Data Videos:

Turning Data into Engaging Narratives

By

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DEDICATED TO MY FAMILY.

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Portions of Chapter 1,2 & Majority of Chapter 3

Fereshteh Amini, Nathalie Henry Riche, Bongshin Lee, Christophe Hurter, and Pourang Irani. Understanding data videos: Looking at narrative visualization through the cinematography lens. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 1459–1468. ACM Press, 2015.

Portions of Chapter 1,2 & Majority of Chapter 4

Fereshteh Amini, Nathalie Henry Riche, Bongshin Lee, Andres Monroy-Hernandez, and Pourang Irani. Authoring data-driven videos with dataclips. *IEEE transactions on visualization and computer graphics*, 23 (1): 501–510, 2017.

Portions of Chapter 2,5

Fereshteh Amini, Mathew Brehmer, Gordon Boldun, Christina Elmer, and Benjamin Wiederkehr. Evaluating data-driven stories & storytelling tools, *chapter 11 of Data-Driven Storytelling book*. CRC Press, 2018.

Portions of Chapter 1,2 & Majority of Chapter 6

Fereshteh Amini, Nathalie Henry Riche, Bongshin Lee, Jason Leboe-McGowan, and Pourang Irani. Hooked on data videos: assessing the effect of animation and pictographs on viewer engagement. In *Proceedings of the 2018 International Conference on Advanced Visual Interfaces*, page 21. ACM, 2018.

ABSTRACT

Communicating data-driven insights typically through narrative visualizations is gaining increasing popularity in both practice and academia. Data videos identified as one of the main genres of narrative visualization are short motion graphics that incorporate visualizations about facts. Their unique characteristics make them a great candidate for telling compelling data stories to a broad audience. However, very little is systematically recorded about what elements are featured in data videos, the processes used to create them and what features make data videos effective. As a result, the solutions available to facilitate crafting these videos and taking advantage of their storytelling power are scarce and demand much needed attention from the research community. To this aim, in this thesis work, I present a series of exploratory studies to shed light on data videos, their constituent components, and creation process. Based on the lessons learned from these studies, I have designed and developed, DataClips, a web-based authoring tool to consolidate the creation of data videos by lowering the skill level required to create data videos using common data visualizations and animations. To apply the resulting data video authoring solution, I demonstrate use cases in which effective communication of the data insights to a broad audience is of significant importance. Through a large-scale online study, I have tested different design features of data videos to find answers to basic questions regarding their effectiveness. In particular, I have assessed the effects of animation, pictographs and icon-based visualizations on viewer engagement and preference in comprehending the communicated information. The results provide design implications for authoring effective data videos by maximizing viewer engagement and comprehension.

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"The idea is to go from data to information to understanding."

Hans Rosling

1 INTRODUCTION

Hans Rosling's talks on human development trends (Figure 1), supplemented by the data-visualization tool, GapMinder [118], are great examples of the practical power that visualizations can have in communicating data-driven facts and opinions. Journalists

Figure 1. The late Hans Rosling, professor of international health, telling a data story about child mortality rates over the years.

working for leading media outlets such as the New York Times [9] and the Guardian [5] as well as data enthusiast [4] are increasingly exposing the general public to stories with visual depictions of data, or narrative visualizations [20, 27]. The is due to the growing need to communicate complex data to broad audiences, which has led to the emergence of *data-driven storytelling*.

Storytelling, or narrative communication, has been integral to human civilization throughout recorded history. In science and academia, storytelling has been less prominent, as communication in these areas has traditionally been more objective, with less of a reliance on narrative structure. Kosara and Mackinlay [94] point out that the natural progression of moving from exploration, to analysis, to presentation highlights the need for more research work focusing on presentation and storytelling in the visualization of information. In short, the information visualization community has started recognizing the power of storytelling as an effective way of using data visualization to convey insights otherwise hidden in the data [73, 101, 136].

Lee et al. [97] take a closer look at data storytelling pipeline (Figure 2) and identify

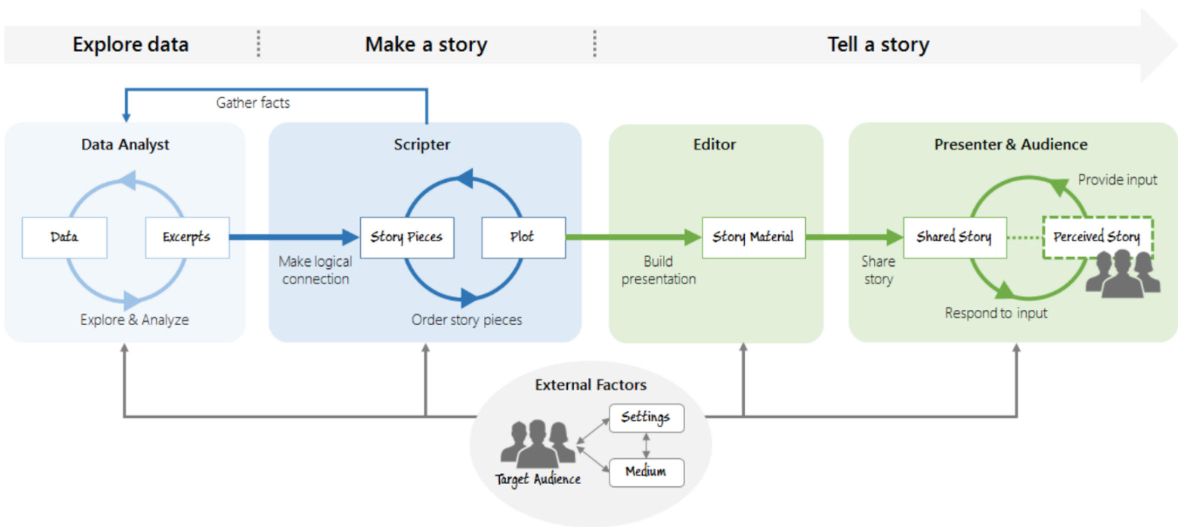

Figure 2. Storytelling process: transforming data into visual stories [97].

the steps needed to be taken in each phase from data analysis to sharing a final story. The first phase in the process of data storytelling involves exploring and making sense of the data (i.e., *finding story* pieces) which can be done using visual analytics tools to facilitate the harnessing of interesting insights from data. These insights are further used as story pieces in the *"making story"* phase. However, constructing data stories *goes beyond simply organizing data visualizations in a sequence* and requires a myriad of interdependent decisions about the selection and interplay of the constructing components depending on the genre and medium. Segel and Heer [123] have studied a corpus of more than 70 narrative visualizations to identify the range of visual and narrative components used in different genres of narrative visualization to tell stories with data. Film, animation, and video-based data stories are recognized among the seven genres of narrative visualization.

In this thesis work, I focus on using video as a powerful medium to tell stories with data. Short data-driven motion graphics, also known as *Data Videos* [32], combine both visual and auditory stimuli to promote a data story and are gaining popularity among leading media outlets such as the New York Times and the Guardian (e.g., [17]). I argue that data videos can be highly impactful due to the diverse forms of narrative structures and the wide range of visuals data videos expose an audience to, within a short presentation time, making them a particularly interesting form of narrative visualization to study. Moreover, despite the great potential that data videos can offer, little knowledge is available about their constituent characteristics such as types of content, narrative structures, attention cues, etc. Such knowledge can be instrumental in allowing a broader audience to design and craft data videos.

My research objective is twofold, first, I aim at investigating the design aspects of data videos, which will provide the understanding required to achieve my second goal to support authoring of engaging narratives to communicate data insights to broad audiences. The first part of my research is centered around understanding data videos and a basis for developing novel tools geared towards generating compelling data stories using this medium. As empirical knowledge can be the cornerstone for early design implications [11], I attain my goals with two exploratory studies. In a first exploration, I identify the high-level narrative structures found in professionally created data videos and expose their key components. I carry out a qualitative examination of the narrative structures in 50 professional data videos collected from a range of reputable sources through the lens of established disciplines such as film theory and cinematography [63, 71]. My findings are structured around the four narrative categories classically used in comics and cinematography: Establisher, Initial, Peak, and Release [63, 107]. I report on the different types of narrative structures formed by the sequencing of these categories and characterize the videos' contents through the varied types of data visualizations, and attention cues used.

Furthermore, to gain an understanding of the various strategies used in the *process* of creating visual narratives, I observed professional storytellers create storyboards from data and visualizations I provided them. I gain valuable insights through a series of workshops I conducted with experienced storytellers, such as screenwriters, video makers, and motion graphics designers. I describe my observations on the most common processes they employ to build a narrative structure and their consultations for making their video storyboards visually compelling.

I learned that crafting data videos is not an easy task. It requires a significant amount of time and effort, a broad set of skills, dedicated software or programming capabilities, and often involves a plethora of tools. For example, the creation process for a data video [22] can span several days, involving people with different backgrounds (such as a data analyst generating the data and insights, a scripter crafting the narrative, along with designers and motion graphics professionals generating the video material), each of which may hinge on one or more specific software tools [75]. A main goal of this thesis work is to consolidate the creation of data videos through the major use of one tool, DataClips, and by lowering the skill level required to create data videos using common data visualizations and animations.

In chapter 4 of this thesis, I build on the results of my initial study and take a step further to examine elemental video sequences of data videos composed using animated visualizations and infographics. I refer to these elemental units or building blocks of a data video as data-driven clips. My examination of over 70 professionally crafted data videos reveals the presence of seven major types of data clips across all videos. This led to the development of *DataClips*— a web-based tool allowing data enthusiasts to compose, edit, and assemble data clips to produce a data video without possessing programming skills. I demonstrate that DataClips covers a wide range of data videos contained in my corpus, albeit limiting the level of customization of the visuals and animations. I also report on a qualitative user study with 12 participants comparing DataClips to Adobe Illustrator/After Effects software, commonly used to create data videos. Non-experts in motion graphics could create a larger number of data videos than those with expertise using the commercial tool, and with no loss in data video quality.

While I aim to facilitate crafting narrative visualizations, it is also important to assess if a crafted narrative visualization is of high-quality. However, commonly used performance metrics such as task completion time and accuracy or similarly, other evaluations methods such as insight-based evaluation or longitudinal studies are not directly applicable. Therefore, new metrics and methods are necessary for effectively structuring the evaluation of narrative visualizations. In chapter 5 of this thesis, I investigate and reflect on multiple aspects that I believe are important when assessing narrative visualizations and their quality. I reveal how evaluation of narrative visualization can assume many forms beyond classic experimentation, and that evaluation is not solely within the purview of researchers.

To assess the quality of data videos, I focus on the ability to engage, understand and retain information from the communicated insights. Data videos heavily rely on data visualizations, and various creative design techniques are incorporated into the visualizations to engage the viewers and sustain their attention [32]. Designers often use animation techniques to attract viewers' attention and keep them engaged [61]. In addition, icon-based and pictographic representations commonly replace standard charts in data videos to elicit viewers' engagement through personification of otherwise abstract data. However, the effect of these design strategies on viewer engagement and communication of the data has rarely been explored.

Although visual designers have been incorporating animation and pictographic representations to make visualizations more compelling [60, 68, 83], researchers have drawn contradictory conclusions regarding their effectiveness. While there is strong intuition about the usefulness of motion to communicate [70], studies have shown that animation can be distracting and challenging to interpret [117]. Similarly, researchers have argued that pictographs and icon-based representations may distract from the data itself, merely contributing to an accumulation of "chart junk" [132]. On the other hand, empirical work has shown that including pictures and illustrations in data visualizations positively affects memorability [43] and can lead to better recall [47]. More recently, Haroz et al. [78] have distinguished visual embellishments from pictographs representing data and have concluded that only the latter can be beneficial by enticing people to inspect visualizations more closely.

In addition to the lack of consensus on the effects of animation and pictographs, findings from the literature are not directly applicable to data videos. Moreover, their effects have not been tested on viewer engagement, an important factor determining the effectiveness and impact of a narrative visualization [102]. I have composed a scale-based questionnaire covering five factors impacting viewer engagement in data videos: (1) affective involvement, (2) enjoyment, (3) aesthetics, (4) focused attention, and (5) cognitive involvement. Focusing on pictographs and animations to setup and create a visualization scene, I used my questionnaire and conducted a series of studies through the Amazon's Mechanical Turk platform. The results suggest that, although both animation and pictographic representations can elicit viewer engagement, they do so through different facets of viewer engagement. The results reveal a possible interaction role for congruent combinations of pictographs and setup animation in stimulating viewer engagement and viewer comprehension of the communicated insights.

Figure 3. Thesis Overview.

An overview of the research path followed in this dissertation, from the initial studies around understanding data-driven videos to facilitating the authoring of data-driven videos and finally surveying possible approaches to evaluation of such videos and conducting studies to evaluate engagement and comprehension in data videos.

1.1 Research Objective and Contributions

The primary research objective of this thesis is as follows:

Investigate the design aspects of data videos and support authoring of engaging narratives to communicate data insights to broad audiences.

Figure 3 outlines the research path towards the final objective. This thesis makes several contributions to the research community, as follows:

1. An exposition of the common narrative structures and visual components in data videos through qualitative examination of 50 professionally crafted data videos.
2. Insights gathered from workshops with experienced storytellers on the storyboarding process to create engaging data videos as well as a discussion on the broad implications for the design of data video authoring tools.
3. *DataClips*, a web-based authoring tool to consolidate the creation of data videos by lowering the skill level required to create data videos using common data visualizations and animations.
4. A taxonomy of data-driven clips and a comparative demonstration showing the ability to create and sequence data clips in an efficient manner.
5. An outline of different metrics, methods, and constraints for evaluating data-driven stories and storytelling tools and the development of an easy-to-use engagement scale to assess viewer engagement in data videos.
6. An empirical study, assessing the effects of setup animation and pictographs on viewer engagement, and guidance for the design of engaging data videos.

2 BACKGROUND & RELATED WORK

There are several different research areas related to this thesis, which build upon prior work in visualization, human-computer interaction, computer graphics, and multi-media communication. In this section, I distinguish between specific areas in these domains to present a summary of literature work that has influenced my thesis.

2.1 Visualization for Communication

A common belief in the visualization community with regards to visualization design is that visual representations avoid unnecessary decoration as much as possible [132] to maximize the data-ink ratio. Most visualization systems today follow this principle to inform perceptually effective visual encodings of data [62, 79, 130]. It is only recently that researchers have started exploring other aspects of visualization design such as memorability [47, 48], aesthetics [110], and engagement [50, 80]. These metrics are related to communication and presentation, rather than data exploration and analysis. Recent studies have examined the benefits of visual embellishments on comprehension and recall [43, 46, 78, 85].

Although visual embellishments can have a negative impact on visual search time [46] or certain analytic tasks [127], it is now generally understood that embellishment is not equivalent to chart junk. Judiciously embellished visual representations can help to engage the audience and communicate data in a manner that makes it easier to remember and recall. As a result, novel presentation-oriented visualization techniques [93, 128] that are beginning to find applications in visual storytelling [94, 96], are enjoying active and renewed development. In this thesis, I aim at investigating and providing appropriate tools and techniques to facilitate the design and authoring of engaging visualizations to communicate insights extracted from data.

2.2 Data Storytelling

While using data visualizations as a means to "show and explain" is not a recent topic [12], storytelling with data has recently begun to gain more attention in the research community [73, 101, 136]. Previous studies have investigated the roles of visualizations in data stories [73, 84, 123] and different data storytelling genres including animations [117], annotation [114], and data comics [37-39]. In particular, the spread of infographics to a wide audience and the development of fields like data journalism has created unique opportunities for research in information visualization [94].

Constructing data stories goes beyond simply organizing data visualizations in a sequence and requires a myriad of interdependent decisions regarding the interplay of disparate components. Hullman et al. [87] state, "*Story creation involves sequential processes of context definition, information selection, modality selection, and choosing an order to effectively convey the intended narrative*". Shapiro [125] explains that creating an effective story using data visualization usually starts with a question, followed by finding or creating proper visual representations of the data ([122]) in an effort to answer the question and contextualize viewer in a manner which ensures the data is meaningful. Furthermore, Gershon and Page [73] present storytelling techniques that can be used together with the proper visual representation required to communicate data narratives. These techniques include setting mood and place in time, improving continuity, filling gaps, resolving ambiguity (e.g. zooming and panning), increasing attention (e.g., highlighting), and reducing redundant messaging, each of which imply different types of components depending on the genre and medium. In this thesis work, I study data storytelling by focusing on video-based storytelling.

Storytelling & Visual Analytics

Thomas et al. [131] recognize techniques which support the production, presentation, and dissemination of analytical results as integral to visual analytics, and the communication of of properly contextualized information to a variety of audiences. While the task of analysis itself is the main focus of a visual analytics solution, there is little done to bridge the gap between analysis and the presentation of the results. The last step in any data-analysis cycle, is to take action based on the findings. In some application domains, failing to take the appropriate actions, in a timely manner could mean having to deal with the aftermath of a disaster.

Ideally, a data analyst can discover new insights from visualizations to ultimately communicate or convey a story about the data to its stakeholders. Recently, there has been an upsurge in transforming data insights into visual stories [97], through various perspectives [73, 94, 101]. A number of visual analytics systems have also integrated storytelling features in their design (e.g., in-place annotations in GeoTime Stories [67] , exporting selected graphical history states using Tableau Story Points [82], and highlighting and annotating bookmarked visualizations in ManyEyes [134]). However, how to support creating rich and diverse stories based on data insights gathered through visual analytics systems is still an open question.

Video-Based Storytelling

Video-based storytelling media is also referred to as "annotated videos" and/or "multimedia presentations" [109], and is an active research topic. Authoring a video-based story involves developing a narrative using a collection of media assets and added annotations. Bulterman and Hardman [56] identify key authoring problems which should be addressed when designing an authoring environment for video-based stories. I argue that a similar paradigm can be extended and considered for authoring data videos.

Shen et al. [126] have developed a video-based authoring system that suggests candidates for the "next scene" based on semantic relationships between scenes. Similarly, video story creation tools for non-experts, such as iMovie Trailers [7] and Animoto [88], provide templates that help novice video editors follow a fixed narrative structure and arrange captured content. However, these tools rely on users to decide the appropriate types of story elements and how to best include them in their stories. To eliminate this burden from authors, as part of this thesis work, I build an authoring tool, DataClips, based on the concept of predefined story abstractions within a library of data-driven clips, thereby allowing non-experts to rapidly generate a variety of data stories.

2.3 Narrative Visualization

Segel and Heer [123] coined the term "narrative visualization" to refer to visual data stories as a result of the growing research interest in the study of storytelling techniques for creating more engaging and compelling data stories or *narrative visualizations*. Furthermore, they conducted a design-space analysis of 58 narrative visualizations. By separating visual and narrative design dimensions, the authors break-down different components and tactics for each genre. Film and video-based data stories (e.g., data videos) are recognized among the seven genres of narrative visualization. However, only four sample narrative visualizations in the video and film genre were included, making it difficult to draw general conclusions from the findings, for use in data videos.

More focused studies of narrative visualizations have explored specific genres or aspects of narrative visualizations. Bateman et al. [43] and Borkin et al. [47, 48] focused specifically on understanding infographics and what makes them appealing or memorable to a large audience. Hullman et al. [84] discussed categories of rhetorical techniques affecting reader interpretation, drawn from an online journalism corpus. Researchers have also looked at methods of sequencing [87] and transitioning between[40] elements in a narrative visualization.

While previous studies have deepened our knowledge on the composition of narrative visualizations and identifying what makes them compelling or memorable, larger body of knowledge on narrative visualizations is required to characterize their key components and structures. This is especially true in the case of data videos where related work is even more scarce. Such knowledge will inform the design of tools that would help a wide range of people consume and craft stories with data videos. In this thesis, I aim to study the data-video creation process and design an authoring tool that enables the creation of the necessary components, which allow the crafting of a range of compelling data-driven videos.

2.4 Narrative Structure in Videos

Structuralist theory of film has proposed that film narrative is composed of two parts: story and discourse [45, 59]. The story refers to the events, actions, setting, and characters that closely concern the plot. The discourse answers the question of "How is the story told?", involving aspects of style, mode(s) of presentation, the arrangement of story events temporally. Analyses of visual narratives such as comic strips suggest that viewers construct logical and emotional links between frames as well as structural narrative arcs over the entire sequence [42, 63, 69]. In well-structured sequences, the viewer is found to have the capacity to identify large sections of plot elements (also known as "narrative categories") [63].

