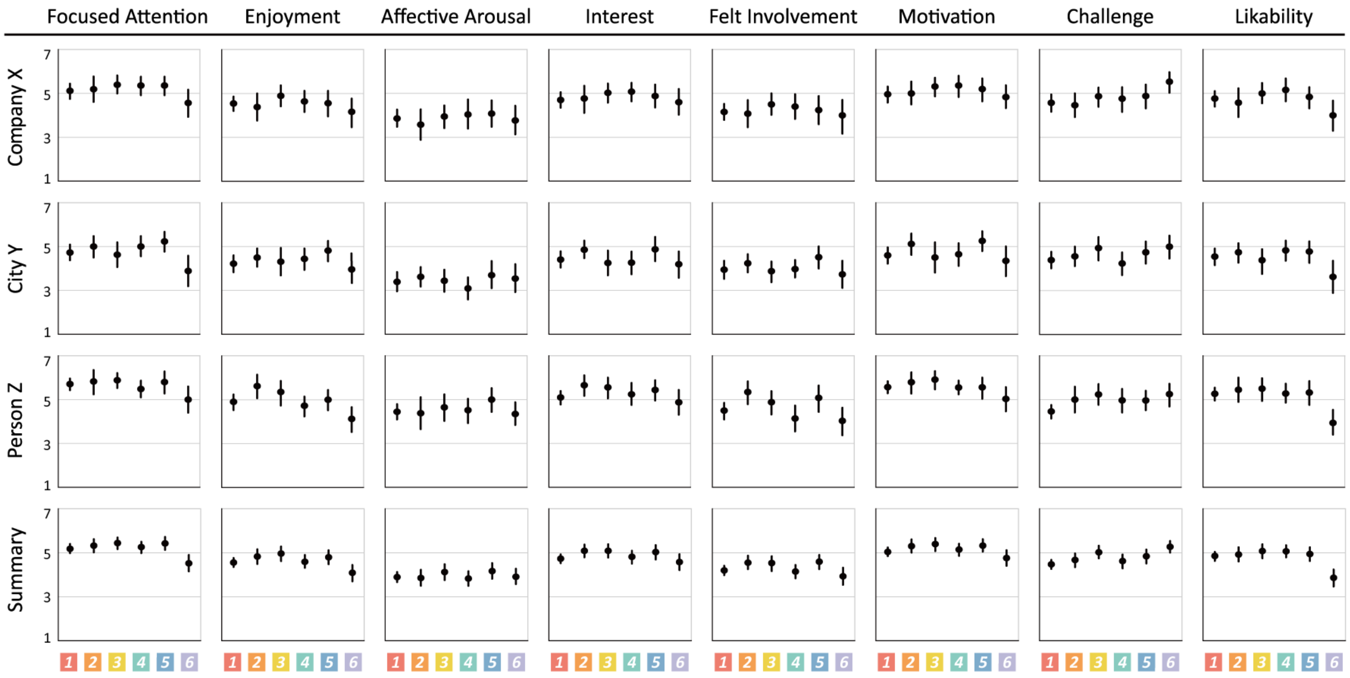

Figure 4: Quantitative results for the six narrative orders, each with three datasets and eight measurements for engagement. Error bars show the 95% confidence intervals (CIs) of the means. The last row shows the summary result of the three stories.

In the question session, the participants were first asked to recall and describe the narrative order of the story. We used this qualification question to make sure that the participants understood the key concept in this study and to filter out unqualified answers. Then, the participants were asked to retell the story by writing down anything they remembered. Afterward, the participants rated their engagement level by answering the questions about focused attention, enjoyment, affective arousal, interest, felt involvement, motivation, challenge, and likability (e.g., "I think the narrative order of this story holds my attention", "I think the narrative order of this story encourages me to think") using 7-point Likert scales (1 denoted "strongly disagree" and 7 denoted "strongly agree"). Next, the participants were asked to score the expressiveness and comprehensibility of the narrative order in a grid where the X-axis showed the scale of expressiveness (-3 to 3) and the Y-axis showed the scale of comprehensibility (-3 to 3). A cursor was placed at the origin of the grid by default. The participants scored the expressiveness and comprehensibility of the narrative order simultaneously by dragging and dropping the cursor. The participants were also required to provide reasons for their cursor placement.

After reading the three stories and completing the above questions, the participants entered the survey session and filled out a questionnaire. The questionnaire contained two demographic questions (age and gender), one question about visual literacy (i.e., "I can understand the timeline visualization in this study"), one question about user preference (i.e., "Which story has the best narrative order?"), and one optional question for leaving any comments.

5.2 Analysis and Results

Before conducting statistical tests with the data, we removed an answer if: (i) the participant reported that he/she failed to understand the timeline visualization, (ii) its task-completion time was an outlier (2 standard deviations from the mean), (iii) the answer was incomplete, irrelevant, or too general (e.g., "I scored it because this is how I feel"). Also, Shapiro-Wilk tests were done, showing that the quantitative data we collected were not normally distributed. Therefore, we used Wilcoxon Signed-Rank tests to compare chronology with anachronies and Kruskal-Wallis H tests to compare the six patterns mutually. We report the analytical results below:

5.2.1 Recall. We measured story recall through the Narrative Structure Score (NSS) [40]. Two coders analyzed the participants' responses for the open-ended recall question by coding the presence or absence of each narrative point. A NSS of 100% would indicate that the participant mentioned all the narrative points. The coders first coded the responses independently, and then discussed until reaching consensus.

Results indicated that 4 recurrence (NSS = 57.33%), 1 chronology (55.67%), and 3 trailer (55.08%) yielded slightly better recall, compared with 5 halfway-back (54.42%), 6 anchor (51.34%), and 2 trace-back (50.70%). However, no significant difference in recall was found between chronology and anachronies (z = -1.151, p = .250) or between the six patterns ($H(5)$ = 6.108, p = .296). We also noticed that most participants were able to reorganize the narrative points into chronological order when they recalled the stories. Some participants, however, recalled the stories also in nonlinear

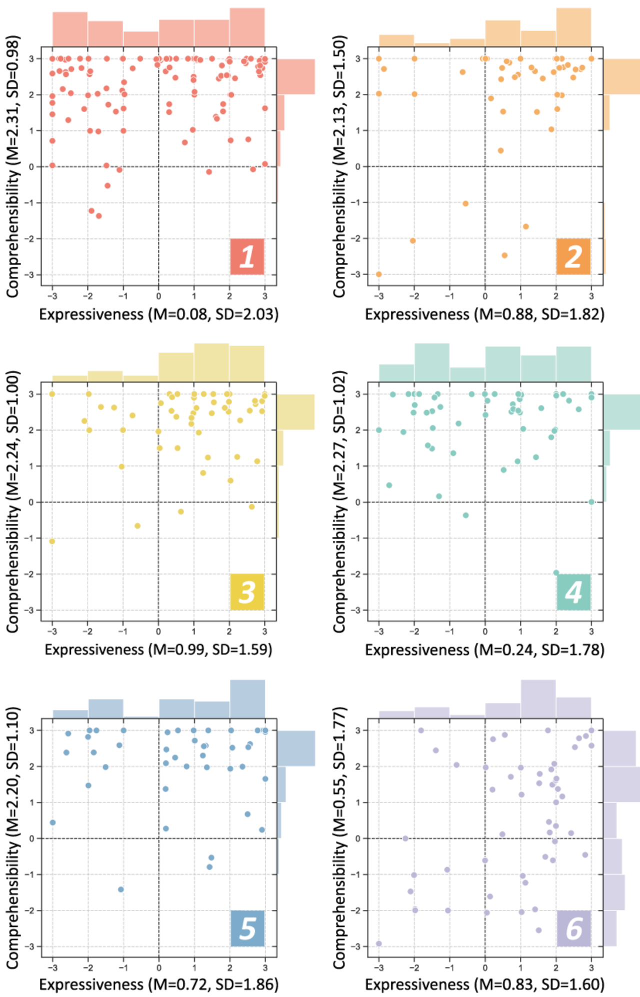

Figure 5: Grid-scoring results, including the raw scores (scatters) and their distributions (histograms).

order after reading anachronies, suggesting that the narrative order may have influenced how the participants memorized the stories.