Visual Narrative Grammar (VNG) posits that, analogous to the way that sequential words take on grammatical roles that embed within a constituent structure in sentences, sequential images take on narrative roles that embed within a constituent structure in visual narratives [63]. This is similar to previous "grammatical" approaches to narrative and discourse, such as the story grammars from the 1970s (e.g., [103]), yet these models differ in important ways (see [63], for more details). Cohn [64] argues that narrative grammar uses a similar structural architecture as syntax, and these constructs are believed to operate in comprehension similar to the processing of syntactic representations. VNG uses basic narrative categories to organize sequences, which I adapt in this thesis:

1. **Establisher (E):** sequences that "provide referential information without engaging them in the actions or events of a narrative."

2. **Initial (I):** sequences that “set the action or event in motion.”
3. **Peak (P):** sequences where “the most important things happen; the culmination of an event or the confluence of numerous events.”
4. **Release (R):** sequences that show “the aftermath of the Peak.”

Narrative structure represents the structural framework that underlies the order and manner in which these narrative categories are presented to a reader, listener, or viewer. In this thesis work, I apply the concept of narrative structures to data videos, which might lack the fictional drama that is the core to fiction movies and dramas. As such, I borrow from the conventional ideas of narrative structures to identify different narrative structure applicable to data videos. Through studies of sample data videos, I have found that data videos have prominent narrative structure patterns that can be framed using Cohn’s narrative categories.

2.5 Authoring Narrative Visualizations

The widespread adoption of infographics in fields such as data journalism has motivated researchers to investigate ways for making it easy to author narrative visualizations. One approach involves automatically generating explanatory visualizations from data [72, 86, 90]. This is made possible by tailoring the algorithm to a specific data visualization type or dataset. In addition, the storytelling elements of the generated narrative visualizations are limited to annotations overplayed on top of data visualizations, thus consequently not allowing for a rich data story.

Most existing visualization tools allow for the production of one visualization at a time, making it difficult to design a comprehensive narrative. Recent research has examined the integration of communicative visualization within a linear narrative sequence [87]. This research is reflected in another category of tools that focus on sequence and narration. This category includes commercial tools including Tableau's Story Points [28] and Bookmarks for Microsoft's Power BI [27], which provide interfaces for composing a sequence of story points with embedded visualizations. Meanwhile, tools emerging from the research community aim for greater expressivity. Examples include: Timeline Storyteller [52], which augment a sequence of visualizations with annotations and state-based scene transitions; Vistories [76], which leverages the interaction history produced during data exploration to automatically generate a sequence that can be curated and annotated into a presentable story. To support diverse data stories and to lower the barriers for creating narrative visualizations, Satyanarayan and Heer [121] introduced Ellipsis, based on a set of abstractions for storytelling with data visualizations. The graphical user interface (GUI) of Ellipsis allows users to import data visualizations and add storytelling elements to create multiple scenes. However, similar to existing solutions for auto-generation of narrative visualizations, the storytelling abstractions are limited and require fine-grained manipulation of available parameters. Additionally, Ellipsis requires that authors have expertise with JavaScript programming, making it hard for non-programmers to use.

In each of these tools, a set of annotated visualizations are arranged in a linear narrative sequence revealed one at a time via stepping or scrolling interactions [108]. The data comics editor by Zhao and Elmqvist [138], allows for the composition of linear slideshow comics and the embellishment of visualization with speech bubbles and a narrator character. However, like illustration software, this tool requires the importation of pre-existing visualization generated by other tools. In contrast DataToon [92] provides a visualization and narrative design tool where multiple panels can be arranged freely on a page. However, providing such flexibility and an all-in-one authoring experience, can result in increased complexity of the tool.

In this thesis, I aim at striking a balance between ease of use and providing flexibility to create a wide range of data stories.

2.6 Evaluating Narrative Visualization

The information visualization community has established a set of empirical methods to evaluate interactive visualizations [58]. Most of these techniques have been used to study how users explore their data with visualizations, attempting to understand what makes an exploratory system or a given visual representation effective for which task or type of data. Thus, the community has put an emphasis on the readability aspect of visual representations, using metrics such as answer accuracy, task completion time, and/or number of insights discovered.

The body of related literature includes considerably fewer works attempting to evaluate the communicative power of visualization. The existing studies have not focused on the readability of these visualizations, but rather their memorability. Memory refers to the faculty by which things are remembered; the capacity for retaining, perpetuating, or reviving the thought of things past according to the Oxford English Dictionary [30]. A good visualization technique engages the viewer's attention and increases the story's memorability [87].

Bateman et al. [43] studied the embellishments added to static visualizations, attempting to capture their advantages and drawbacks. The result of their study suggests that these embellishments may increase the memorability of a chart without significantly altering their readability. Saket et al. [119] illustrate that map-based visualization can improve the accuracy of recalled data, compared with node-link visualization. Borkin et al. [47] developed an online memorability study using over 2000 static visualizations to determine which visualization types and attributes are most memorable. This study tackled the memorability aspects of infographics attempting to understand the factors that are most memorable. The result in their memorability comparison test demonstrates that measures of memorability are reliability consistent, between individuals, for stimuli such as scenes, faces, and also visualizations, thus memorability is a generic principle with possibly similar generic, abstract features. Higher memorability scores were also positively correlated with visualizations containing pictograms, more color, low data-to-ink ratios, and high visual densities. Furthermore, infographics including recognizable symbols (such as a dinosaur icon) made these visual representations more memorable.

Moving beyond memorability, Borkin et al. [48], recently conducted a study to determine what components of a visualization attract attention, and what information is encoded into memory. In order to measure how visualizations are recognized and recalled, the authors take advantage of eye tracking data, as well as data generated by the participants, to describe the visualizations in question. The authors concluded that the memorability of a visualization is improved when the content can be memorized 'at-a-glance'. Furthermore, titles and text are key elements in a visualization and help recall the message and pictograms do not hinder the memory or understanding of a visualization. Redundancy facilitates visualization recall and understanding.

Another important research topic in evaluating narrative visualizations is viewer engagement. Mahyar et al. [102] address how prior research in different domains has attempted to define and measure user engagement. Mahyar et al. discuss existing frameworks for engagement from other related fields and propose a taxonomy based on previous frameworks for information visualization. Five levels of of user engagement in information visualization are presented:

1. Expose (Viewing): the user understands how to read and interact with the data.
2. Involve: the user interacts with the visualization and manipulates the data.
3. Analyze: the user analyzes the data, finds trends, and outliers.
4. Synthesize: the user is able to form and evaluate hypotheses.
5. Decide (Deriving Decisions): the user is able to make decisions and draw conclusions based on evaluations of different hypotheses.

Mahyar et al.'s work is based on the previous work of Bloom's taxonomy [31] and adapts it to information visualization. With respect to narrative visualizations and author-driven data storytelling, the focus in this thesis will be on the "expose" and "decide" levels to engage the audience through viewing and deriving decisions respectively. As part of this thesis work, I take a closer look at different factors involved when evaluating narrative visualizations and suggest evaluation metrics to capture them.

3 UNDERSTANDING DATA VIDEOS

Despite the great potential that data videos can offer, we know very little about their constituent characteristics to help create narratives using this medium. Such knowledge can be instrumental in allowing a broader audience to design and craft data videos. I consider this work as a first step toward understanding data videos and a basis for developing, in the future, novel tools geared towards generating compelling data stories using this medium.

As empirical knowledge can be the cornerstone for early design implications [51], I attain my goals with two exploratory studies. In a first exploration, I identify the high-level narrative structures found in professionally created data videos and expose their key components. I carry out a qualitative examination of the narrative structures in 50 professional data videos collected from a range of reputable sources through the lens of established disciplines such as film theory and cinematography [63, 71]. The findings are structured around the four narrative categories classically used in cinematography: Establisher, Initial, Peak, and Release [63, 71]. I report on the different types of narrative structures formed by the sequencing of these categories and characterize the videos' contents through the varied types of data visualizations, and attention cues used.

Furthermore, to gain an understanding of the various strategies used in the process of creating visual narratives, I observed professional storytellers create storyboards from data and visualizations I provided them. I gain valuable insights through a series of workshops I conducted with 13 experienced storytellers, such as screenwriters, video makers, and motion graphics designers. I describe my observations on the most common processes they employ to build a narrative structure and their consultations for making their video storyboards visually compelling.

3.1 Study1: Analysis of Data Videos

To better understand the content and structure of data videos, I conducted a qualitative analysis of 50 data videos from 8 reputable online sources. A complete list of the videos is included in a companion website [24] and Appendix A.

Methodology

Data Video Selection

To ensure videos collected have a good quality and likely to have been created by experienced professionals, I selected several from a range of reputable sources as well as those with a high number of views on YouTube.com and Vimeo.com. I collected data via online magazines, government and research center websites, graphic design company websites, and visualization blogs.

In addition, a data video had to meet the following three inclusion criteria to be added to the dataset: 1) it contains a core message and presents arguments supported by data; 2) it includes at least one data visualization; and 3) it follows a narrative format which refers to the spoken or written account of connected events given in a sequence [11].

Data Video Analysis

We conducted both open [74] and close [115] coding of the data. In the first phase, the lead researcher used an open-coding approach to characterize the content of 10 (20%) of the videos. Through the discussion of these codes among three researchers over three sessions, we selected two dimensions: types of "data visualizations" and "attention cues". Since our final code-set was composed of well-defined types such as bar charts and scatterplots for visualizations or animation and highlighting for attention cues, the lead researcher completed the coding on the remaining set.

In the second phase, I sought to characterize the Narrative Structure of data videos. Looking at this data through the cinematography lens [63], I opted to analyze the data around four main narrative categories: Establisher, Initial, Peak, and Release. I analyzed the type of content included. Two researchers independently coded five (10%) data videos and refined the coding until they had reached agreement on the segmentation of each sequence (at about 2 seconds precision) and their codes. The lead researcher completed the coding on the remaining videos.

Characterizing the Content of Data Videos

I describe the content of data videos along the two identified dimensions: Data Visualization Types and the types of Attention Cues.

Data Visualizations

In data videos, visual data representations are the primary means for conveying a story. Data videos I collected present a large amount of visuals in a short amount of time.

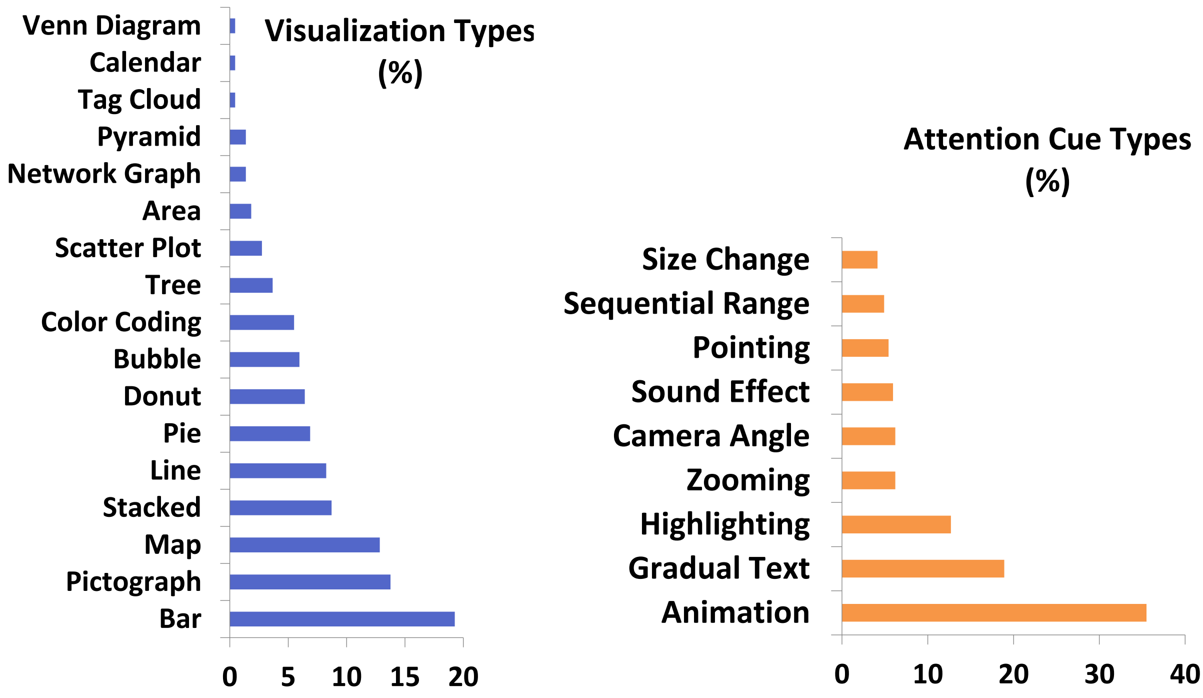

Figure 4. Percentage of visualization types (left), & attention cue types (right) coded.

While the average duration of a data video was found to be 3 minutes (ranging from 1 to 7.5 minutes), the average number of data visualizations presented is six (ranging from 1 to 19 visualizations). On average, 48% of the total duration of a data video is dedicated to data visualizations. However, despite this high content dedicated to visualizations, 72% of the data videos tend to rely on only 5 different types of visualizations on average (Figure 4-left). For example, more than half of the data video duration in [18] contains data visualizations but they are limited to only 3 types of representations (scatter plots, bar charts, and maps).

Attention Cues

One of the most important and unique design dimensions with regards to data videos are Attention Cues or tactics used to keep viewers engaged during the delivery of a story.

I identified nine major types of visual and auditory effects, aimed at drawing the viewer's attention. These include camera motion effects such as zooming, building tension in the story via soundtracks, and emphasizing salient information via gradual text appearance or highlighting (Figure 4-right). The top three most commonly used effects were animation, appearing/disappearing, and highlighting (e.g., the data video in [16]includes several attention cues). Surprisingly, I did not identify many cues specifically related to data visualizations except for animated sequential data presentation.

Characterizing the Narrative Structure of Data Videos

Narrative is defined as a spoken or written account of connected events [11]. The organization and ordering, in which these connected events are presented (i.e., the narrative structure) may greatly impact the understanding of the narrative and, in case of data videos, the viewing experience. In this section, I present the findings regarding the narrative structure of data videos. I analyzed them through the lens of the dramatic structure as initially defined by Freytag [71] and further refined for visual narratives by Cohn [63]. Below I describe different types of narrative structures encountered, and present findings regarding their content.

Narrative Structure and Categories

Following Cohn's theory of visual narrative structure, I split data videos into temporal sequences and coded these sequences regarding their role in the narrative. I used Cohn's definitions for the four major narrative categories:

1. *Establisher* (E): sequences that "provide referential information without engaging them in the actions or events of a narrative."

2. *Initial* (I): sequences that "set the action or event in motion."
3. *Peak* (P): sequences where "the most important things happen; the culmination of an event or the confluence of numerous events."
4. *Release* (R): sequences that show "the aftermath of the Peak."

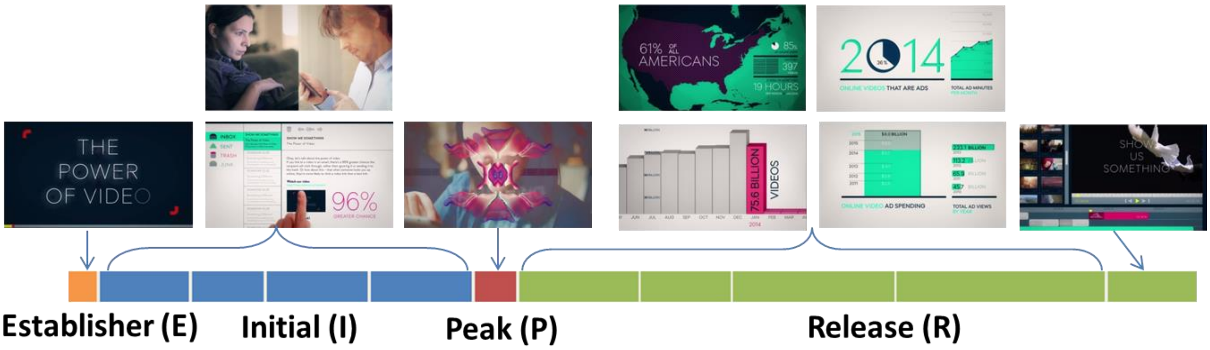

Figure 5. Coding of an example data video [21].

Screen captures from the video are associated with the corresponding narrative category. This data video is 2.07 minutes long and follows the (EI+PR+) narrative structure pattern; the combination of voice narration, video footage, data visualizations, and attention cues provides a balanced video with a powerful story about our evolving relationship with media. The Establisher unit sets up the video indicating that the video is about "the power of video", quickly transitioning to the Initial category that includes 4 units. The first 3 Initial units each include a new fact such as stats about the rising use of video. At the beginning of the forth Initial unit, the narrator asks "why video?" followed by footage of everyday people and by reflecting on the information already presented, builds the tension for the Peak unit that answers the question in one sentence. The Peak ends with drastic audio and animation effects to grab the viewer's attention. The video then continues by presenting more facts that supports the answer given in the Peak. This is done through 4 Release units, all of which include data visualizations (i.e., bar, pie, line, and stacked charts, and a map). Animated charts, highlighting a single bar in the bar chart, and sequential change of the year range are amongst attention cues used within the data visualizations. The fifth and last unit in the Release includes a take away message which asks the viewers to create videos: "Show Us Something".

As described by Cohn, I observed that data video categories are also hierarchical and can be further decomposed into units: sequences that put forward different points contributing to a single category. Figure 5 describes the coding of an example data video [21].

Narrative Structure Patterns

A given sequencing of categories and the number of units composing them form a narrative structure pattern. My analysis revealed many different patterns (Figure 6). Even though some are subsets of others, I show them to demonstrate variety. I labelled these patterns using regular expressions composed of narrative categories: [Element+] where Element is one of {E,I,P,R} and the "+" sign indicates repetition of the preceding element. Among these, three recurrent patterns emerged and I could loosely correlate them to the types of message they convey.

The most common pattern I identified in 34% of the videos is the "E+I+PR+" pattern. Videos following this pattern are usually well-balanced, solidly grounding their story with several units in Establisher (E+), building some tension with several units in Initial (I+) and leading to a single Peak (P), usually occurring around the middle of the

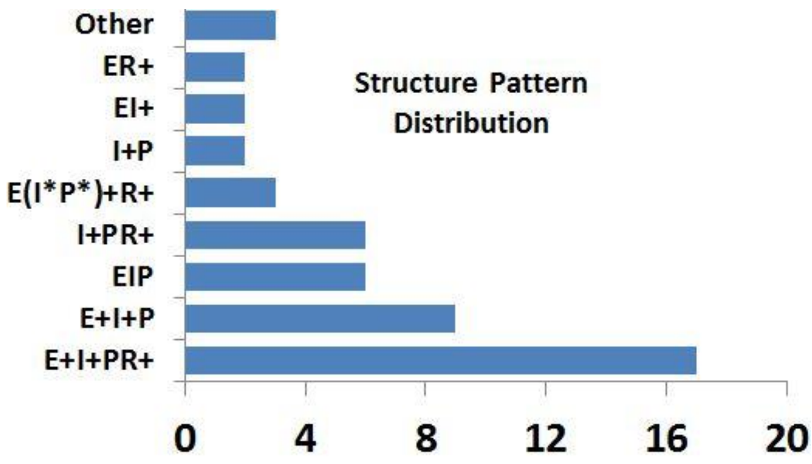

Figure 6. Distribution of narrative structures patterns.

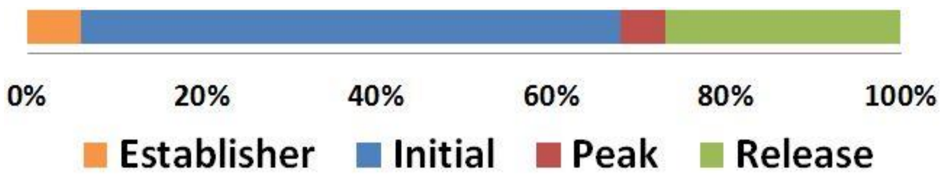

Figure 7. Average duration percentages of narrative categories out of the total duration of the video.

video. The multiple Release units (R+) ensure ample time for conveying the take away message.

Two other dominant patterns are "E+I+P" and its subset pattern of "EIP"; these structures contain a single Peak unit (P) without any Release units. Cohn [63] refers to this complex structure as the left-branching tree not commonly seen in comics. Data videos of this narrative structure finish the narrative by leaving the viewer with a "question" or "something to think about" after presenting some facts within the data (e.g., [17]).

I also observed structures that break away from the common pattern with an escalating tension followed by a single Peak [71]. First is "E(I*P*)+R+" which depicts data videos including multiple Peak units proceeded by multiple Initial units. The videos pertaining to this pattern are longer in duration when compared to other patterns and include alternative visualizations of the same aspect of the data or multiple new facts all having the same tension level. Two other surprising patterns are somewhat similar: "EI+" and "ER+," both of which do not contain a distinct Peak unit in the narrative structure. The data videos following these patterns present "multiple problems" or "multiple solutions," respectively.