5.2.2 Engagement. Results showed that anachronies had significantly higher scores in challenge than chronology (z = -3.593, p = .000), which means that anachronies work better at encouraging the audience to think. Anachronies also showed higher mean in interest (z = -1.855, p = .064), felt involvement (z = -1.582, p = .114), motivation (z = -1.278, p = .201), enjoyment (z = -1.079, p = .280), and affective arousal (z = -.960, p = .337) than chronology, but the differences were not statistically significant. Then, a Kruskal-Wallis H test was conducted to compare the six patterns in terms of user engagement. Results showed that there were significant differences in likability ($H(5)$ = 30.307, p = .000), challenge ($H(5)$ = 22.896, p = .000), focused attention ($H(5)$ = 16.332, p = .006), enjoyment ($H(5)$ = 15.642, p = .008), involvement ($H(5)$ = 11.851, p = .037), and motivation ($H(5)$ = 11.561, p = .041) among the six patterns. Dunn's post hoc tests (p-values adjusted using the Bonferroni correction) indicated that 5 halfway-back (p =.010), 3 trailer (p =.012), and 2 trace-back (p =.034) had the highest scores of focused attention, which were significantly higher than that of 6 anchor. 3 trailer (p =.007) earned the highest score in enjoyment, which was significantly higher than 6 anchor. On the other hand, 6 anchor had a significantly higher score of challenge than 1 chronology (p =.000) and 4 recurrence (p = .048); however, its score in likability was significantly lower than all other patterns (1 chronology: p = 0.000, 2 trace-back: p= 0.001, 3 trailer: p = 0.000, 4 recurrence: p= 0.000, 5 halfway-back: p= 0.001). Statistics within each story also indicated that despite the variability caused by story content, the improvement of user engagement through manipulating linearity was somewhat global (see Fig 4).

In summary, the above results have suggested that 2 trace-back, 3 trailer, and 5 halfway-back are good at holding attention and triggering affective responses; 6 anchor encourages the audience to think but may be too challenging and not liked by the audience; 4 recurrence is most similar to chronology but performs a little bit better in user engagement than chronology; 1 chronology is not outstanding in all the user engagement indicators.

5.2.3 Expressiveness-Comprehensibility Tension. As shown in Fig 5, in terms of comprehensibility (Y-axes in the grids), while 1 chronology earned the highest score (M = 2.31), 4 recurrence (M = 2.27), 3 trailer (M = 2.24), and 5 halfway-back (M = 2.20) were also thought highly comprehensible. 6 Anchor (M = 0.55) was thought the least comprehensible. A Kruskal-Wallis H test confirmed that there existed statistically significant differences among the six patterns ($H(5)$ = 51.190, p = .000) in comprehensibility, mainly caused by the low score of 6 anchor. However, for expressiveness (X-axes in the grids), while 3 trailer (M = 0.99) , 2 trace-back (M = 0.88), 6 anchor (M = 0.83), and 5 halfway-back (M = 0.72) were rated high, 1 chronology (M = 0.08) and 4 recurrence (M = 0.24) were scored low in expressiveness. A Kruskal-Wallis H test indicated that such differences were statistically significant among the patterns ($H(5)$ = 14.062, p = .015), mainly caused by the low score of 1 chronology.

In addition, the distributions of the ratings in the grids (see Fig 5) indicated that for some patterns, more conflict existed between expressiveness and comprehensibility. For example, participants generally agreed upon the comprehensibility of 1 chronology but showed polarized opinions on its expressiveness. This situation also holds for 4 recurrence, where about half of the participants rated it as expressive while the other half did not. 6 Anchor was both controversial in expressiveness and comprehensibility as the dots are scattered in all quadrants. By contrast, 2 trace-back, 3 trailer, and 5 halfway-back had relatively concentrated data distributions, showing that the three patterns were thought both comprehensible and expressive by most participants.