Composition of Narrative Categories

To gain an overview of the relative importance of these categories, I report on the

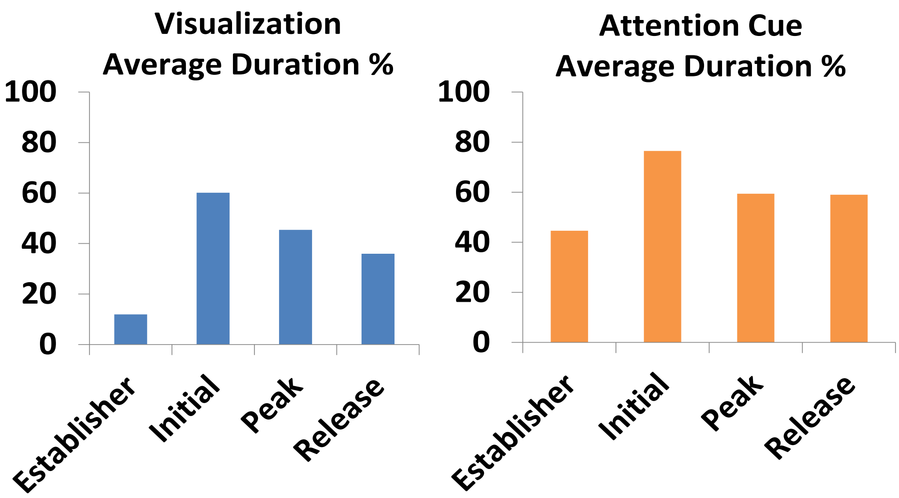

Figure 8. Left: the average duration percentage of data visualizations, and Right: the average duration percentage of attention cues out of total duration of each category.

proportion of average time devoted to each category as well as the proportion of data visualizations and attention cues in each of these.

I note that the Initial category is the most prominent in data videos (Figure 7) implying that the structures in the data videos break away from the traditional narrative structures in which the Initial category is shorter in duration stretching up to the middle of the narrative where the Peak is (e.g., Buster Keaton's silent film, the general [14], perfectly aligns with the traditional structure). Figure 8 shows that on average about 60% of the Initial category of units contain some type of data visualization. This finding suggests that data visualizations are used even for setting events in motion and not necessarily for only presenting closing facts, as might be the case when they are used in the Peak or Release categories of the narrative.

In addition, the proportion of attention cues in each category follows a distribution similar to data visualizations suggesting that they could be directly related and that data visualizations are usually accompanied by some type of attention cue to guide viewers' attention to the most interesting insight. Attention cues are also used when transitioning between narrative category units to guide viewers' attention from one scene to the other.

Figure 9 presents the duration distribution of different types of content for each category. As it can be expected, I observed that it is common to initiate the narrative with a question (20%), and conclude the narrative with a spoken or written take away message (30%). My analysis also revealed that data videos contain a large amount of repetitions: 46% of new facts are accompanied by a repetition. While it may be expected that these repetitions occur later in the video, a good proportion is present in the Initial category (22%). It is also worth noting that several videos introduce new facts in the Release or the last category of the narrative (27%). For example the video in Figure 5 includes new facts

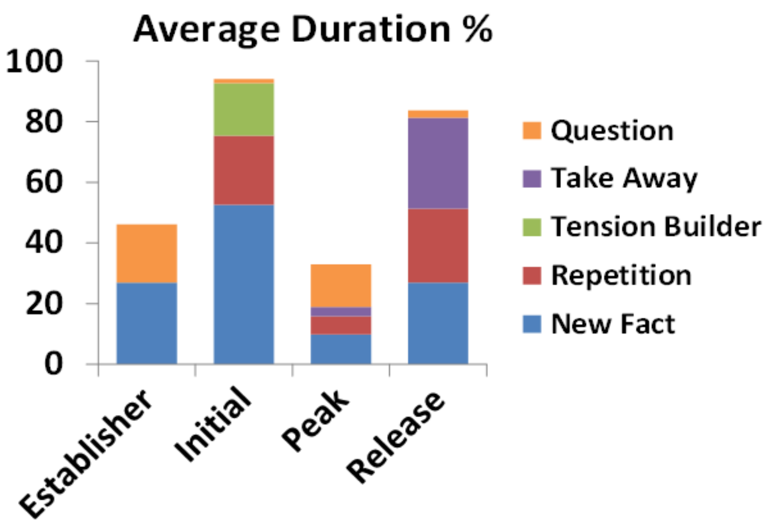

Figure 9. Duration distribution of different types of content.

Average percentages of new fact, question, and repetition occurrences in each narrative category.

in Release units as further evidence of the claim made in the peak.

3.2 Study2: Analysis of Storyboarding Process

Continuing my mission for understanding data videos and to complement findings from Study 1, I conducted a second study to gain insights on the process of creating data videos. I designed a series of workshops to observe how professional storytellers create data video storyboards.

Methodology

Participants

I recruited 13 experienced storytellers (5 female and 8 male, aged 27 to 65 years) for this study, asking them to create storyboards for data videos. I recruited participants with formal training and significant experience crafting stories for a wide audience through motion graphics with or without data visualizations (4 participants), cinematographic pieces including trailers, advertisements, TV series, and movies (5 participants), and other storytelling format such as screenplay, novels, comics, and infographics (4 participants). I conducted five sessions with pairs having the same background and three sessions with a single participant. Participants were unfamiliar with one another.

Study Material

I opted to provide all participants with a set of facts and visualizations to select from to create a data video storyboard. I selected data of general interest on marriage and divorce [10]. I hypothesized that such data could lead to polarized take away messages such as advocating for or against marriage, stimulating discussions between participants and possibly leading to different design or narrative structures.

Using the findings in Study 1 and four pilots with one pair and three single students in cinematography and human-computer interaction, I refined the facts and visualizations to use. I extracted a set of 12 different data facts covering several distinct topics in hopes of providing enough material for participants to create different stories. Examples of facts I provided are "the majority of divorces happen between ages 40 and 44", "the average duration of marriage before divorce is 10 years", "there are peaks in the number of divorces after world war 2 in 1945 and after the divorce reform act in 1971". To illustrate each of the facts, I used 22 data visualizations and infographics all of which were amongst the most common types found through the first study and extracted from blogs or news websites covering these stories such as the Guardian; or created from the raw data using Excel.

Procedure

I conducted 3-hour sessions including a 15 to 20 minutes break in the middle. I initiated the session with a presentation of the study and a collection of demographics. Participants watched two data videos and I presented a hand-drawn storyboard I created for one of them to illustrate the type of output I expected. To motivate them to create the most compelling data video, I told them they would enter a contest with other groups. The most compelling storyboard would win a prize.

An experimenter was present in the experimental room at all times, to introduce the data and later play the role of the data analyst, answering questions about data and visualizations. The experimenter instructed participants to build their story from the data given to them, not allowing them to search or make up new information. The experimenter also informed the participants that data visualizations were provided as

Figure 10. Example storyboarding session.

Two participants collaborating to construct their storyboard on paper.

examples only and they were encouraged to design or alter the visual representations to best fit their story. Participants built their storyboards on pen and paper, using pens, pencils, markers, rulers, scissors, and colored sticky notes (Figure 10). I asked them to provide enough details for us to create the actual video from the storyboard. I also instructed them to "think aloud" (if single) and video recorded the session. Finally, the experimenter conducted a semi-structured interview, asking participants to describe the video they envisioned from the storyboard, to comment on their design process, and gather their impression on the quality of their story. Participants received two software gratuities.

Session and Storyboard Analysis

I collected 10 storyboards and recorded over 24 hours of video from the eight storyboarding sessions I conducted. We analyzed videos of the sessions using an open-coding approach as well as the narrative structure codes from Study 1. Two researchers (who had observed and conducted sessions) developed two initial code-sets independently and reached to an agreement on a final code-set by iteratively coding 10% of the videos. Based on these codes, one researcher proceeded to code the remaining videos.

Figure 11. Example Storyboard (Royal Wedding UK).

The first panel features a video clip from William and Kate's royal wedding and voice over stating that marriage rates were about 49% in 2012. The next panel features a video clip from Charles and Diana's wedding, 20 years earlier with the voice overstating that marriage rates were 62% then. The third panel stars a bar chart, representing the trends in marriage rates over by different heights of wedding cakes. The fourth panel shows a cupcake representing the projected low rates 30 years from now. The final panel invites the viewer to turn this trend around, featuring an animation where cake layers are added below the cupcake.

Characterizing Storyboard Elements/Appearance

I collected a diverse set of storyboards, differing not only in their form but in their content and general intent. In this section, I report on key observations on their content. As an example of the artefacts I collected, Figure 11 shows a short storyboard (S10) calling viewers to action, such as collectively working toward reducing divorce rates.

Narrative Structure

I was generally surprised by the variety of stories that could be told with the same data. I gathered the intent and take away message during the final walkthrough and reported them in Table 1. All finished storyboards could be matched to narrative structure patterns I identified in study 1. For example, factual stories employed an EI+ narrative structure without any peak, but rather going over a subset of facts in order. In contrast, the storyboards building tension, or reflecting participants' viewpoints featured a peak towards the second third of the storyboard, utilizing E+I+P, one of the most common narrative structure pattern.

Strategies to Engage Viewers

As most storyboards I collected were not polished (due to time limitations), I do not report the detailed account on visual effects or animations used in them. However, I

Story Type	Storyboard Content
Factual (3)	**S1** & **S2**. Presents temporal trends in marriage and divorce rates **S3**. Presents temporal trends in marriage and divorce rates and speculate on reasons
Tension builders (2)	**S4**. Unveils only part of the trends then reveal recent changes. **S5**. "Are they going to divorce?". Sets up a married couple undergoing therapy.
View points (3)	**S6**. "Marriage is not inevitable". Advocates that lower marriage rates correspond to a positive societal change where unmarried people are better accepted. **S7**. "Marriages can still work out". Advocates that even if divorces are going up, there are marriages that last. **S10**. "Marriage rates are going down, let's turn this around".
Inciting Reflection (2)	**S8**. "Marriage is not about couples, it is about individuals". Demonstrate that higher divorce rates today from the fact that it is less advantageous for individuals to be married. **S9**. Advocates that in a world increasingly materialist, husbands and wives become disposable commodities, leading to higher divorce rates.

Table 1. Contents of 10 storyboards created by participants.

identified a recurring viewer engagement strategy: the degree of personification of the story. Participants in 4 sessions explicitly discussed introducing recurrent human figures or topic-related recognizable objects (e.g., wedding ring or cake) to raise the degree of personification of the video and help the viewer relate to the message and project themselves in the video. In fact, only 2 storyboards did not feature these elements; and for one of them the participant commented that she did not add human characters by lack of time. The remaining storyboards had varying personification degrees, from a few pictograms and icons to the integration of realistic objects or human acted video footage.

Characterizing the Storyboarding Process

Our analysis of the session videos revealed four main activities participants engaged with during the session. I first describe what these activities encompass and report my findings on their temporal sequencing.

Four Main Activities

The first category of activities I identified dealt with **reading and interpreting data** and the corresponding visualizations. As all participants had to do this before they start building their story (see green segments in Figure 12), it is not surprising that they dedicated the beginning of the session to these activities. Interestingly, in 3 out of 5 pairs, this task was mostly achieved by one participant while the other took notes or started composing a narrative structure.

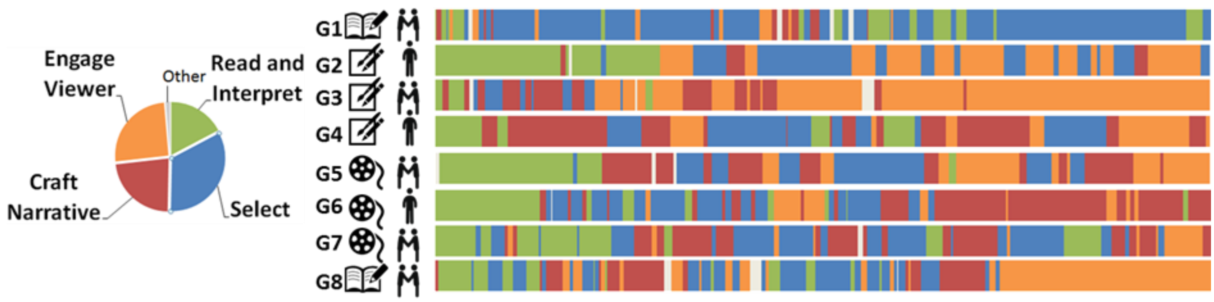

Figure 12. Storyboarding Activities.

The proportion of time spent on each storyboarding activity over all 8 session groups (G1-G8) (left). Temporal sequence of activities shown for 8 separate storyboarding workshop sessions each lasting about 3 hours (right). The icons indicate group vs. individual sessions and participant backgrounds (Writer, Graphic/Motion Graphic Designer, and Cinematographer).

The second category of activities I observed centered on **selecting data** and corresponding visualizations and physically grouping them into piles of interest (see blue segments in Figure 12). This process was closely coupled with the read and interpret process in 5 of the cases. Participants in 4 of the sessions made a first round of decisions on which information to use or to discard, even before discussing a general story line. For example, one participant referred to this process as “looking for inspiration for a story.” It is also interesting to note that a common criterion for selecting data visualizations was its complexity and the estimated low visual literacy of a broad audience. Two participants pointed out the need to “simplify and appeal to a very broad audience.” This finding correlates with my analysis of visualization types in study 1.

The third category of activities focused on discussing and **crafting the narrative structure** and the content of its different categories (see red segments in Figure 12). Amongst activities belonging to this category, about 30% of the time on average was dedicated to identifying the general theme, figuring out a logical flow and identifying meaningful connections between scenes. 49% of the time on average was devoted to identifying a Peak, the ending scene and discussing the take-away message. Most interesting discussions revolved around the creation of a rhythm in the video. Specifically, finding a good opening scene to hook the viewer and integrating salient points distributed throughout the video to keep the viewer watching until the end of the video were discussed in 7 sessions. Hooks people discussed dealt with posing questions that a general audience could have, identifying a controversial point or a statement contradictory to popular belief. Participants also discussed the need of several Peaks in the story, where important points are clearly stated, repeated or summarized.

Finally, a set of activities was dedicated **to integrating strategies to engage viewers** (see orange segments in Figure 12). Participants felt that it was crucial to include such strategies to avoid overwhelming the viewers with massive amounts of data referred to by one participant (G2) as "information dump". The line is sometimes blurred between activities for making the narrative structure more compelling and activities aiming at story material to engage viewers. In coding activities in this category, I focused exclusively on discussions and design of techniques that can be dissociated from the story content such as the addition of animation, sound effects or various visual effects. Groups with "graphic/motion graphic design" background spent significantly more time on this process (20 minutes more).

Non-Linear and Iterative Process

While participants devoted about the same amount of time for each set of activities overall (Figure 12-left), my detailed analysis of the activities during the sessions (Figure 12-right) confirmed that the creation process was **non-linear**. Participants in all eight sessions alternated between different set of activities. For example G3 (3rd sequence from top in Figure 12) closely coupled selecting data and crafting the narrative structure (blue and red segments) and later in the session alternated between crafting the narrative structure and integrating strategies to engage viewers (red and orange segments). I was surprised to observe some participants (e.g. G3) incorporating user engagement strategies early in the session, before having crafted an end-to-end narrative structure or even before deciding on a take-away message.

I also observed that the process was **iterative**. Participants may craft an end-to-end narrative structure with a first set of data and visualizations and iteratively add to their storyboard. This could either be done by selecting additional data visualization to expand on some points, or by altering the narrative structure to integrate elements to engage viewers. Semi-structured interviews at the end of the session revealed two types of iterative process. A writer in G1 explained that she works in waves, as she write novels: first crafting a logical flow from end-to-end, second reviewing this flow to extract the most exciting plot, adding and removing elements, third integrating engaging elements such as humor or recurring characters and fourth designing visual materials to provide a consistent feel. In contrast, a motion graphics designer in G3 explained that he would build a complete vision in his head, capture it through a rough draft and iterate on this draft to turn it into a product.

3.3 Design Implications

I summarize my main findings regarding common practices for data videos design and derive a set of implications for data video authoring tool for novices.

Data Video Content

Visualization types: It is not surprising that the designers of data videos heavily rely on data visualizations to present the facts within data (48% of the total duration on average). However, despite the viewers' general impression that data videos each feature diverse custom visualizations, most videos rely on only a few types of well-known visualizations (e.g. bar charts, pictographs, and maps).

Limiting novice designers to a small set of commonly used visualization types but giving them the flexibility to customize their rendering options and color palette would appear as a good strategy to enable the creation of data videos that may be comprehensible to a large audience. Along this line, one of the most powerfully customizable, yet easily understood visual representations is certainly the pictograph, composed of icons representing data units. While most visual analytics tools and commercial charting tools do not offer much support to create these visualizations, they are heavily present in data videos and certainly should feature in data video authoring software.

Whether an authoring tool should also support the creation of more advanced visual representations, or even help authors design their own custom visual encodings remains an open question. I believe that such direction could prove beneficial but would require assisting the author with creating an accompanying set of visuals and attention cues to help a general viewer correctly decode and understand the visualization. Further research is needed to understand how to preserve viewer engagement while respecting the general level of visual literacy as seen in our current day society.

Attention Cues: Attention cues are used throughout data videos to guide viewer attention, highlight specific parts of the data, or help a seamless transition between different aspects of data. While camera effects, highlighting, and text animations are commonly integrated in presentation software such as PowerPoint, data video authoring should also provide support for including voice narration and soundtrack which are present in almost all data videos I studied. Enabling authors to carefully time these different cues to support the narrative rather than obfuscating the facts poses a challenge. By guiding authors into using an explicit narrative structure for their videos, hints on the type, frequency and strength of attention cues they can use, based on concrete examples as from my sample list, can help authors achieve the right balance. I was also surprised that only few of these attention cues were tightly coupled with the data (mostly highlighting and filtering). Other cues such as gradually changing the layout or visual encoding according to different data attributes could enhance data videos with data-driven attention cues.

Engaging Viewers: My observations in both studies indicate that the audience is more engaged if facts told in the story relate to something they know. Observations from workshops hinted at several degrees of personification, such as including human figures or object icons, introducing recurring characters or human-acted video footages (e.g., initiating the video on marriage statistics by the video footage of the UK royal wedding in Figure 11). Supporting authors in finding such assets and enabling them to tightly couple them with visualizations (e.g., animating a pie chart into a wedding ring, using the wedding ring in a pictograph) would ease one of the most tedious part of visual editing. In addition, providing features to tie the video together, such as including recurring animated characters or objects (e.g., whiteboard sketching hand as in the VideoScribe software) could help create more engaging videos.

Narrative Structure

Narrative Categories: I believe that identifying different building blocks of a narrative (Establisher, Initial, Peak, and Release) could play a central role in a data video authoring tool. Making these building blocks explicit and suggesting the types of content commonly used in them, as well as their duration, could certainly streamline the process. In particular, I observed that authors of data videos generally include a small number of different facts about the data but tend to repeat these facts with alternate visualizations. Supporting authors in clearly identifying the data facts they introduce and providing features to ease the generation of repetitions of these facts with alternative representations would streamline the process. By providing statistics on common practices and making the video structure more explicit, authors may reflect on the video content they are creating and adjust the information density to their audience.

Narrative Structure: I observed that there are many different arrangements for the units composing the narrative. Thus, it seems important to provide flexible narrative structure, allowing authors to generate their own patterns. It would be also useful to provide sample templates based on our observations that guide the author through a selected narrative structure by making sure the right narrative units are defined and sequenced according to common practices. In particular, showcasing patterns that tend to be associated with different types of videos (e.g., “call-to-action” or “educational” videos) may guide authors in making well-structured videos for their intended messages. For example, a call-to-action could benefit from building tension through repeating several units of the Initial narrative category, concluding with a single Peak unit. Educational data videos, on the other hand, may have multiple Peak units for teaching about different aspects of the topic.

One-of-a-kind Data Video: There is a trade-off between encouraging novices to follow common practices and enabling them to create a one-of-a-kind engaging and memorable data video. I believe that a successful authoring tool will limit authors in some dimensions (e.g., types of visualizations, narrative categories) to ensure they create comprehensible narratives; while enabling them to customize other dimensions (e.g., visual rendering, narrative structure pattern) to create unique one-of-a-kind videos. In particular, I believe that suggesting alternatives at the right time of the video creation process can stimulate creativity by giving authors a glimpse of other possible choices. This could be achieved by incorporating video sample examples (by analogy to code examples in programming environments) to show a diverse set of designs and inspire authors.

Authoring Process

Non-linear and Iterative Process: I collected evidence that crafting data video storyboards is a non-linear process and requires going back to the data throughout the process. I expect it to be even more common if we enable end-users to create data video.