5.2.4 Qualitative Feedback. The open-ended preference question revealed the following:

Chronology. 69 of the 221 participants chose 1 chronology as their preferred narrative order. The primary reason was that chronology is simple and intuitive: "*chronological order is easier to follow*", "*it was the one that made the most sense*", "*it was the easiest and most comprehensive because it happens almost every day.*" Some participants also mentioned that chronology left the story ending to the last, thus preventing spoiling the story: "*I think the suspense* *and not knowing the outcome is suspenseful and makes for a more interesting story.*", "*It did not tell how it ends at the start so there was an element of surprise in the end.*"

Anachronies. On the other hand, 152 of the 221 participants appreciated anachronies more (2 trace-back: 34, 3 trailer: 40, 4 recurrence: 30, 5 halfway-back: 28, 6 anchor: 20), and their reasons resonated well with what we concluded from the expert interviews. For example, anachronies were thought to help spark interest and guide attention: "*starting with the summary of the end results (trace-back) was like a teaser that created interest and curiosity*", "*I really enjoyed that it (trailer) told me the first part and then the end result first. It left some gaps that needed to be filled so I paid a lot more attention*", "*it (halfway-back) is more engaging and allows for an emotionally-driven 'where have you come from, where will you go' approach, rather than just linear reportage.*" Also, anachronies such as 4 recurrence, and 6 anchor were appreciated for helping strengthen the memory or forcing intensive reading: "*it was interesting being reminded of the first and last parts of the story (recurrence), as it was almost like a summary that showed how far the characters have come*", "*surprisingly story three (anchor) was the easiest to remember as it focused on the initial incident, and then worked backwards, and then forwards, made me think a bit harder to try and remember the order of events.*"

Personal Variance. We also found that people's acceptance level of anachronies varies. While some participants appreciated simplicity and intuitiveness (e.g., "*I like starting in the middle to give me a taste of what's going to happen, but having most of the story be linear helps me understand what's going on*"), some participants looked for more twists in narratives (e.g., "*I was actually expecting something which jumped around a lot more*"). This may help explain why 6 anchor received the lowest score in likability but was still preferred by many participants: "*going in reverse from a point was really interesting and kept me wanting to find out more; then when it jumped back to the mid point I wanted to learn where it went; it had a small feeling of suspense to it which was really cool*", "*although this (anchor) was the most complex of the narratives in terms of narrative order, I felt like I was more engaged and interested in the story for the way it worked backwards before then skipping forwards.*"

In summary, although the recall scores differed slightly between the six patterns, we could not find evidence to fully support **H1**. Second, we observed statistically significant differences in some user engagement metrics between chronology and anachronies as well as between the six narrative order patterns. Besides, anachronies generally earned higher mean scores in user engagement metrics, thus confirming **H2**. Last, by analyzing the grid data, we found that while patterns such as chronology were controversial in expressiveness, some nonlinear patterns were thought to be both comprehensive and expressive, thus confirming **H3**.

6 DISCUSSION

This section discusses the implications and opportunities arising from our study as well as limitations and future work.

6.1 Expressive Narrative Visualization

As early as narrative visualization was proposed, Segal and Heer [60] discussed user experience as a promising future research direction. But so far, we still know little about *what* people expect from data-driven storytelling and *how* to improve narrative expressiveness. This work tackles the *what* problem by conducting in-depth studies with both professional storytellers and the general audience to understand their needs. Their responses are quite consistent: people look for expressive data stories except for comprehensible data facts. They want the data narratives to be eloquent, emotion-laden, efficient, memorable, and novel. However, to assess these aspects, traditional measurements (e.g., accuracy and speed) are insufficient [58] and may overlook much useful information about user experience. Therefore, we claim that more user-centered measurements that respond to user experience should be incorporated into the evaluation of narrative visualization.

As for the *how* problem, we prove that for time-oriented stories, manipulating narrative linearity can help restructure the story, take the audience on varied journeys, and open up possibilities for expressive storytelling. In line with our initial supposition, the narrative orders used in data stories are more concise and less artistic than those in films or novels [29, 36]. The six narrative order patterns we identified more or less follow the chronological telling order and use little reverse chronology. However, we are excited to find that even a slight deviation from linearity (e.g., trace-back, trailer) can bring about different experiences to the audience and refresh the narratives. This result is also in line with the previous finding that human brains tend to prefer linear narratives, but can be engaged by a certain amount of disruption [22]. We believe this work is a step towards incorporating more storytelling elements from psychology, literature, and cinematography into expressive narrative visualization.