This process is also dependent on the authors' background and work practices. Some authors envision everything at once including the story, custom-made graphics, and animation while others build a logical flow with abstractions of the facts (e.g., outline notes, default visualizations, etc.), go back to add elements that will engage viewers, return to edit the visualizations, and finally take another iteration to dissociate the logical flow from the story plot and the story material. An authoring tool with storyboarding facilities based on rapid sketching may help in capturing the authors' initial vision and allow iterative refinement. Such a tool can also integrate features to enable authors to easily go back and forth between different storyboarding activities.

3.4 Discussion and Limitations

Findings from study 1 are reported from the analysis of a limited corpus of videos. While I believe results from study 1 are likely to generalize to other online data videos provided for the general public consumption, further studies are required to examine data videos designed for a specific audience or targeted to a specific discipline or industry. I expect that further research will expand this corpus and build on my findings.

I decided on several criteria to include data videos from the limited inventory of available videos online, such as number of views or rank in the search results. However, assessing their actual quality, whether or not they comply with best design practices, or the level of engagement of their audience remains an open research question. More research on audience reactions is needed to develop appropriate metrics for evaluating these data videos and their reception by the audience. A key challenge is that such evaluation metrics depend on factors such as intended message, audience background as well as accurate measures to capture engagement. Creating such metrics could help advance storytelling research and pursue exciting questions such as investigating most compelling narrative structures.

Considering study 2, I originally aimed at recruiting experienced designers of data videos. However, since data video storytelling is a relatively new phenomenon, recruiting enough participants specializing in this medium proved challenging. I broadened my selection criteria and recruited participants with formal training (i.e., having a degree or certificate) and significant experience creating stories with and without videos. I believe that triangulating the perspectives of these experienced “storytellers” with diverse backgrounds is still valuable to understand the creation process.

As with all laboratory studies there are tradeoffs in studying experts outside of their working environment in a relatively short period of time. While longitudinal studies with individuals in work settings may be necessary to deeply understand each step of the creation process, my goal was rather to gain an overview of design practices and understand if and how they may vary amongst different individuals or professions. Engaging with 13 of these experts over 3-hour sessions shed some light on the diversity and breadth in crafting storyboards and enabled us to derive a set of general implications for supporting the creation process of novices.

3.5 Summary

Data videos are a relatively new yet popular medium for storytelling with data. Our research community can benefit from in-depth studies that help to catalog our knowledge on this exciting medium. Such knowledge can also inform the design of tools to make it possible for a broader audience to craft compelling ones. This work is a step toward this goal. Through two exploratory studies, I advance the body of knowledge on what constitutes data videos as well as provide insights on the processes involved to create them. I first reported on the qualitative analysis of 50 data videos, extracting their most salient elements including types of visualizations and attention cues. I also examined their narrative structure and described the wide range of patterns used in data videos. Finally, I observed how experienced storytellers from cinematography and screenplay writing design storyboards for data videos and reported on their process. I concluded on a set of broader implications for the design of data video authoring tools to enable general users to create the necessary pieces. In the next section, I iteratively design a data video authoring tool to assist novice users in creating engaging data videos.

4 AUTHORING DATA-DRIVEN VIDEOS

The information visualization community has recently focused attention on empowering data analysts and data enthusiasts in communicating insights through data-driven stories [73, 94, 136]. A wealth of data-driven stories can now be found online, as journalists, working for media outlets such as The New York Times [9] and The Guardian [5], as well as data enthusiasts [4], craft custom narrative visualizations for broad audiences [123]. Short data-driven motion graphics, also known as data videos, which combine both visual and auditory stimuli to convey a story, have garnered renewed attention [32]. Endowed with desirable properties, such as having a short duration and engaging visual effects and animations, data videos are a promising medium for conveying a data-driven narrative.

Yet, crafting data videos is not an easy task. It requires a significant amount of time and effort, a broad set of skills, dedicated software or programming capabilities, and often involves a plethora of tools. For example, the creation process for a data video [22] can span several days, involving people with different backgrounds (such as a data analyst generating the data and insights, a scripter crafting the narrative, along with designers and motion graphics professionals generating the video material), each of which may hinge on one or more specific software tools [75]. The goal of this work is to consolidate the creation of data videos through the major use of one tool, DataClips, and by lowering the skill level required to create data videos using common data visualizations and animations.

As part of this thesis work, I [32] have explored the components and structure of a corpus of data videos, identifying different video sequences and how these sequences play in a narrative (i.e., establisher, initial, peak, and release). In this work, I take a step further and examine elemental video sequences of data videos composed using animated visualizations and infographics. I refer to these elemental units or building blocks of a data video as data-driven clips. The examination of over 70 professionally crafted data videos reveals the presence of seven major types of data clips across all videos. This led to the development of DataClips— a web-based tool allowing data enthusiasts to compose, edit, and assemble data clips to produce a data video without possessing programming skills. I demonstrate that DataClips covers a wide range of data videos contained in my corpus, albeit limiting the level of customization of the visuals and animations. I also report on a qualitative user study with 12 participants comparing DataClips to Adobe Illustrator/After Effects software, commonly used to create data videos. Non-experts in motion graphics could create a larger number of data videos than those with expertise using the commercial tool, and with no loss in data video quality.

To summarize, my contributions are threefold: (1) the DataClips tool; (2) a library of data-driven clips that can be easily extended with new clips; and (3) a demonstration showing the ability to create data clips in an efficient manner.

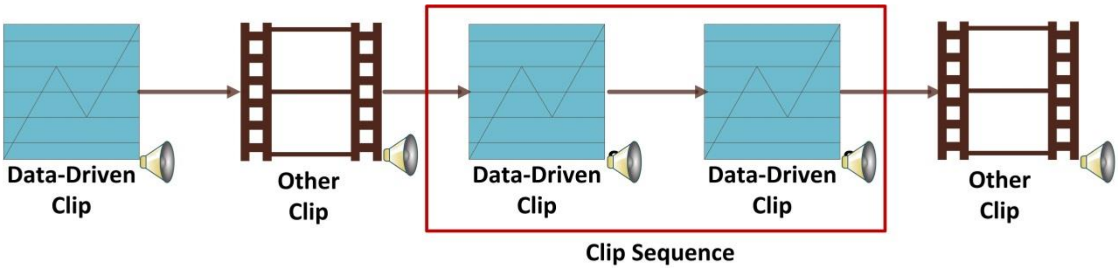

Figure 13. A typical data video structure.

A data video may contain a sequence of data-driven clips. It can also include other non-data-driven clips (e.g., video and image clips) as well as background music and/or voice overs.

4.1 DataClips

Motivations

The building blocks of data videos are individual data-driven video sequences, or data clips, each targeting a specific insight of the story conveyed by an animated visualization (Figure 13). Many data videos found online are produced by a dedicated department, e.g., The Guardian visuals [5], or crafted by an independent company. Through an informal interview with the directors of the company who has created several data videos [75] as well as data journalists at a Dagstuhl seminar on data-driven storytelling [25], I learned that one minute of data video, excluding data analysis and insights extraction, takes about a week's worth of work from a scripter and an experienced motion graphic designer. Iterating over the video material is costly as each sequence involves several hours of work using Adobe Illustrator [6] for the visual designs and After Effects [1] for the animations. Thus, a significant time is spent upfront on scripting and storyboarding; but iteration is often unavoidable as clients have trouble envisioning the final product without experiencing earlier versions. As design and animations are customized, updating a video with new data also requires a significant amount of time. While these comments may not be representative of the creation of all existing data videos, they give an idea of the overhead and skills required for their creation. I aim at lowering the barriers to authoring data videos, to help a wider audience to use this storytelling medium.

Usage Scenarios and Target Audience

I closely engaged with two professionals who communicate stories supported by data on a regular basis: Kate, an investigative journalist, and Matt, a finance manager. Both are experts in data analysis but have no expertise with programming or video editing. I met three times with them, gathering their usage scenarios, relevant data, and creating data videos included on the companion website [26] and Appendix B.

Figure 14. Example data-driven video generated by a data journalist using DataClips.

Snapshot images illustrate events and negotiations between the school board and the union's board of directors on the pay raise request by the teachers during a weeklong strike. The effect of these negotiations on the amount requested by the teachers and granted by the school board is showed in the video. The timeline of these events is shown using an annotation line chart clip coupled with an annotation bar chart clip (the two clips are repeated and sequenced to give transitioning effect between the line and bar chart). The last two creation pictograph clips show how long the strike lasted and how many days schools were closed as a result of the strike.

Rapid video prototyping tool: Kate works for a national news outlet. Her role is to find data and facts, and analyze them to craft news stories on a variety of topics. Kate finds data videos and animated visualizations effective for telling a data story to her TV Channel audience on its website or on social media. She rarely creates them herself, however, because they require a substantial amount of time and resources from a dedicated department in her company. She saw the greatest opportunities for an

Figure 15. Example data-driven video generated by a financial analysis using DataClips.

Snapshot images illustrate the con-tent of the video using 9 different clips: animated text, bar chart and line chart depicting the history of sales and salient events, pictograph and bar chart comparing production and sales, and unit pictograph, bar chart and donut chart illustrating sales during promotion.

authoring tool to support her (1) to quickly craft short data videos for informal breaking news to be shared on social media sites (Figure 14), and (2) as a prototyping tool to experiment with different narratives and ease communication with her graphics department when producing a high-end data video.

Data video clips authoring tool: Matt's role is to report on financial results and opportunities for a series of products. Matt spends about a fourth of his time compiling presentations to report to executives in the company. Matt found short animated visualizations (illustrating a single insight) the most compelling to "*bring dry and static charts to life*" in presentations and reports. He mentioned that dues to time constraints, he does not create such animations in Microsoft PowerPoint or other tools, especially as they are tedious to update (for each quarter and each product). Figure 15 shows clips created with DataClips based on Matt's data and insights to support a story of sales and the evolution of promotional events affecting the sales.

Design Considerations

Considering motivations and scenarios, I settled on four design considerations (DCs) for an authoring tool for non-programmers and non-video producers. The premise is that the author has already collected and analyzed data to extract a set of insights for the video.

(DC1) ***Lower the barrier for authoring data videos:*** I strive to strike a balance between predefined templates and customizable data-driven videos. My target audience includes those who have collected and explored their data but are unlikely to have the skills or time to master visual design skills or video editing software. While video templates (e.g., iMovie Trailers [7]) are easiest to create, they are unlikely to cover the wide range of stories people can tell with their data [32]. I propose to rely on a set of templates for short video clips that authors can populate with their data and sequence together.

(DC2) ***Emphasize pictographs.*** The use of pictographs or isotypes is heavily present in data videos [32]. Such icon-based data visualizations, reinforces data semantics, may require less interpretation time and increase story retention [43][78]. However, most editing tools [6] today only support manual graphical creation, leading to inaccurate visual encodings. My goal is to support the creation of accurate animated pictographs by generating them from data.

(DC3) ***Support data-driven attention cues.*** Attention cues and strategies are extensively used in data videos to engage viewers and guide their attention during the delivery of a story [32]. For example, it is common to progressively disclose annotations while highlighting related elements within a data visualization. I aim at supporting the creation of data-driven attention cues, enabling authors to import them along with the data, rather than adding them manually on a case-by-case basis. I also propose to include animated transitions between visualizations [81]. Such animated transitions are uncommon in data videos today as they are complicated to craft.

(DC4) ***One-of-a-kind data video.*** The first goal is to provide an authoring tool for novices with a reasonable level of customization: to easily create videos with a different look and feel. For example, rather than enabling users to select the animation timing and behavior of each individual element of a visualization (as PowerPoint does), I chose to enable users to have controlled timing for sets of elements (e.g. axes and bars in a bar chart). The architecture is modular: it allows advanced users, able to produce code, to easily extend the capabilities of the tool by adding clips.

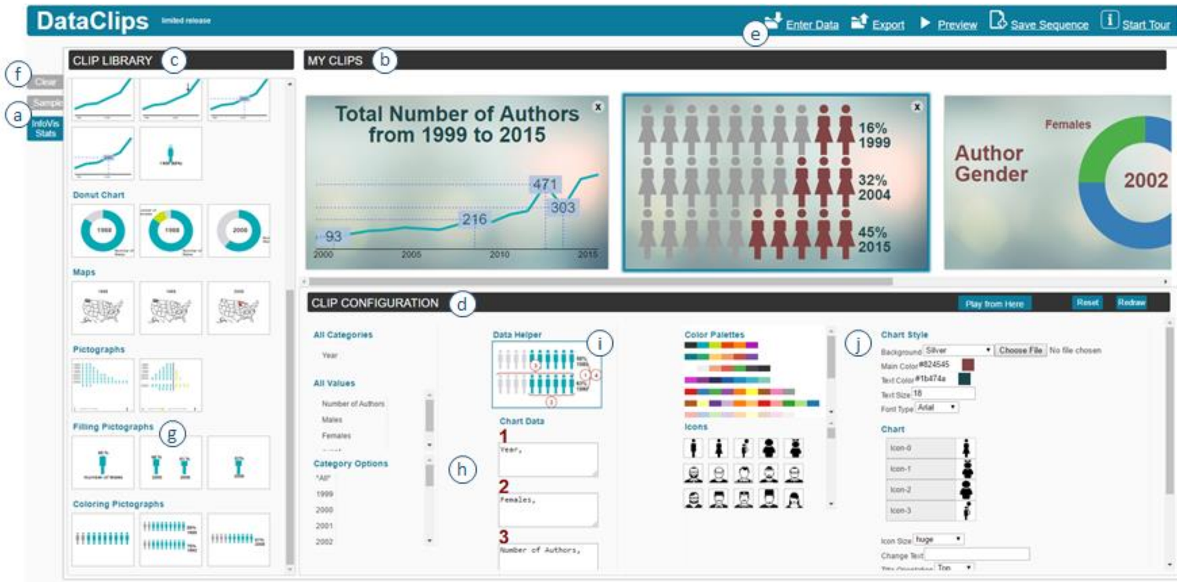

Figure 16. Annotated screenshot of DataClips tool interface.

a) saved clip sequences, b) clip preview and sequencing panel, c) the clip library panel, d) clip configuration panel, e) import new data, f) clear all clips in preview/sequencing panel, g) category of clips for filling pictographs, h) data configuration options and corresponding input boxes, and i) helper images including numbered items corresponding to the input boxes, j) visual and animation configuration options and corresponding input fields.

4.2 User Interface

With the considerations above in mind, I implemented DataClips [26]. Its interface (Figure 16) is composed of three panels:

1. ***Clip Library***, populated with a set of data-driven clips I describe in detail in section 4;
2. ***My Clips***, a workspace panel where clips are previewed and sequenced to form a longer video, and;
3. ***Clip Configuration panel,*** where users can assign data to each individual clip and customize its visual appearance.

I illustrate the main components and features of DataClips through the creation of a short video. Let us imagine Emma, InfoVis paper co-chair this year, who would like to create a short data-driven video to illustrate statistics on the conference attendance and its evolution over the past five years. Emma has gathered the data into a spreadsheet and collected a number of insights to communicate the evolution of the number and gender of authors over the years.

Familiarization and Data Import

Emma connects to DataClips on the web and takes a first look at an example story including five clips already loaded into the tool (Figure 16a). She goes through the story sequence in the workspace (Figure 16b) and selects each clip in turn, which triggers the selected clip's configuration options to appear below the workspace in the configuration

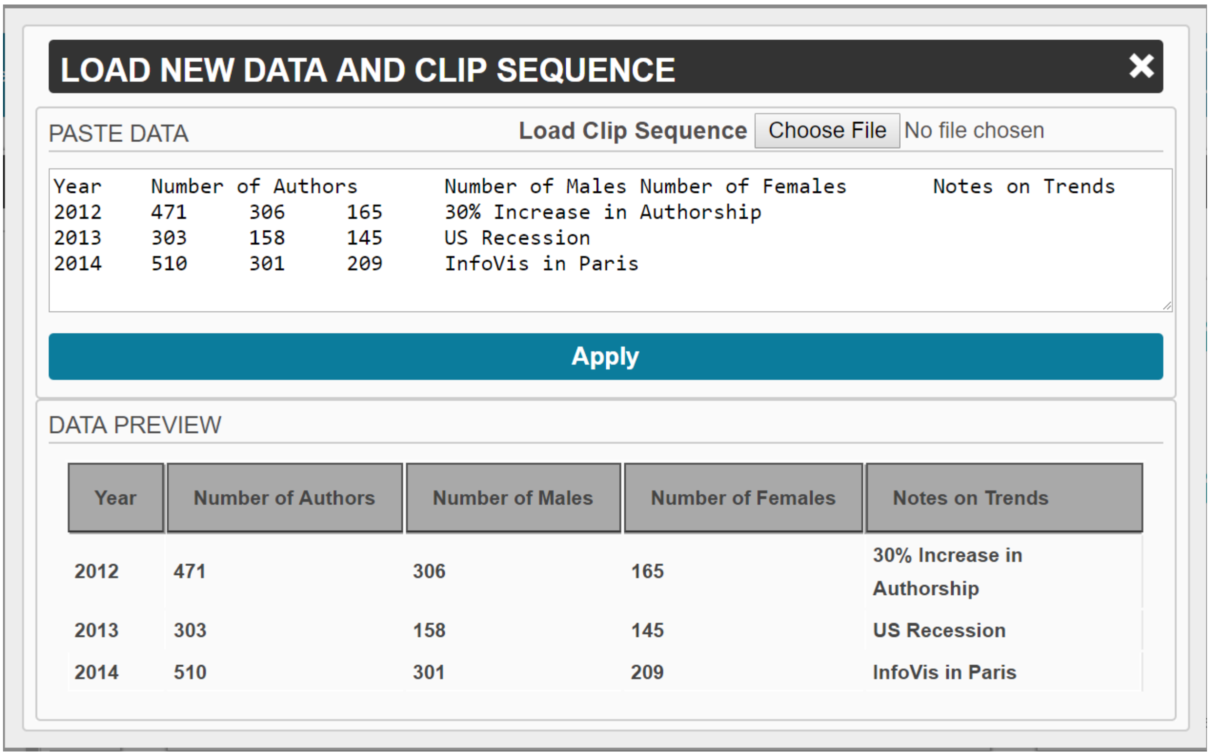

Figure 17. Data import pane showing Fictitious sample dataset about IEEEVis conference attendees.

panel (Figure 16d). Then, she explores the Clip library panel by placing her mouse pointer on the images in Figure 16c to play the animations.

Emma decides to import her data (Figure 16e). DataClips currently supports a specific data format and does not handle data manipulation within the tool. Thus, she copies and pastes her data table from a spreadsheet software into the data import form in DataClips (Figure 17). The example sequence in her workspace is populated with the new data and she can now review each clip loaded with her data values. Clips requiring specific data columns such as ones figuring maps appear unavailable as her table does not contain geographical data. Emma clears her workspace (Figure 16f) and starts from scratch.

Data Configuration

Emma's attention moves to the filled stick figure among the pictograph-based clips category (Figure 16g). She wants to see what it would look like with the percentage of female attendees. She drags the clip to the workspace, and upon dropping it into the My Clip panel, the animation plays with an automatic assignment of her data columns. However, the DataClips default assignment does not show the number of females, but the number of males instead. She selects the clip, which brings up its configuration options in the panel below.

Emma notices that the data binding (Figure 16h) is composed of two columns: (1) a column with all her data attribute names separated based on post-processing of the data types (i.e., dimensions or categories vs. measures or values) and (2) a column containing three input boxes which are populated by the system based on the type of imported data columns. To ease the data configuration, a helper image of the visualization conveys the binding between data column and visual encoding (Figure 16i). Emma replaces the column "Number of Males" by the column "Number of Females" in the first box to populate the clip with her target data column and continues by adding an additional clip: a line chart with arrow annotations. Each clip has a different set of input boxes depending on its data requirement. Overall, there are six types of input boxes to bind to data, the ones noted with a * are required for each clip, others are optional depending on the clip:

Categories*: column names of categorical data attributes such as date-time or geolocation. Emma places her column "year" in this box for creating her line chart.

Selected Categories*:* a specific value of the attribute selected in categories (for filtering purposes). For example, dragging and dropping a subset of years allows her to use only this subset for her line chart instead of all available ones.

*Values**: column names of numerical data attributes. For example, Emma selects "Number of Authors" for populating the y-axis of the line chart clip she has added to her clip sequence panel.

Base Values: are used by clips depicting ratio of values out of a total (e.g., percentage). Emma populated the filled icon with "Number of Females" as values and "Number of Authors" as base values.

Drill-down/Roll-up Values: animations involving drill-down and roll-up operations require an additional data attribute to be specified. For example, after creating her line chart, Emma could select and add a "line to pictograph" clip that will drill-down into a specific year and show the percentage of females. She would then drag the year value into this column.

Annotations: column name containing textual annotations associated with specific values. For the line chart Emma is creating, she places the column name "Notes on Trends" in this box. As the line is drawn, the animation pauses and displays the annotation if present.

Visual Configuration

Each clip also has a set of options for the configuration of its visuals (Figure 16j). The visual configuration is composed of two columns: a column with options to select from, and a column with fields and widgets to adjust parameters. Overall, there are five options depending on the clip type:

Color: different color configurations are available to the users of DataClips. There is a scrollable list of color palettes that an end-user can pick from to set the overall color theme of the selected clip. Upon clicking on the desired color palette, two other color fields get populated with default colors based on the selected pallet: main color and text color. These colors can further be customized through a color picker widget giving users more control on customizing colors of some main visual elements. Obviously, it is possible to enable more control over similar visual customizations, however, I argue that the amount of customizations available to the users is proportionally related to the complexity of the system, an important factor to keep in mind when designing for a wider audience.

Icon-based styling*:* inclusion of a wide variety of icon-based representations demands for the flexibility to change the icon figures depending on the context and data story. This is made possible by providing a list of 138 additional icons ranging from people and animals to devices and logos. Depending on the clip, the number of icon customizations varies, hence, an equal number of input fields are added to the configuration panel. The user can simply drag the target icon from the list and drop it into the associated field to replace the icon. Other icon-based configurations such as the relative size of the icons are also adjustable.

Axes and orientation: axes in the form of reference lines can be added to clips where applicable (line chart, bar chart, and tally pictograph). By default only category (horizontal) axis box is checked. The choice of default setting is to eliminate visual clutter, hence, reducing the time needed for interpretation of the visualizations [95] . This is usually done by incorporating numeric values where it is absolutely needed to convey the story and in a way that it can immediately grab viewers' attention (e.g., through animated labels overlaid on top of the data-driven elements within the chart). The orientation of the data visualization can also be set to be horizontal or vertical which consequently changes the positioning of the axes.

Title and legend: textual descriptions are especially important in cases where no voice overs are included to explain the content of each clip. This is made possible in DataClips using "text" clips (available in the clip library) to be added before and/or after each data-driven clip. Textual descriptions can also be included as titles and legends embedded alongside the visual elements of each clip. The visibility, content and positioning for the text clips as well as titles and legends can be configured through simple text inputs in the configuration panel. Similar to axes and to avoid unnecessary visual clutter, legends and titles are set to be hidden unless the author checks the associated box where he/she sees fit.

Animation style and timing: Perhaps the most important configuration option when it comes to animated data clips is the ability to configure style and timing of the animations. The style of animation varies greatly depending on the clip type and refers to ordering and staging of the animations for the visual elements to be included in the clip. For example, the animation involving creation of a bar chart has the author selecting between "*staggered*" and "*together*" growing of the bars. Furthermore, careful considerations need to be taken into account when timing animations for clips in the library. For example, let's consider a chart with staggered growing bars. One approach could be to dedicate separate but equal duration for animating each bar (i.e., animate 1st bar for S seconds, animate 2nd bar for S seconds ...). This might not be desirable in cases where the bar heights vary drastically since the duration appropriate for one bar might be too slow or too fast for the other. Once again, I also want to keep the complexity of the system to minimum therefore, leaving authors to set the timing separately for each bar is not acceptable. The other approach would be to have a single animation duration configuration (easy for the users to adjust) and use that for animating all the components (i.e., animate bars one by one but take S seconds from start to finish). The second approach is a compromise between configuration simplicity and animation timing based on the characteristics of the visual elements included in the clips. However, selecting a default is a challenging task: S needs to be adjusted based on the number of bars and whether or not the animation is staggered or all together. To mediate this problem, I decided to select a default animation duration for five bars which is the common maximum number of bars used in data videos for a staggered style of animation. Please note that the animations can always be disabled by setting the animation duration to zero.

Clip Sequencing and Export

Emma has now created two clips. However, she would like to first play the line chart showing the evolution in number of authors, and then display the number of females as a filled pictograph for the current year. To rearrange the order of the clips, Emma simply drags the line chart into the first position. Emma then saves her sequence (stored locally in her browser for later edits) and exports the current version as a video file that she saves to her disk (Figure 16e).

Iterative Design

To investigate the usability of the interface, I performed an hour-long usability session with five users from diverse backgrounds: two storytelling experts with no expertise in video editing and programming, one graphic designer, and two motion graphics editing experts. I asked our participants to reproduce an existing video [20] from a printed storyboard, and observed usability issues as they executed the task with DataClips. I iterated over the interface design as follows:

Interface layout and icons: I rearranged the position and visibility of the three major panels and their content to better match the observed authoring workflow (Figure 18): **selection → sequencing → configuration**. I initially used static icons representing each clip within the library panel and organized them by type of clip as described in section 4.2. They were organized by role in the narrative rather than by visualization types, and used static icons to convey the fact that they can apply to any data. However, participants spent a long time finding the clip they had in mind, and icons failed to depict the actual animations. Thus, I designed animated icons that would show the clip format as the user hovers the cursor over the icon.

Assignment of data attributes: Perhaps the most salient change in the interface was the data configuration. Participants were unable to understand the terminology and assign data attributes to input boxes configuring the clip. I iterated over several terms, but none was satisfactory. To solve this, I created helper images including numbered items corresponding to the input boxes (Figure 16i). I also pre-populated each box based

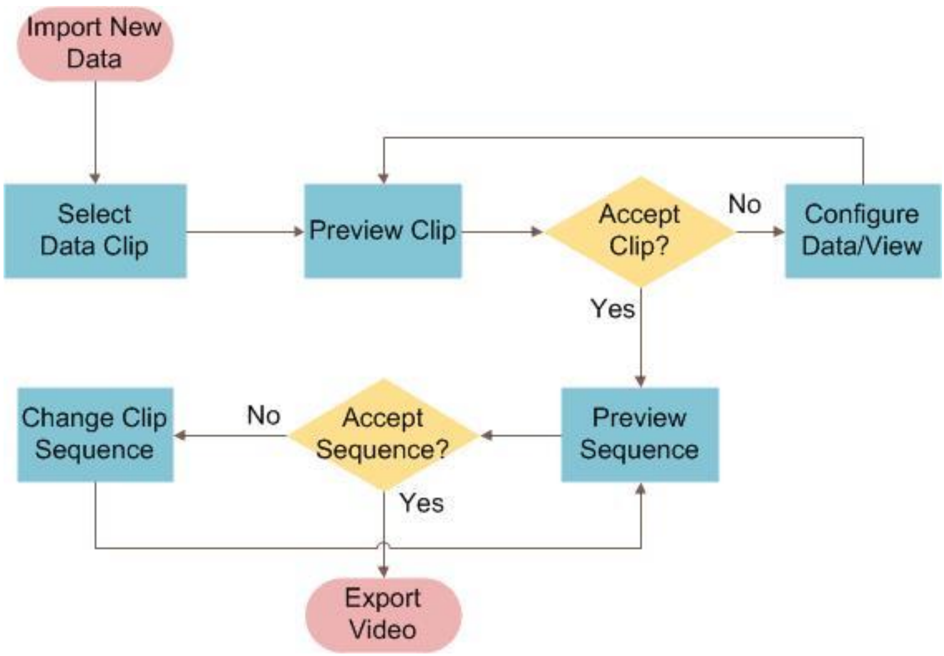

Figure 18. Authoring workflow in DataClips.

on the column types.

4.3 A Library of Data-Driven Clips

In this section, I describe my methodology for selecting the visualizations and clips to create DataClips' library.

Methodology

To compose a library of clips that would enable the creation of a broad range of data videos, I examined a corpus of over 70 data videos available on news media, government and research center websites, visualization blogs, and online video portals such as YouTube.com and Vimeo.com. I used several search keywords such as "data video," "animated infographic," "infographic video," "motion infographic", etc. and processed the top returned results. I kept videos that (1) presented arguments supported by data, and (2) included at least one data visualization.

Clip Type → Vis Type ↓	Creation	Cycling	Accumulation	Embellished	Annotation	Transition	Drill & Roll	Destruction
Line/Area Chart	Grow axis & first line	Morph line paths	Grow each line	Add icon to line grow	Display reference line	Transform line chart into pictograph	Transform data point into filled icon	Remove lines & axis
Bar Chart	Grow axis & first bar or set of bars	Adjust bar lengths	Grow each stack of bars	Add icon to bar grow	Highlight bars	Transform bar chart into pictograph	Transform bar into filled icon	Remove bars & axis
Pie/Donut Chart	Draw donut layout & grow 1st slice	Adjust slice level	Grow slices	Add icon to donut chart	Display information label	Transform bar chart into donut chart	Transform slice into filled icon	Shrink slices & Remove donut layout
Map	Draw map borders	Change colored regions	Color each set of regions	Add icon to map	Point to map regions	Transform map into pictograph	Transform region into filled icon	Wipe map borders
Pictograph	Grow axis & draw 1st set of icons	Adjust the number of icons	Draw each set of icons	Add icon to pictograph	Display information label	Transform pictograph into other vis	Transform icons into other vis	Destroy icons
Colored Pictograph	Color 1st set of icons	Change color	Color each set of icons	Add icon to colored pictograph	Point to icons	Transform icons into other vis	Transform icons into other vis	Decolor icons
Scaled Icon	Draw icon layout	Adjust icon size	Draw and size each icon	Add icon to scaled icon	Flash/move icon	Transform icons into other vis	Transform icons into other vis	Shrink icons until they disappear
Filled Icon	Draw icon layout	Adjust icon fill level	Draw and fill each icon	Add icon to filled icon	Display information label	Transform icons into other vis	Transform icons into other vis	Empty icons

Table 2. Taxonomy of clip types.

This table illustrates the clip types as a function of visualization types (rows) and animation types (columns). Icons and descriptions inside cells show one example implementation for each type.

I proceeded to segment each video from this corpus into clips. I grouped the clips into different categories based on the clip's role in the narrative (e.g., introducing by setting up the scene, explaining a fact in data using annotation, etc.). I then counted the occurrences of each type of clip, excluding the same animated visualization of the same data. For example, the data video in [19] includes an animated bar chart with growing bars three different times throughout the video, but it reuses the same dataset; hence, I

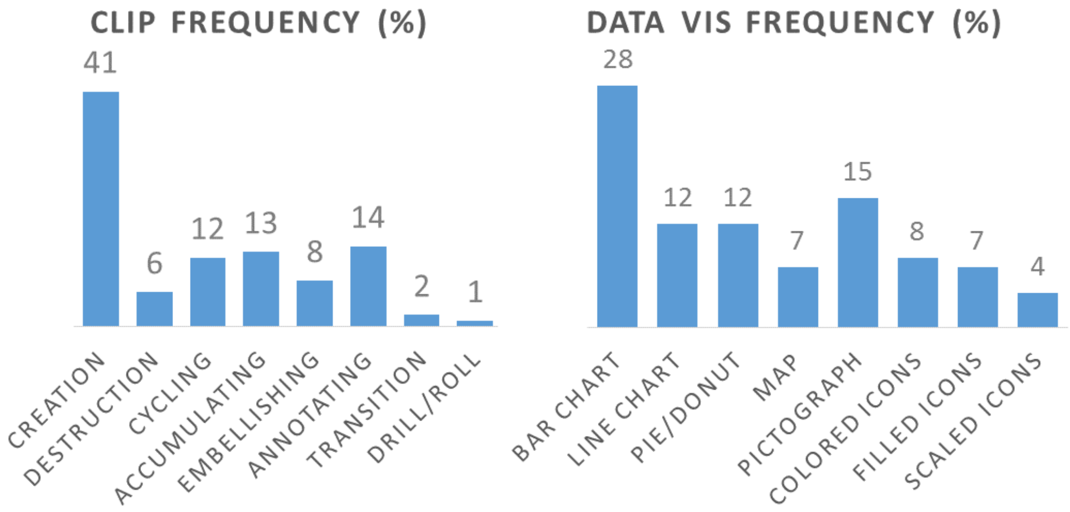

Figure 19. Frequency of types of clips and data visualizations.

counted it a single time.

Our analysis led to seven types of clips that I describe below, each applied to eight types of visualizations most commonly found in the videos. Table 2 gives an overview of the visualization type by type of clip. Note that each clip × visualization combination has different variations. For example, a line chart can be created by drawing both axes and lines together, or one after the other. Figure 19 shows the frequency of clip types and visualization types in the corpus.

Visualization Types

DataClips supports eight types of visualization: four standard charts, and four pictographs representations (DC2), most commonly found in data videos.

Standard charts (maps, bar, line, and donut charts). Figure 20a–d shows standard charts in DataClips and the first column in *).* Figure 20 shows the relative percentages found in the corpus. Note that, in line with [32], more than half (59%) of the total data visualizations I observed are standard charts.

Pictograph representations: Figure 20e–h present pictographs or isotypes (International System of TYpographic Picture Education), encoding data using pictorial representations (icons). In the simplest form, a pictograph or pictorial unit bar graph [54] divides the value to encode into equal portions, each represented by one icon (Figure 20e). Different categories can be distinguished by changing the icon shape or color (Figure 20f). A variation of pictographs uses colored icons (Figure 20g) to encode ratios and percentages. The proportion is represented by coloring *n* icons out of a total of *m* representing the total value. Note that these representations may result in approximations.

Other iconic representations used to compare numerical values over time or for different attributes are icons scaled based on value or partially filled to encode percentages (Figure 20h). These representations are engaging, as their animation mimics physical objects growing or filling out. However, the effectiveness of these encodings is questionable as our perception is not accurate for estimating areas [132]. I opted to

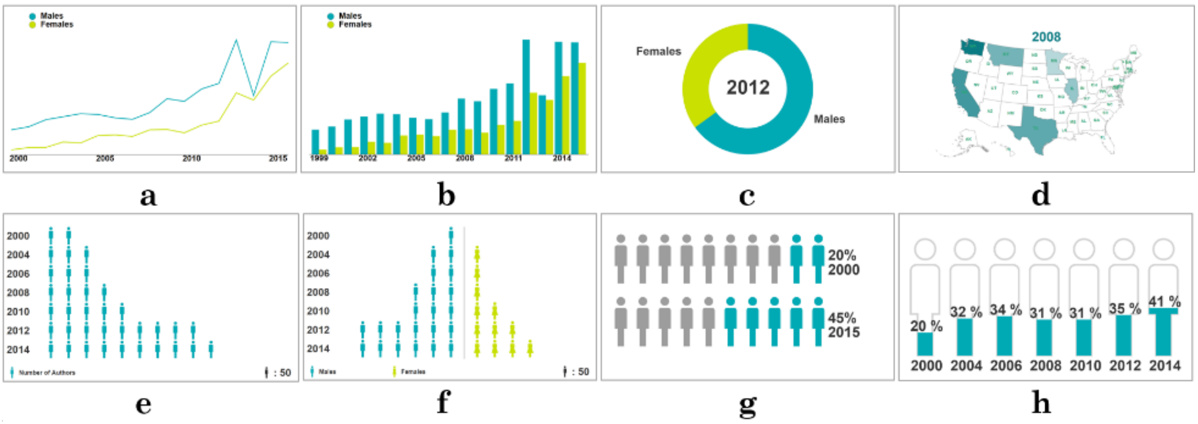

Figure 20. The eight visualization types supported by DataClips.

On the top row are standard charts: (a) Line chart, (b) Bar, (c) Donut, and (d) Map; and on the bottom row are pictograph-based representations: (e) Tally Pictograph, (f) Tally Pictograph-Comparison, (g) Colored Pictographs, and (h) Filled Pictographs.

implement the filled icon, most commonly seen in data videos. The icon area filled with color encodes a value *n* out of a total value *m*. Increasing (or decreasing) *n* causes the icon to appear to be filling up (or emptying out).

Clip Types

I briefly describe seven types of clip that I gathered empirically from existing data videos, covering a wide range of animations and attention cues (DC3). Note that a subset of these clip types correspond to animations identified in the taxonomy presented in [81].

Creation and destruction: these clips provide animated sequences to create a visualization (e.g., staggered appearance of bars) or to destroy it (e.g., staggered disappearance of bars).

Cycling: these clips cycle through years to convey the evolution of values as dynamic changes of the visualization (e.g., iterating over percentages of females as filled icon year after year).

Accumulating: these clips gradually add data attributes to the visualization. Most common ones are bar charts starting off with one series (e.g. # of males) and then adding a second one, (e.g. # of females).

Transitions: these clips are rarely data-driven in existing videos. Most transitions in these videos are a combination of destroy/create clips rather than staged transitions, attempting to match elements of both visualizations as described in [81]. I suspect that they are rarely done due to the complexity of realizing them accurately in existing video editing tools. I opted to support these clips in DataClips and extended existing chart transitions [81] to and from pictographs.

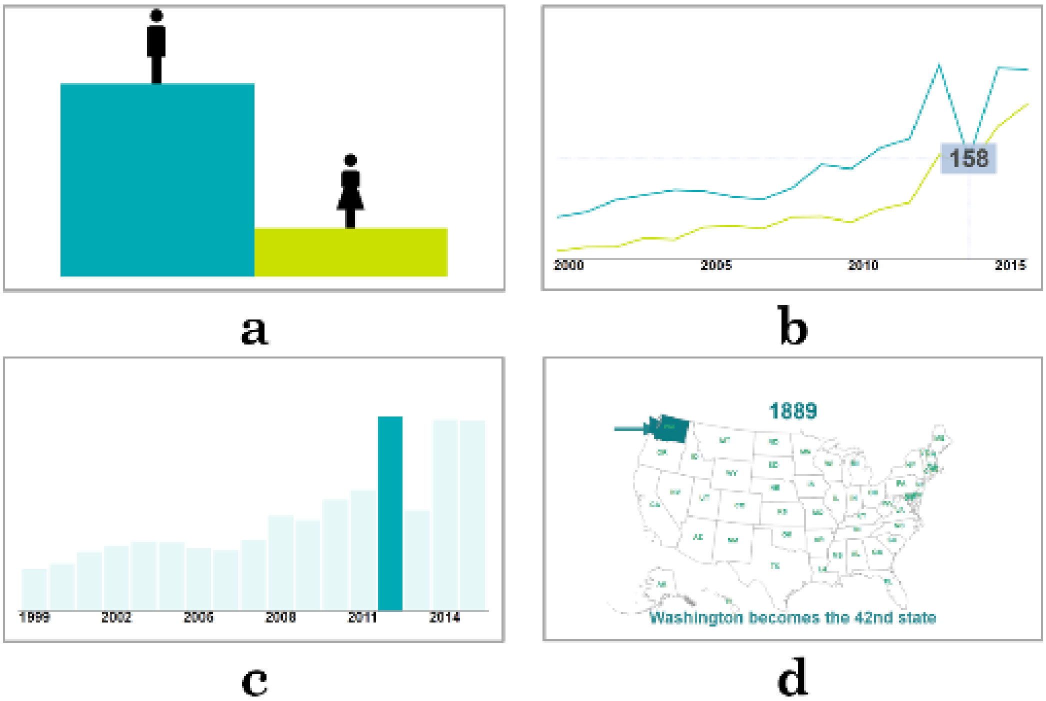

Figure 21. Annotation clips.

(a) male and female icon embellishments above bars, (b) line chart with annotated value and reference lines, (c) bar chart with highlight, and (d) US map with arrow annotation for a given state.

Drill-down and roll-up: these clips support the transition to a subset of the data visualized in a previous clip. For example, drill-down is used when transitioning from a point in a line chart (for a specific year) to an icon-filled representation of the percentage of female attendees for this specific year.

Annotations: animations cover a variety of techniques that guide the viewer's attention to selected portions of the visualizations and reveal specifics annotations. Commonly found examples include highlighting or filtering elements of visualizations, adding a graphical or textual annotation on a specific part of a visualization, or integrating reference lines and numerical values to charts. Data videos also include annotation clips in which icons are overlaid on top of standard data visualizations. Icon annotations are used to distinguish between different types of attributes (Figure 21a) or simply as an embellishment to make the clip more engaging by personifying abstract data visualizations.

Multiple views: clips consisting of multiple views appeared less frequently in the data video corpus I examined; these feature several visualizations at once either side-by-side or as an overview+detail setup. Due to their large screen real-estate and the small portions of videos containing them, I decided not to include them.