6.2 Layered Narrative Orders

While coding the corpus, we found that several samples had more nested and layered narrative orders than the six patterns we identified. For example, *A network of science: 150 years of Nature papers* [50] introduces the science paper network using trace-back as its grounded narrative order: starting from the present network, then going back to the beginning and continuing chronologically. However, when explaining the network evolution chronologically, the video flashbacks and flashforwards several times to show how the clusters of physics, biology, and genetics evolved respectively during certain periods. In this story, the intermediate winds in the narrative order are caused by hierarchical data (i.e., science and its sub-domains). In another case, when presenting a presentation about reducing child mortality [64], the storyteller first presents the data of African countries chronologically, then turns back to 1800 and shows the data of Sweden chronologically. This narrative shifts from time to time because the data has multiple series so that the storyteller chooses to present one series at a time.

The above findings imply that when data is hierarchical or multi-dimensional, the narrative order patterns we identified for manipulating linearity may be nested with transitions such as granularity, comparison, and spatial transitions [33], thus leading to more complex narrative sequences. Understanding the mechanism and effects of these combined narrative orders is challenging but can certainly take our knowledge of data narratives to the next level.

6.3 Implications for Future Tools

For tools that help create data-driven stories, determining narrative orders is a must. The six narrative orders as well as their story spines we identified have shed light on some archetypal structures or the basic templates of time-oriented stories. Given such story templates, storytellers can create various stories more easily by fleshing them out, thus opening up great potential for generating expressive narrative visualization automatically or semi-automatically.

This study about anachronies also leads us to rethink stories' *transformation cost*, a concept describing narrative sequence effectiveness proposed by Hullman et al. [33]. According to [33], transformation cost is the total number of changes required to transform the state of visualization to another, and it should be minimized. So, for a time-oriented story, the most effective narrative sequence should be chronology. However, while such a way of generating narrative orders could guarantee story consistency, it may limit expressiveness. As suggested by our studies, instead of minimizing the transformation cost, people may intentionally add extra turns or jumps (i.e., bigger "cost") to the narrative order to vivify a story. Thus, we claim that future tools for narrative visualization should generate narrative sequences by taking story expressiveness into consideration. For example, the algorithm may be able to compute the possible climax or the tension underlying the data or enable users to appoint their communicative intent or desired amount of non-linearity [20], thus recommending optimal narrative orders.

6.4 Limitations and Future Work

Our analysis of the six narrative order patterns is based on a manually collected corpus of 80 time-oriented stories, which were intentionally diverse but are by no means exhaustive. Future studies can expand our corpus and examine additional samples targeted at a specific audience or industry. Second, due to the nature of controlled experiments, the factors we could investigate in the crowdsourcing study were limited. For example, we limited the data visualization to only timelines and examined only three different stories. To generalize our findings, future work could examine more data visualization types such as line charts and stream graphs as well as more data stories crafted based on various datasets, topics, and have different cognitive complexity.

We view this work as an initial step towards understanding the narrative linearity in time-oriented stories. To further take advantage of the power of ordering narratives, future research may look into more aspects such as how the narrative orders are nested and how to choose the best narrative order for a given dataset. Another interesting fact we found in our corpus is that when there is audio narration, most storytellers tend to use anachronies rather than chronological narratives. A possible reason is that audio narration provides the audience with additional information to follow the narratives, thus making more complex narrative order acceptable. Therefore, how narrative orders can be influenced or supported by multimedia factors such as audio narration and visual cues is another potential research avenue.

7 CONCLUSION

This paper introduces the idea of narrative linearity into narrative visualization and investigates how different narrative orders affect expressive time-oriented storytelling. First, we conducted preliminary interviews with seven experts from data journalism to gain insights into the motivations and challenges of manipulating narrative linearity. Then, we manually collected and analyzed a corpus of 80 time-oriented stories, through which we identified six most salient narrative order patterns. Next, we conducted a crowdsourcing study with 221 participants to evaluate and compare the six patterns in terms of increasing story expressiveness. Results suggested that anachronies (trace-back, trailer, and halfway-back, especially) have the potential to increase user engagement and lead to expressive storytelling without hindering comprehension. We consider our work as the first step in examining narrative visualization through the lens of narrative linearity. We hope that our findings can advance the body of knowledge on what makes an expressive data-driven story as well as inform the design of authoring tools to craft compelling data narratives.

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