Library Coverage

To demonstrate that the principles behind DataClips can lead to a wide range of videos, I reproduced clips from a subset of the corpus of over 70 data videos I analyzed. I demonstrate that Dataclips can recreate about 87% of the corpus, albeit small differences in visual design (e.g., icons placed *beside* growing bars instead of *atop*). I describe my

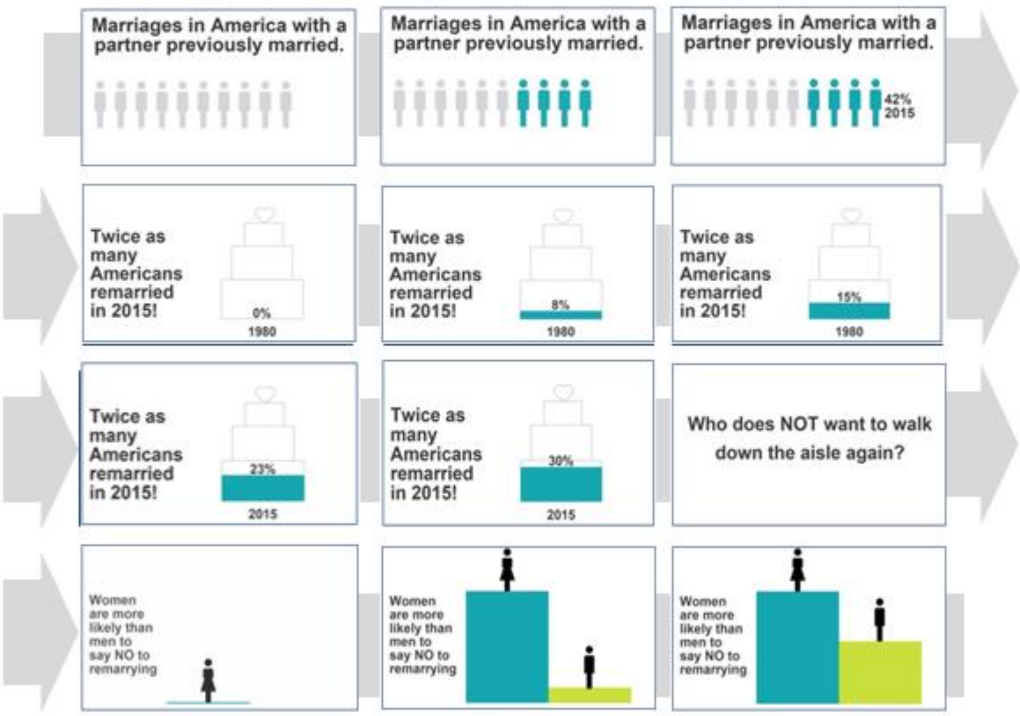

Figure 22. Video recreated about statistics on remarriage by The Guardian [20].

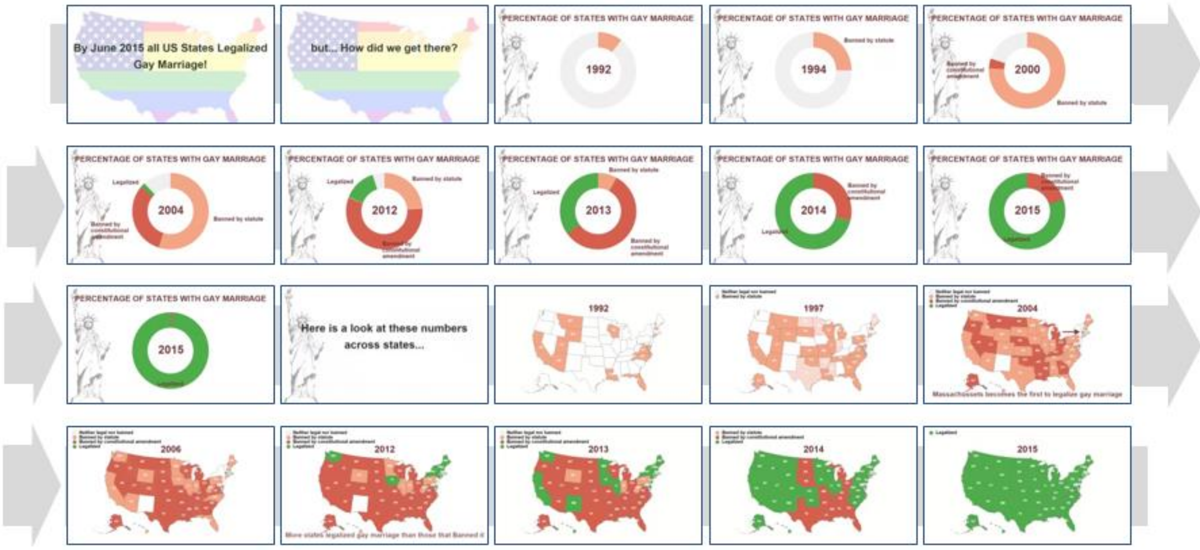

Figure 23. Video recreated about same sex marriage by The New York Times [15].

three levels analysis below:

5. ***Full coverage*** (31% of the corpus) refers to the ability to recreate every data-driven clip included in a video with the current library of implemented clips in DataClips.
6. ***Minor changes required*** (56%) refers to reproducibility with minor changes to the implemented clips, or, the same animation is achievable by replacing the original clip with another similar one selected from the current library of implemented clips in DataClips.
7. ***Major changes required*** (13%) refers to the implementation of new clips or new visualizations. An example of such a video is [4].

Figure 22 and Figure 23 show snapshots from two videos I recreated with DataClips. The companion website [26] includes more examples and demonstrates how DataClips supports the authoring of these videos.

```
/*
 * JavaScript class for Clip view
 */
(function(dataclips) {
      "use strict";

      /**
        * Bar Chart Clip View
        * @type {*|void|Object}
        * @lends ClipLibraryView.prototype
       */
      dataclips.ClipView = Backbone.View.extend({

            /**
              * @class ClipView
              * @augments Backbone.View
              * @contructs
             */
            initialize: function(){
                  this.addModel();
                  this.listenTo(this.model, 'change', this.buildClip);
                  this.buildClip();
            },

            buildClip: function(){
                  //Extend and build custom visualizations and animations
            },

            addModel: function(){
                  //Instantiate the model & add it to the main collection
                  this.model = new dataclips.ClipModel();
                  dataclips.collections.add(this.model);
            },
      });
}(dataclip));
```

Figure 24. Code snippet demonstrating how a clip model is instantiated and associated with a view.

4.4 Implementation

DataClips is a web application using a traditional client-server architecture with HTML, JavaScript, and CSS, as well as d3.js [49] for animated visualizations. The functionalities on the server side of the application are limited and mostly responsible for handling access to the file system, image conversion, and video generation. The client side is designed based on model–view–presenter (MVP), which is achieved using Backbone.js [2]. In this paradigm, each clip has a corresponding model and view, which create a presenter when associated to each other. The clip model is a placeholder for data mappings as well as any configurations affecting the clip (i.e., data visualizations and animations). Figure 24 contains a code snippet demonstrating the idea behind a clip view and how a clip model is instantiated and associated with a view.

Having such structure makes it possible to separate data from the clip components representing the visual elements. When the model triggers a "change" event, all the views that display the model's state (i.e., are associated with the model) can be notified of the change. For instance, saving clip sequences requires saving the corresponding clip model collection which also holds the order of the clips. Rebuilding the sequence now becomes as simple as instantiating the clip views with clip models in the collection and populating the panel with these views.

Furthermore, modularizing the custom functionality of each clip through the concept of views makes feasible the future collaborative development and expansion of the clip library. Data clip designers can develop data clip views (e.g., linked highlighted map and bar chart clip) by extending the DataClips view class and associating it to an instance of DataClips model with minimal changes.

As the first step towards this goal, I am planning on releasing DataClips' code via an open source repository hosted online to give access to other developers interested in contributing to the current library of data clips by adding new data clips or polishing the code for the existing ones

4.5 Evaluation

I conducted a user study to evaluate if non-experts could create data videos using DataClips, and gain insights on how the authoring experience and output would compare to videos created with professional tools. The study was a between-subjects design with two sample groups: one group of participants used DataClips; the other group used Adobe Illustrator and After Effects, commonly used to create data videos. I asked participants to generate data-driven clips based on a list of insights and accompanying dataset I provided. I report my qualitative observations during this process and provide insights on the quality of the videos generated from both groups by asking 40 different volunteers to rate them.

Participants

I recruited 12 participants (4 males, 8 females; aged 18–35) through advertisements on university bulletin boards and email announcements. The six participants who used DataClips had over 3 years of experience in creating charts using Excel, but had no experience in creating videos. The six participants in the Adobe Illustrator and After Effects group had over two years of experience with this software, and had created videos before. I rewarded participants with $50 at the beginning of the session, independent of their performance.

Data and Experimental Material

I extracted data and insights from a data video on drug usage published by The Guardian [99]. I selected this video because output and data were publicly available, and it contained 20 facts of general interest that did not require a specific sequence. The dataset contains a set of statistics based on surveying 15,500 drug users via a global drug survey. Instead of asking participants to create an entire video following a narrative supported by a sequence of insights, I asked them instead to create individual clips for a subset of facts they selected, which could potentially be assembled later. I felt this enabled to keep the study to a reasonable duration and avoided the skills of participants in crafting a compelling narrative to interfere too much with the quality of the final outcome. To ensure variety, I selected the subset of ten insights most different from each other, out of 20 presented in the original video. Participants used the material in a spreadsheet document, with each insight and corresponding data in separate sheets. Insight: “In both US and UK, there are more Cannabis users than Tobacco or Energy Drinks”

Table 3 shows an example insight and corresponding dataset sample provided to the participants in the study.

Country	% Cannabis	% Tobacco	% Energy Drinks
UK	91	85	79
US	89	76	78

Insight: “In both US and UK, there are more Cannabis users than Tobacco or Energy Drinks”

Table 3. Example of one insight and its corresponding data sample.

The study was run in the lab, using a computer with a 1600x1900 screen resolution. In the Adobe group, participants were given the option to use their own laptop and other equipment like trackpad, stylus, etc. All used Adobe Illustrator and After Effects CC 2015. Two of them used their own laptop. In both groups, participants had access to the internet in case they required to download images or icons. I also provided them with sketching materials, such as blank sheets of paper, color markers, and pens.

Procedure

We ran individual 2-hour long sessions. The experimenter asked participants to think aloud and was present in the room to observe. The experimenter started the session by showing four data videos with a high number of views and including diverse types of data visualizations and animations. I divided the study in two main phases: (1) *idea generation and sketching,* and *(*2) *authoring*.

In the idea generation phase, the experimenter first introduced datasets and insights using a written sheet. Then participants were asked to review each insight and rapidly sketch ideas for an animated visual representation. The experimenter asked participants to generate storyboard-like sketches focusing on: (i) convey the insight to the general public; (ii) select a visual representation that fits the data and insight best; and (iii) think about possible types of animations, and additional text or images required. Participants were encouraged to ask questions if they needed clarification about the data or insights. At the end, the experimenter asked them to describe the storyboards they had created.

In the authoring phase, the experimenter instructed participants to select and implement as many of their sketched ideas as possible in one hour. To motivate them to create high quality videos, I notified them that all of the videos they produced would enter a contest and the author with the highest ratings would win a prize. In the DataClips group, the experimenter first demonstrated the capabilities of the tool using an automated step-by-step tutorial included with the tool, using Intro.js [8]. Participants could also ask questions about the system and the instructor provided additional explanations. Note that this training lasted from 15 to 20 minutes in addition to the one hour authoring phase. The experimenter concluded the session with a semi-structured interview asking participants about their overall authoring experience and the issues they encountered, if any.

4.6 Results

I recorded video and audio of sessions (which participants consented to) and took notes during sessions. I analyzed these to extract: (1) selected insights and ideas with rationale, (2) pros and cons vocalized by participants, and (3) the duration required for creating each video clip. I also analyzed the artifacts produced by the participants (storyboards and videos) and asked a group of 40 volunteers to rate their quality. Study material and artifacts are available on the companion website [26].

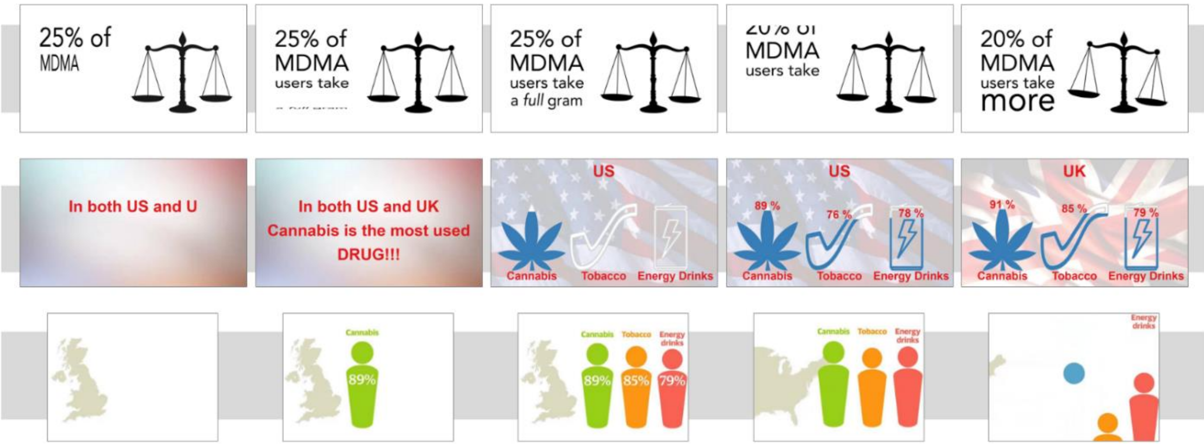

Figure 25. Examples of clips created by the participants.

DataClips group (top), Adobe software group (middle), and The Guardian example I found online (bottom) based on the same dataset [99].

Generated Data Videos

I collected a total of 31 videos (each composed of one or more clips, see Figure 25). Table 4 presents a set of interesting differences in the quantity and nature of videos created in both groups.

To gather an independent opinion on their quality, I asked a separate group of 40 volunteer students recruited through university bulletin boards, to view each video clip and rate them from 1 (very poor) to 10 (excellent). I randomly presented each of the videos generated, including clips extracted from the original video from The Guardian (but without voice narration). I asked each of the 40 volunteers to rate each video on a printed questionnaire. I asked volunteers to simply provide their "overall impression" of each video. These rankings would inform us of the following: (1) whether videos generated by non-experts using DataClips were of sufficient presentation quality to equal that of videos created by experts using the Adobe suite; and (2) whether there were any trade-

Authoring Tool(s)	Clip Sequences	Average # of Clip Sequences	Average # of Clips in sequence	Distinct Insights (out of 10)	Distinct Vis Types	Average Time (first video)	Average Time (all videos)
DataClips	23	3.83	2.5	8	7	9.4	15.8
Adobe Software	8	1.33	1.2	5	3	45.1	37.5

Table 4. Participant performance using DataClips and Adobe Software.

The table includes numbers for clip sequences created, distinct insight items used, distinct visualization types included, as well as the average time (in minutes) it took participants to create each video.

offs in using DataClips, e.g., would participants create more videos with DataClips, but of lesser perceived quality. I summarize the outcome of these rankings below, instead of presenting them in a separate discussion, to provide a holistic view of the rankings in the context of the results from authoring the clips.

More clips with more variations with DataClips: Participants using DataClips were non-experts in video editing but still generated more clips than did experts using Adobe software. As I expected, the average time to create the first clip was considerably shorter with DataClips. However, I was surprised to observe that clips created with Adobe did not employ custom data visualizations (beyond standard charts) given the freedom offered to the users. Overall, I counted seven types of visualization covered in DataClips whereas only three different ones were used in videos created with the Adobe software.

Data-driven clips: Perhaps one objective measure of the quality of a data-driven video is its accuracy regarding the data it conveys. As data binding comes for free with DataClips, all visualizations occurring in the videos were accurate without additional effort from the user. However, with Adobe software, participants did not always create accurate visual encodings. When asked, participant 2 (PA2) replied by saying that "*it does not matter if the bar height is not exact*." Pointing to the resulting video, PA2 also commented that "*this is not supposed to be read by machines but by humans who don't care about the exact numbers.*" While this issue may not prove crucial for professional designers or data analysts with a strong background in visual perception, it is certainly concerning for non-experts.

Similar rating between sources: I find that volunteers' overall impression of videos created with DataClips was equivalent to that of videos generated using the Adobe tools, and even more interestingly, equivalent to video clips extracted from the initial video produced by The Guardian (note however that I removed the voice narration to compare to the other two conditions). Figure 26 illustrates the ratio of average rankings between the three conditions. Through calculating the weighted rank average, I find 36%

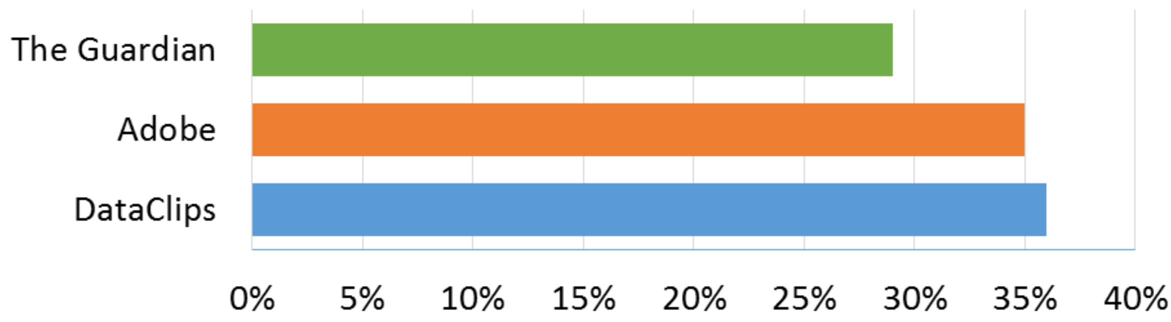

Figure 26. Ratio of the average viewer rankings for videos produced with DataClips, Adobe Illustrator/After Effects, and clips from the initial video from The Guardian.

of the rankings were in favor of DataClips, 35% on average in favor of the Adobe tools, and 29% for the data videos from The Guardian. This outcome indicates that the perceived quality of videos with DataClips matched that of the other two conditions, despite the former being created by non-experts.

Overall, these findings are encouraging, as they indicate that participants who were non-expert in video editing generated more videos with DataClips than experienced participants did with professional Adobe software, without any apparent differences in viewers' rating.

Authoring Experience

Our analysis of recordings led to three major insights regarding the use of DataClips to create data-driven videos.

Learnability: I confirmed that all six non-expert participants using DataClips were able to learn and use the main features of DataClips with a short training period. The data configuration was perhaps the most difficult for them to understand. However, I observed that participants could correct their mistakes without intervention from the experimenter and find configuration options for each clip without much difficulty. I also hypothesize that a part of the difficulties participants encountered was due to the lack of familiarity with the dataset, as I observed a lot of back and forth between spreadsheet and list of column names in the DataClips panel.

Rapid ideation:. I observed that 11 clips (out of 23) created by participants with DataClips had some changes compared to their initial storyboard. While four of these were relatively minor changes, due to lack of control provided by DataClips regarding the layout or type of animation effects, other changes were more substantial. I observed at least three particular instances in which participants changed their design upon investigation of the clip library. Their comments indicated that they saw a more visually interesting clip or a clip better suited for their data. For example, regarding the use of a standard pie chart, PD2 stated that *"I guess I can show the percentage better using this [the filled icon clip]."* I believe this ability for non-experts to ideate on how to convey data insights is important.

Rapid prototyping. The average number of videos generated by the group with Adobe software was less than 2. All of the videos also only featured standard data visualizations and animations. All participants reported on the lack of time for them to achieve what they wanted. PA1, PA4, and PA5 commented that "*if I had more time, I could have* [...]" PA1 remarked that "*if I had more time, I could have made the video more sophisticated.*" From their comments, I also noted that most of these participants avoided picking certain insights (e.g., trend data) due to the amount of work it would require them to produce the video. I did not observe any of these issues with the participants using DataClips. These results suggest that even a more experienced video editing audience could benefit from using DataClips as a rapid prototyping tool before polishing videos with professional software suites like Adobe Illustrator/After Effects.

4.7 Discussion and Limitations

Results of my study show that the six non-expert video editing participants could generate more videos with DataClips than expert video editing participants with professional software. In addition, ratings tend to indicate that the perceived quality of videos created with both tools is equivalent. Additional insights on the authoring process appear to confirm that DataClips can lower the barrier to creating data-driven videos and possibly fulfill both of the intended usage scenarios.

However, as with all qualitative studies with *small sample size*, these results should be treated with caution and DataClips warrants further evaluation to confirm if the initial insights apply more generally. In particular, I did not compare DataClips to other software designed for enabling non-experts to create data videos. Note that during a pilot, I had initially included a group in which non-expert participants used Microsoft PowerPoint to create data videos, reasoning that this software might be used by non-experts to create animated data visualizations. However, I decided to discard the group, as the two pilot participants struggled to create even a single data-driven clip.

Furthermore, I opted to use Adobe software due to the *lack of an existing tool* supporting the same capabilities as in DataClips. The purpose of Adobe software is much broader than authoring data videos and proper utilization of all its features requires a larger time window.

Another limitation of this study is the *evaluation of the quality of the videos* generated. Assessing data-driven storytelling media (and data-driven videos) remains an open research question in our community. This study provides a first step into assessing data video quality but does not delve into all relevant metrics (e.g., engagement, memorability). Thus, I cannot make any assertions regarding the effectiveness of communication and evaluating the quality of data videos remains an open question.

Our observations also pointed to the need for *several iterations of the tool*. For example, participants asked for more control over the layout, which could easily be enabled via direct manipulation. Similarly, it is also possible to add other features like "the ability to include a voice narrations" to add richness to the videos produced. A less straightforward iteration relates to control over the animation effects and the addition of variations of clips. There is a tradeoff between adding several variations of a clip to the library versus providing a generic clip with more configuration settings. In the first case, searching through a large library might become cumbersome and overwhelm first-time users. In the second case, the task of configuring a high number of parameters may also become cumbersome, and labeling them meaningfully for use by non-experts is not trivial. I aim at iterating over the design to strike the right balance.

4.8 Summary

As interest in presenting data moves beyond the confines of data analysts, more general-purpose tools are needed to allow the easy creation of data-driven stories. In this thesis, I introduce DataClips, an authoring tool for creating data videos, aimed at non-experts. I developed DataClips based on close examination of 70 data videos available in the mainstream media and developed by reputed data journalism organizations. From this exploration, I identified the major components necessary for creating compelling data videos. This includes a significant library of data clips, which allow presenting data-driven insights using different visualization styles (including pictographs) as well as different methods for engaging viewers through the use of motion graphics. I report on my design rationale for DataClips, its implementation details, and a qualitative evaluation. From the latter, I find that non-experts can create data videos having the same visual caliber as those created using commercial animation tools (not necessarily for data videos) but also can create more videos in a limited time than tools currently used for creating such videos.

In future work, I envision two main research directions. First, I aim at enabling non-experts to craft compelling narratives [40] for data-driven videos by offering a set of templates geared toward different styles of insights based on the intended message. Second, I will deepen our understanding of what makes compelling data videos. I aim at exploring different evaluation methods and metrics to attempt to better capture the characteristics that make good data videos.

5 EVALUATING NARRATIVE VISUALIZATION

Many narrative visualizations (e.g., data videos) are considered to be a compelling way of getting across a message based on facts emerging from data that has been amassed, analyzed and synthesized. As a result, I call on our research community to further study this form of data delivery to offer concrete design guidelines and equally important, evaluation metrics to help people create and consume high-quality narrative visualizations.

A first step towards this goal is to advance our knowledge about how to assess if a narrative visualization is of high-quality. Commonly used performance metrics such as task completion time and accuracy or similarly, other evaluations methods such as insight-based evaluation or longitudinal studies are not directly applicable. Therefore, new metrics and methods are necessary for effectively structuring the evaluation of narrative visualizations. In this chapter, I investigate and reflect on multiple aspects that I believe are important when assessing narrative visualizations. In [34], I discuss a diverse set of evaluation goals, acknowledging the different perspectives of storytellers, publishers, readers, tool builders, and researchers. I review the possible criteria for assessing whether these goals are met, as well as evaluation methods and metrics that address these criteria (Figure 27).

To generate different metrics to evaluate different aspects of narrative visualizations, here I reflect on a simple schema of their timeline (Figure 28). This cycle involves the author who generates the story and its audience however, in this section, I will focus on evaluating the audience experience.

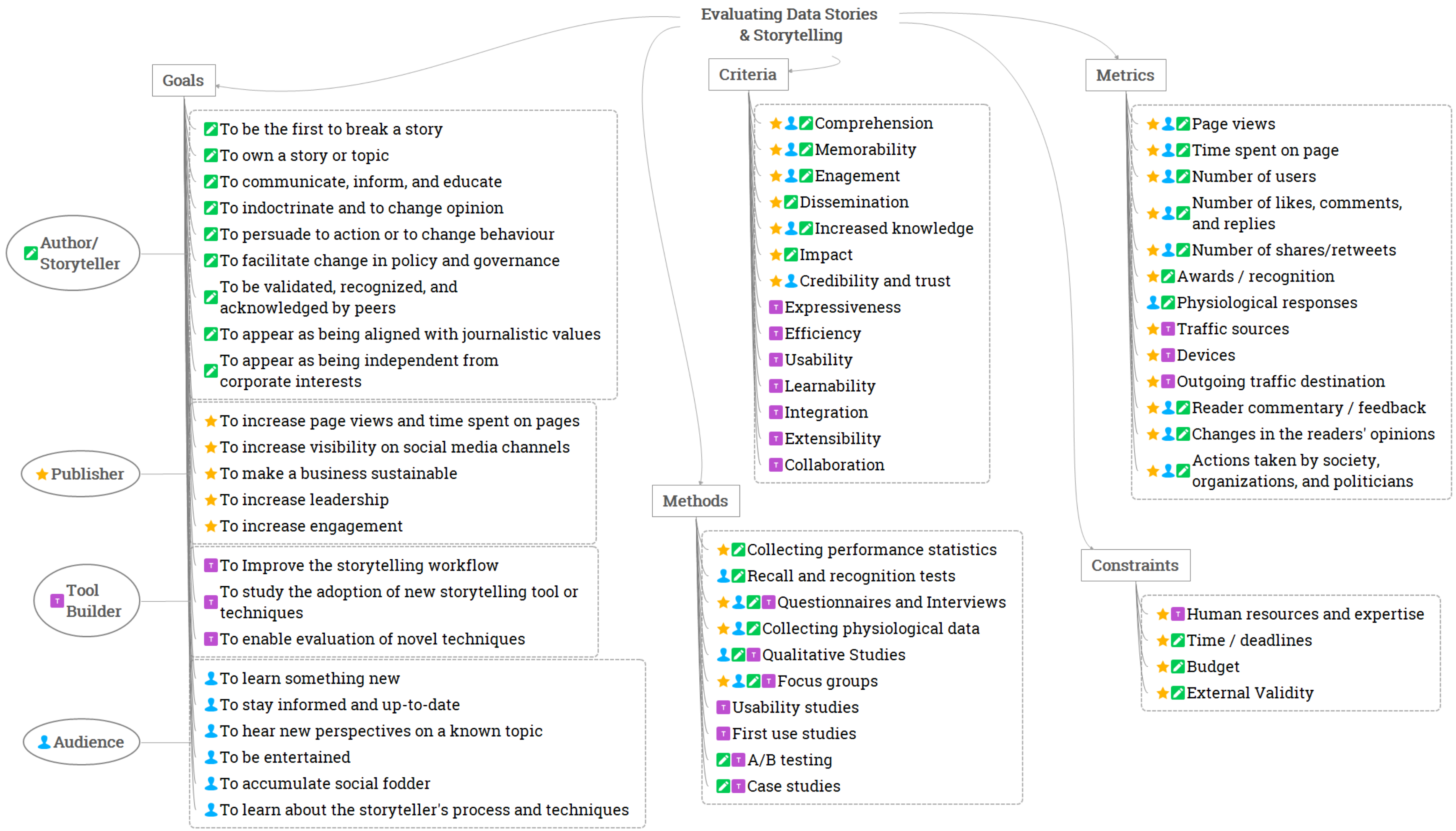

Figure 27. Evaluation goals, criteria, methods, metrics, and constraints flagged for each perspective.

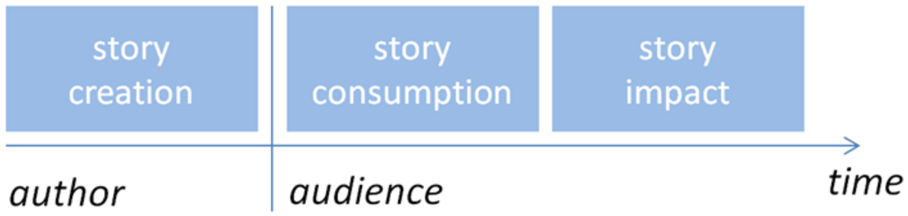

Figure 28. Narrative visualization timeline.

I frame the discussion based on this simplified timeline and suggest evaluating two distinct phases: the actual consumption of the story by the audience and the impact of this story post-consumption. As an illustration, SketchStory study [96] focused on evaluating the story evaluation consumption phase (as well as the authoring phase) whereas the memorability study [47] focused on the story impact phase.

5.1 Story Consumption

I identified two main aspects to capture when an audience is consuming a story: comprehension and engagement. For each of these aspects I propose several metrics.

Comprehension

One of the main goals of a narrative visualization is to have the audience understand the key points during its delivery and to remember them. Since it is not desirable for people to remember "wrong" information, understanding how well people understand the visualizations and collecting the insights they gained during the story consumption is a key aspect to assess.

To evaluate comprehension, we can borrow some existing evaluation metrics and methods designed for exploratory visualization systems. Time spent for the story consumption (or number of times reviewing of an earlier frame in data videos) is an ambiguous metric since it could indicate a confusing moment in the narrative visualizations or in contrast an engaging moment. Therefore, adapting insight-based evaluations to storytelling seems a more promising direction. In such method, one could attempt to capture the insights the audience gained shortly after the story consumption via multiple-choice questions, questionnaires or interviews for example.

Visual analysis tools studied in our community are typically targeted at experts such as data analysts or data scientists, who are knowledgeable in the data they want to study and are familiar with visualization or capable of investing significant amount of time to learn complex visualizations. In contrast, narrative visualizations may target a much broader audience, including people who may not have much visualization or data knowledge. Thus, an important aspect to evaluate is the level of visual literacy required by the visualization. This topic is a growing interest in the visualization community and the recent VisLit Workshop [23] at VIS 2014 reflected on visualization literacy measures. Furthermore, interactive visualizations are increasingly integrated into data stories on the web. It would be important to understand the readability of these data stories, which would require people to understand not only visual representations but also how to interact with visualizations.

There are a number of objective measures we can devise to capture the readability of narrative visualizations. These can be borrowed from perception research [135] and attempt to capture the effectiveness of certain visual encodings chosen, such as the most effective choice of color palette. Objective measures can also help assess the quality of the flow in narrative visualizations. For example, this flow corresponds to visuals and their sequencing in data videos. Metrics that attempt to capture the quality of transitions between visualizations. For example, to tackle this issue, Hullman et al. employ a concept of the cost of transitions from the audience's perspective as a first step toward identifying more "effective" visualization sequences [87].

Engagement

With the explosion of information and stories that are freely available on the web, it becomes a challenge to keep people's attention during the delivery of a story whether it is a live presentation or asynchronous sharing. Therefore, it is important to evaluate the effectiveness of narrative visualization in terms of how well it could make people engaged during the delivery.

One way to measure the level of engagement is through a questionnaire. For example, in evaluating SketchStory designed to provide a new, more engaging form of storytelling with data, Lee et al. asked a set of questions intended to measure the subjective level of engagement [96]. We could build a standard questionnaire to measure engagement, which will make it possible to compare different narrative visualizations. Towards more objective measures, we can leverage physiological sensing such as heart rate, pupil dilation, respiration, and skin conductance [116]. The choice of methods to use varies depending on the genre and medium and each method may not provide complete data, but it would be still possible to gain initial understanding of the audience's level of engagement. Furthermore, when used in conjunction with freeform comments, they together shed more light on how much people were engaged with the narrative visualization.

Another issue to note is that, when people consume narrative visualizations, understandability may not be the only goal; a narrative visualization could serve as something just fun or exciting to watch (enjoyability). Thus, we need to have diverse evaluation metrics that could capture a wide range of goals in delivering a story with narrative visualizations.

5.2 Story Impact

Impact is probably the differentiating factor between exploratory and narrative visualizations and it has been valued in disciplines such as journalism. Longing for impactful stories is inevitable if the end goal is to convey a message. This can prove to be difficult and requires moving beyond measuring time and error. In what follows, I cover the standard quantitative metrics as well as the qualitative metrics that are more specific to narrative values and aspects when it comes to evaluating the impact of a narrative visualization.

Dissemination

Advanced analytics tools, nowadays, can produce reams of quantitative data such as number of views, unique viewers, likes (i.e., ratings), shares (i.e., reposts), references made, and more.

Among available metrics, we have the number of people who watch a video as well as the average rating. These metrics have two main issues: first the personal engagement level is low. In this sense the recorded information is prone to numerous biases (multiple ratings by the same person, buzz word, etc.). Second, this rating merges many criteria and only gives a global and personal data video assessment. For instance it mixes the data video design quality and its embedded topic. It is not possible to assess if the rating is related to the design quality or the underlying message. As such, these metrics are inaccurate and difficult to rely upon. They are only correlated to the global data video popularity.

Ratings, however, can go beyond numbers by breaking down the narrative into story units and asking the audience to not only rate each unit separately but also to provide reasons as to why the particular rating was assigned. Doing so will provide deeper insight into the impact of the effectiveness of a narrative visualization.

Memorability

Representing one of the most interesting metrics for measuring narrative visualization impact is the idea of evaluating whether or not the audience can recall 1) the content (e.g., different components, story units, and visualizations, etc.); 2) the message(s) conveyed; and, 3) the reasoning behind the story. As mentioned previously, narrative visualizations mostly focus on delivering a message and therefore the ability to memorize and recall the message(s) is important. On the other hand, every visualization and element in a narrative visualization serves that exact purpose (i.e., conveying the message), hence, by making these components memorable, individually, we can make sure that the main goal is achieved even more powerfully. Furthermore, the organization and sequence of these components to depict the broader image of the narrative visualization must also be taken into consideration when measuring memorability to understand if the audience has followed the story.

Methods for measuring memorability include more quantitative ones through questionnaires and counting the number of components, story units, visualizations a user can remember [43], and/or qualitative methods such as surveys and interviews to understand whether or not the audience remembers the intended key messages within the body of narrative visualization.

While examining memorability immediately after an audience is exposed to a narrative is indicative of retention, it is the later recall scores that build a stronger case for evaluation of a long lasting impact.

Increased Knowledge

While on many aspects, narrative visualizations differ from exploratory visualizations, we can draw a parallel regarding insight-based evaluation. The purpose of a visualization is to facilitate insight extraction [57]. Narrative visualization aims to better communicate this insight to the target audience. Furthermore, understanding the key points or insight comprehension can be thought as two separate but closely coupled parts as described by G. Dove et al. [66]: the insight experience and the product of experience. The former refers to what psychologists describe as overcoming a mental block to achieve understanding. This occurs during the delivery of a narrative visualization. Here, I focus on the latter which represents the changed mental model resulting in new knowledge.

In the context of learning strategies, the effectiveness of storytelling is typically verified through post-viewing questionnaires and interviews [89]. Questions can be designed to target whether or not a narrative visualization has increased knowledge about a topic. Examples of such questions are listed in [41]:

1. What did you learn that you did not already know? In other words, describe new

information/knowledge you gained.

2. Did you learn something that contradicts what you already know about the topic? What is it?

Answers to the above questions can also be correlated to different visualizations and story units included within the narrative visualization to learn about the more effective components when it comes to extracting knowledge.

Real World Impact

If narrative visualization's intent is to deliver a strong message, perhaps the most relevant impact can be seen as its echo in what journalists often call "real world". The effects can vary from changes in audience behavior, to influencing one's belief, all of which can ultimately result in an action.

Pre-internet, there was usually no easy way of capturing data on the spread of a story and studying its "ripple effect". However, it is possible now to extract such data to generate hypotheses about possible connections between stories delivered via a narrative visualization and changes in the real world. The study of these relationships can also be conducted in a more controlled way similar to Bond et al. [44] who performed a large scale experiment that tested the influence of informational messages on voting behavior.

Confounding Factors

In the previous section, I discuss a wide range of metrics for evaluating narrative visualizations. However, there are a number of confounding factors to take into account when designing studies to assess these metrics. I distinguish below two categories: factors relating to the data and factors relating to the audience.

Data

In many situations, it may be challenging to dissociate narrative visualization from the data (content) or weigh the influence of each one independently. There are several aspects to take into account regarding the data.

The novelty effect

Data exposed for the first time to an audience may in itself be the most compelling factor but this also impacts the audience experience and greatly improve the engagement. For instance "200 years that changes the world" [15] had a huge impact and got widely spread. One reported an amazing animation with bouncing circles that shows how the life expectancy increased.

The design effect

The New York Times uses may fascinating visual effects and also takes advantages of the latest available web based technology. As such the audience is supposedly more engaged. In given circumstances this can has a drawback and simply eclipse the impact of the narrative key points. The audience can be incline to remember the specific cutting edge designs and animation rather than the general topic.

The credibility effect

The source (or quantity) of data may impact the credibility of the entire story, independently of its visualization design. For example in the documentary film "An Inconvenient Truth" directed by Davis Guggenheim, the former United States Vice President Al Gore's had credibility when education citizens about global warming.

Audience Background and Knowledge:

The understanding of a narrative visualization by a given audience may be highly dependent of the background and general knowledge of the audience. A key aspect to consider is the visual literacy of the audience. Very low exposure to data visualizations may have a number of positive or negative implications. It may cause difficulties for the audience to understand the points made through visuals in the story, or it may trigger a surge of excitement as they encounter their first visual representations.

Audience Interests and Preferences

Another factor to take into account are the general interests of an audience as well as their general tastes and preferences. Interests in particular topics may cause an audience to be either engaged or disengaged possibly independently of the type of narrative visualization conveying the story. Similarly, techniques such as animated transitions may prove compelling for some people or considered as distractions for others.

Overcoming Confounding Factors

Questionnaires or interviews pre-study as well as a general awareness of these during the entire evaluation process may help controlling for the confounding factors pertaining to the audience background and knowledge.

It is however more challenging to control for the audience interests and preferences as well as for the factors relating to the data. Once a story is consumed it becomes irrelevant to repeat the measures. Thus, to compare multiple techniques one must prepare equivalent sets of data. This task is challenging and controlling for the interest of the audience in these different dataset poses an additional layer of complexity.

5.3 Summary

Evaluation is a wide-reaching concept, and the term evokes different meanings in different domains: evaluation of a data-driven story in a newsroom will be very different from the evaluation of a novel storytelling technique in an academic research setting. Furthermore, narrative visualizations may have a number of different intents. Below are examples of stories that aim the audience at [32]:

- learning a new or unknown fact
- reflecting on a topic
- making a decision
- changing the audience opinion or behavior

Depending on the intent of the author, the respective importance of the evaluation metrics may change. For example, comprehension may be key if the message is to teach people a fact, but engagement may prove more important to encourage people reflecting on a specific topic. Addressing a list of these intents and identifying the weights of different metrics regarding the assessment of their performance is a challenging direction.

For this reason, I outlined the diverse set of goals of storytellers, publishers, readers, tool builders, and researchers (Figure 27). Given these goals, I highlighted evaluation methods and metrics that approximate these goals in the context of data videos.

6 EVALUATING DATA VIDEOS

Data videos heavily rely on data visualizations, and various creative design techniques are incorporated into the visualizations to engage the viewers and sustain their attention [32]. Designers often use animation techniques to attract viewers' attention and keep them engaged [61]. In addition, icon-based and pictographic representations commonly replace standard charts in data videos to elicit viewers' engagement through personification of otherwise abstract data. However, the effect of these design strategies on viewer engagement and communication of the data has rarely been explored.

Although visual designers have been incorporating animation and pictographic representations to make visualizations more compelling [60, 68, 83], researchers have drawn contradictory conclusions regarding their effectiveness. While there is strong intuition about the usefulness of motion to communicate [70], studies have shown that animation can be distracting and challenging to interpret [117]. Similarly, researchers have argued that pictographs and icon-based representations may distract from the data itself, merely contributing to an accumulation of "chart junk" [132]. On the other hand, empirical work has shown that including pictures and illustrations in data visualizations positively affects memorability [43] and can lead to better recall [47]. More recently, Haroz et al. [78] have distinguished visual embellishments from pictographs representing data, and have concluded that only the latter can be beneficial by enticing people to inspect visualizations more closely.

In addition to the lack of consensus on the effects of animation and pictographs, findings from the literature are not directly applicable to data videos. Moreover, their effects have not been tested on viewer engagement, an important factor determining the effectiveness and impact of a narrative visualization [102]. To this aim, I have composed a quick and easy-to-use scale-based questionnaire covering five factors impacting viewer engagement in data videos: (1) affective involvement, (2) enjoyment, (3) aesthetics, (4) focused attention, and (5) cognitive involvement. Focusing on pictographic representations and animations to setup and create a visualization scene, I used my questionnaire and conducted a series of studies through the Amazon's Mechanical Turk platform.

Our results suggest that, although both animation and pictographic representations can elicit viewer engagement, they do so through different facets of viewer engagement. Furthermore, the results reveal a possible interaction role for congruent combinations of pictographs and setup animation in stimulating viewer engagement and viewer comprehension of the communicated information.

Our research contributions in this chapter are threefold [35]: (1) the development of an easy-to-use engagement scale to assess viewer engagement in data videos, (2) an empirical study, assessing the effects of setup animation and pictographs on viewer engagement, and (3) guidance for the design of engaging data videos.

6.1 Pictographs and Icon-Based Visualizations

Simple pictographic elements have been used to encode various types of information including numerical data [53, 83]. For example, unit pictographs include symbols, each representing a fixed quantity, that are stacked to provide an intuitive representation of a total amount (Figure 29-top). In previous work [33], I have identified several different

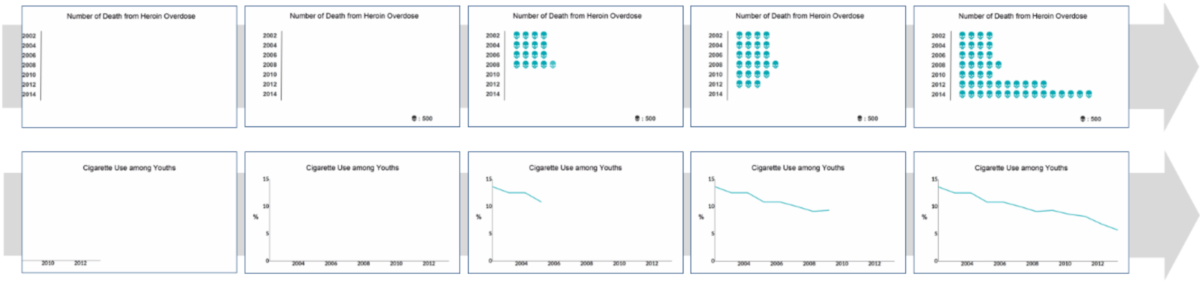

Figure 29. Example use of setup animation to build trend visualization: pictograph (top), standard chart (bottom).

icon-based representations commonly used in the data videos. I consider icon-based representations included in their taxonomy to design the data clips used in the study. The uses and benefits of icon-based visualizations have been debated. Some considered visual embellishments as chart junk [132]. Boy et al. [50] investigated the impact of using anthropomorphized data graphics over standard charts and did not find differences in their effects on viewers' empathy. On the contrary, Bateman et al. [43] reported an empirical study showing that visual embellishments could improve long-term recall. Similarly, Borkin et al. [47] found that people can better recall pictorial visualizations. Borgo et al. [46] found occasional impact on working and long-term memory performance for visualizations with embedded images. More recent studies have shown positive effects of bar chart embellishments on data communication [127] as well as benefits of pictographs representing data through enticing people to inspect visualizations more closely [78].

Our work studies the impact of pictographs representing data on the viewer engagement and communication of data in data videos.

6.2 Animated Data Visualizations

Animation in data visualization can take many different roles [61]. Most commonly, it has been used to facilitate the perception of different changes in data visualization [70]. Researchers have questioned the benefits of animation [133], whereas, others have showed its effectiveness [139]. Heer and Robertson [81] investigated the effectiveness of animated transitions between common statistical data graphics, finding that animated transitions can improve graphical perception. Robertson et al. [117], compared GapMinder like animations with trace visualizations and small multiples. Their results indicated that while participants find animated trend visualizations enjoyable and exciting, they can be challenging to use, leading to many errors. In this thesis, I focus on a class of animation techniques commonly used in narrative visualizations to attract and maintain viewer attention by animating the creation of a visualization scene [33]. I refer to this subset of animation techniques as setup animation. Figure 29 shows examples screenshots demonstrating such animation technique.

6.3 Viewer Engagement

Engagement is a complex and multidimensional construct and is characterized in a multitude of ways depending on the target context and discipline. In sociology, engagement is often associated the degree of immersion, flow, and positive psychology [124]. In marketing, engagement refers to the level of attention to an advertising message, and involvement refers to the degree of interest in its message [137]. In education, the concept of student engagement is usually discussed in terms of motivation, achievement, and interpersonal relationships [104]. Within the context of gaming, engagement is believed to be a generic indicator of game involvement [55] which is encouraged by the sensory appeal of the system [111].

In HCI, user engagement has been viewed in the context of flow and fluid interaction, leading to satisfying and pleasurable emotions [129]. It has also been defined as the emotional, cognitive, and behavioral connection that exists between a person and an object [36, 120]. Engagement is also believed to be the positive user experience associated with being captivated and motivated to use an interface [111]. Additionally, terms such as flow, presence, transportation, immersion, enjoyment, and playfulness are closely related to the concept of viewer engagement [65, 77, 98, 100]. The scope of engagement is in the context of data videos as the combination of viewer's subjectively reported levels for different attributes of engagement.

Assessing Engagement

Several approaches for assessing engagement in various disciplines have been proposed. O'Brien and Toms [112] posited a range of user and system-specific attributes of user engagement in the design of interactive systems: aesthetics, affect, interest, motivation, novelty, perceived time, focused attention, challenge, control, and feedback. Their measures emphasize the user's emotional response and reaction, and the concentration of mental activity. The visualization community has primarily focused on measuring duration and number of interactions with a visual display [50, 120]. Saket et al. have explored subjective reaction cards to capture user feelings [120]. Mayer [105] has looked at audience engagement from the perspective of journalists and newsrooms. Drawing on empirical research with users of data visualizations, Kennedy et al. [91] dentify six social and contextual factors that affect engagement. This study focuses on audience engagement at the data story dissemination phase. I consider different viewer characteristics as possible variables influencing viewer engagement with data videos.

6.4 Engagement Scale Development

Our goal was to construct a single questionnaire (with a small number of items) as a simple measurement tool for capturing a range of engagement characteristics after viewing data videos.

Initial Engagement Scale

I first looked into existing questionnaires from related disciplines such as game design, user interface design, psychology, HCI, communication and marketing, storytelling, and multimedia design [98, 106, 112, 137]. I compiled a list of statements capturing potentially relevant attributes of viewer engagement and eliminated those that did not apply to data videos as they were focused on a specific context (e.g., Para social interaction in game design). I identified 53 statements (available at datavideo-engmtscale.github), covering the five engagement attributes (Table 5).

Attribute	Description	# of Items	Example Statement
Affective Involvement	The interest in expending emotional energy and evoking deep feelings about the stimulus	2	This video triggered my emotions
Enjoyment	A consequence of cognitive and affective involvement and may be broadly defined as a pleasurable affective response to a stimulus	5	This video was fun to watch. I'd recommend its viewing to my friends
Aesthetics	The visual beauty or the study of natural and pleasing (or aesthetic) stimulus	3	I liked the graphics in this video. This video was visually pleasing.
Focused Attention	The state of concentrating on one stimulus without getting distracted by all others	2	I found my mind wandering while the video was being played
Cognitive Involvement	The state of concentrating on one stimulus without getting distracted by all others	3	I found the content easy to understand.

Table 5. The description of five engagement attributes with example questionnaire statements, which are used in the study (Section 6.6). The complete list of items is available at the companion website [29] and Appendix C.

1. **Affective Involvement** refers to the interest in expending emotional energy and evoking deep feelings about the stimulus.
2. **Enjoyment** is a consequence of cognitive and affective involvement and may be broadly defined as a pleasurable affective response to a stimulus.
3. **Aesthetics** denotes the visual beauty or the study of natural and pleasing (or aesthetic) stimulus.
4. **Focused Attention** is the state of concentrating on one stimulus without getting distracted by all others.
5. **Cognitive Involvement** is the interest in learning and thinking about the information communicated through the stimulus.

Refining Engagement Scale

To further examine the appropriateness and utility of the resulting scale, I conducted a study using the 53 item questionnaire to compare each item's ratings on the engagement scale.

Study Design

I designed two drastically different data videos on the topic of drug use including or lacking animation and pictographic representations. I posit that such animated visualizations yield higher levels of engagement in the viewers. The first video consisted of static slide deck with textual descriptions and tabular representation to communicate facts based on data. The second video was designed to be more engaging by using short titles and animated icon-based visualizations to communicate the same data-driven facts. Videos had equal number of data clips organized in the same order to create a longer sequence and were 1.5 minutes in duration. I ran a between-subjects study, where participants view a single video and fill out the engagement questionnaire. I recruited 50 undergraduate students (aged 18-27) from a university's psychology department.

Procedure

On a website hosting the experiment, participants viewed a page with the details about the experiment and what is expected of them. Once ready, they proceeded to watch the video, one at a time. I slightly reworded statements in the compiled engagement questionnaire to make sure they are suitable for data videos. The questionnaire items were entered into the online Qualtrics platform. I also included a short demographic questionnaire at the end as well as a simple question at the beginning of the survey about the content of the video. This question served as a gotcha measure for identifying random responses from participants who may not have paid attention to the video. Upon playback ending, the embedded Qualtrics questionnaire appeared below the video. Participants were asked to provide their score for each survey item on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). Participants were given notice before the automatic playback to prepare for watching an auto-played video for 1.5 minutes.

Results

I ruled out responses from nine participants who provided an incorrect answer to the video content questions, resulting in a total of 41 responses. I saw more incorrect responses for the text and table condition than the animated pictograph condition (7 versus 2); this aligns with my initial assumption that animated pictographs are more engaging.

I performed an independent-samples t-test to compare the mean engagement scores between the two video conditions. Based on my initial assumption regarding the level of engagement for the two drastically different conditions, I opted to only keep survey items with significant and marginally significant differences between their mean scores. After determining that the sample was factorable, I ran factor analysis on the remaining items. Using reliability analysis, I obtained Cronbach's α of .82 for the text and table video condition and .84 for the animated pictograph condition across 15 items. Further analysis indicated strong inter-item consistency as a scale for each dimension, Cronbach's $\alpha > .86$. Table 5 shows example questionnaire statements for the five engagement attributes (visit the website [29] or Appendix C for the complete list of items).

6.5 Research Question and Hypotheses

Drawing on current literature, I pose the following research question and two main hypotheses:

RQ: Will incorporation of animation and icon-based data visualization boost the engagement and understandability in data videos?

H1: Presence of animation to setup and create visualizations in data videos leads to increased viewer engagement and better comprehension of data insights.

H2: Incorporation of icon-based data visualizations in data videos leads to increased viewer engagement and better comprehension of data insights.

6.6 Study: Measuring Engagement

Our goal was to investigate the efficacy of icon-based data visualizations and animation to create the scenes containing data visualizations in data videos. I conducted an experiment in which participants were exposed to 10-second long data clips communicating several different types of data-driven insights. Participants rated the level of engagement and answered questions targeting their comprehension of data insights. In addition, I asked them to pick their favorite clip in a series of paired-sample comparisons.

Study Design, Participants, & Procedure

I conducted the experiment as a within-subjects design; pairs of data-driven clips were presented to participants in four different blocks. I counterbalanced the order of the blocks following a Latin Square design. The study was also setup such that it could only be taken using a computer and not a mobile device to make sure that viewers watch the video clips with attention.

I used the Qualtrics survey platform [13] to setup a crowd sourcing experiment. 120 participants (42 females; age M = 31.8, SD = 9.28) were recruited through Amazon's Mechanical Turk (at least 99% approval rate and at least 100 approved HITs). I did not set any quotas on education, background, or gender to generate a sample representing broad audiences. Participants were from a diverse occupational background with varied levels of education (53% high school or some college, 40% with a bachelor's degree, and

7% with masters degree or beyond). The majority of participants had some level of computer experience (5% basic, 56% intermediate, and 39% expert). Regarding participants' level of knowledge reading data charts, 3% had no knowledge, 32% were at the basic level, 52% were intermediate, and 13% were experts. About half of the participants reported more than five hours of daily online viewing. Participants were compensated $2.00 for their time.

The study began with an introduction page, including a short greeting message, followed by descriptions on the overall purpose of the study, its duration (about 15 minutes), and expectations from the participants. To familiarize participants with the procedure and the types of questions they would receive, I included a practice block. At the beginning of each block, I informed participants about an upcoming short video clip being played for 10 seconds. A single data clip, randomly chosen from the block, played back to the participants without a playback controller. Participants were then directed to a page with a question about the content of the video they just viewed. I repeated the same steps for the second data clip in the block. At the end of each block, participantswere asked to fill out the engagement questionnaire for each data clip just viewed, providing scores for each item on a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7). Participants were also asked to pick one clip over the other based on their overall preference and provide a short reason for their selection. After completing four blocks, the participants were asked to fill out a short demographic questionnaire.

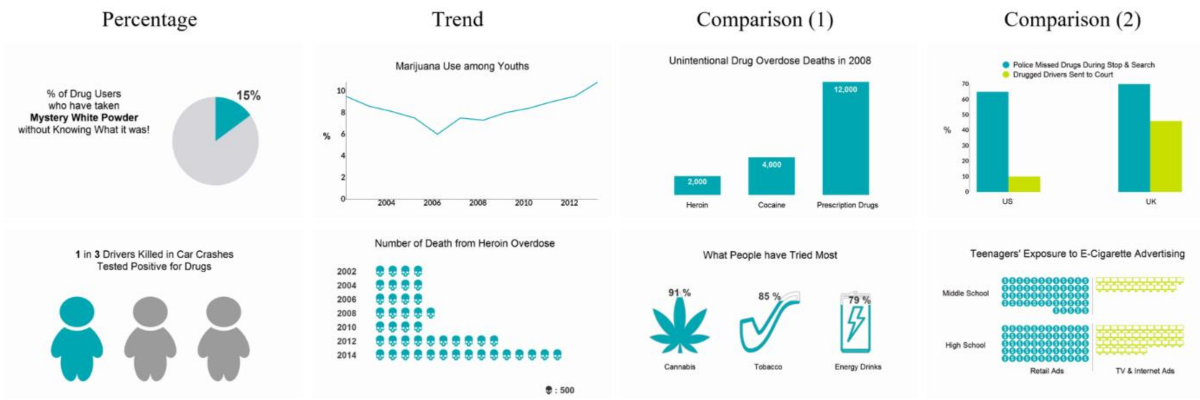

Figure 30. Example use of setup animation to build trend visualization: pictograph (top), standard chart (bottom).

Experiment Treatment Conditions

The independent factors in the design were: Animation Status (static vs. animation) and Chart Type (standard chart vs. pictograph), giving us four conditions: (C1) static chart, (C2) static pictograph, (C3) animated chart, and (C4) animated pictograph. I considered four main insight types [33]: (1) Single value percentage, (2) Trend, (3) Single value comparison, and (4) Multiple attributes comparison. Figure 30 shows screenshot examples of clips used in the study.

All versions of the data clips were made to look similar to optimize treatment equivalence and to better attribute the effects to the use of setup animation or pictographs. I describe the measures I took to achieve treatment equivalency as follows:

1. ***Auditory Stimuli:*** According to the recent statistics on online video viewing, 85% of Facebook videos are watched without sound [3]. Motivated by this phenomenon and to focus on visual stimuli, I opted not to include voice-overs or background music.

2. ***Data Visualizations:*** The types of standard charts and pictographs I used to

visualize data varied based on the type of insight being communicated. Standard charts included pie, line, bar, and clustered bar charts. Pictographic representations included colored pictographs, unit-based pictographs, and filling icon. The color palette I used (from the DataClips tool) contained seven distinctly different colors and accounted for color blindness.

3. ***Data Clip Duration:*** All video clips were 10 seconds long and auto-played to make sure the exposure time was equal across all conditions. In cases of clips lacking setup animation, I displayed the static visualizations for 10 seconds. Participants were clearly informed before each stimuli exposure that they should expect “viewing a chart” for 10 seconds.

4. ***Look and Feel:*** I opted to keep similar ratio of ink to white. The layout for organizing components in the clips was kept consistent to provide similar look and feel. Depending on the size and type of the data visualization used, there was a short title placed on top or to the left of the chart explaining the content of the chart (Figure 30). For all data clips, I used the same font style and size (Times New Roman, 12 pt, black) with white background to guarantee legibility.

Study Material and Measures

For this study, I targeted elemental video segments or data clips. As a building block of data videos, data clips communicate a single data-driven insight using data representations, and can be sequenced together to form a data video. By focusing on these smaller units, I sought to avoid potential confounding effects as a result of sequencing strategy or narrative structure employed in data videos.

The dataset I used to create the data video clips was reverse engineered based on the animated infographics created by the experts in a US government website as well as a data video published by the Guardian [99] on drug use. The selected topic was of general interest and included several different insights on different aspects of drug use. Due to the within-subjects design, I had to vary data insights for each clip. To account for possible bias as a result of topic preference, I extracted equivalent data insights from the same drug use dataset. For example, in an experimental block, a data clip presented cigarette use trend among the youth over the years, while the other showed the trend of Marijuana use among youth over the same time period.

I created a total of 16 data clips using DataClips [33], a web based data clips authoring tool. To best fit the 16:9 aspect ratio of the video player used in Qualtrics, I rendered all video clips with 720p at 1280 x 720 resolution. All materials used in the study can be found in the companion website.

For the purpose of this study, I performed further item reduction on the questionnaire I had derived. I selected a subset of items of which were, among the others, best verbalized and loaded clearly and highly on one engagement attribute. As an example, the item "I responded emotionally" was eliminated in favor of the item "The video triggered my emotions" since it scored high under the affective involvement attribute. I also skipped items no longer applicable to the nature of short data clips. For example, I removed the item "I lost track of time", which measures focused attention of viewers when they are exposed to the stimuli for an extended period of time.

I intentionally designed the online survey to be taken only using a computer and not a mobile device in an attempt to make sure viewers watch the videos clips with full attention.

I selected seven items (Table 5) from the 15-items engagement questionnaire I have developed (Section 6.5). In addition to keeping the questionnaire short, I wanted to include only the statements that are applicable to data clips. For example, "I responded emotionally" was eliminated in favor of "The video triggered my emotions" since the latter scored higher under the affective involvement attribute. I also removed the item "I lost track of time" because it measures focused attention of viewers when they are exposed to the stimuli for an extended period of time.

The questionnaire includes complementary statements for measuring the enjoyment factor in the viewer engagement questionnaire: "This video was fun to watch" and "I'd recommend its viewing to my friends." The latter statement goes beyond enjoyment at a personal level by measuring the viewer's willingness to share the video clip with friends.

Similarly, the two statements, "I liked the graphics in the clip" and "I found the clip visually appealing" cover different aspects relating to aesthetical considerations. The former is intended to measure viewer's preferences with regards to the data visualizations and charts/graphics used in the clip. The latter is to more broadly target the overall look and feel of the clip.

The statement, "I found my mind wandering during the view" targets focused attention through a negative attribute by measuring viewers' attention drift while watching a data clip.

This category taps into cognitive and comprehensibility aspects of viewer engagement. Finally, using the items in the cognitive involvement category, I sought to determine, to what degree, viewers felt comfortable processing the information being communicated.

6.7 Results

Of the original 120 responses from Amazon's Mechanical Turk, seven were rejected and re-run because they were deemed to be random responses by the participants as a result of failure to correctly answer all four gotcha questions. Further investigation of answers to the engagement questionnaire lead to removal of one other response consisting of all sevens (i.e., "strongly agree"), indicating the lack of enough attention. The remaining responses were a total of 119. Average completion time was 13.3 minutes. Scores from the practice block were ignored in the analysis of the results.

I conducted a series of repeated-measures ANCOVA models that included variables from the demographic questionnaire (e.g., age, online viewing, learning style)

Attribute	Animation Status (AS)	ChartType (CT)	Interaction AS × CT
Overall Engagement	**	*	**
Affective Involvement	*	*	**
Enjoyment			**
Aesthetics	**	*	**
Focused Attention	*		
Cognitive Involvement	**		*

Table 6. Quantitative analysis overview. *: $p < .05$, **: $p < .01$

as covariates. The first model tested the effects of pictographs and setup animation on each engagement factor. Similarly, I tested the effects of each condition on viewers' overall preference. To do so, I analyzed participants selections in the pairwise comparison question. Furthermore, I performed a qualitative analysis on participants' comments provided for justifying their selection. Finally, I investigated the effects of each condition on the communication of data insights by analyzing answers given to the comprehension questions. All effects were analyzed at a 95% confidence-level. Throughout my analysis, I investigated the source of possible interaction effects by submitting participants' scores for the two ChartType conditions to separate ANOVAs, treating AnimationStatus as a within-subjects factor.

Attribute	Animation Status (AS)	ChartType (CT)	Interaction AS × CT
Overall Engagement	**	*	**
Affective Involvement	*	*	**
Enjoyment			**
Aesthetics	**	*	**
Focused Attention	*		
Cognitive Involvement	**		*

Table 6

summarizes the significant main and interaction effects I found in the statistical analysis.

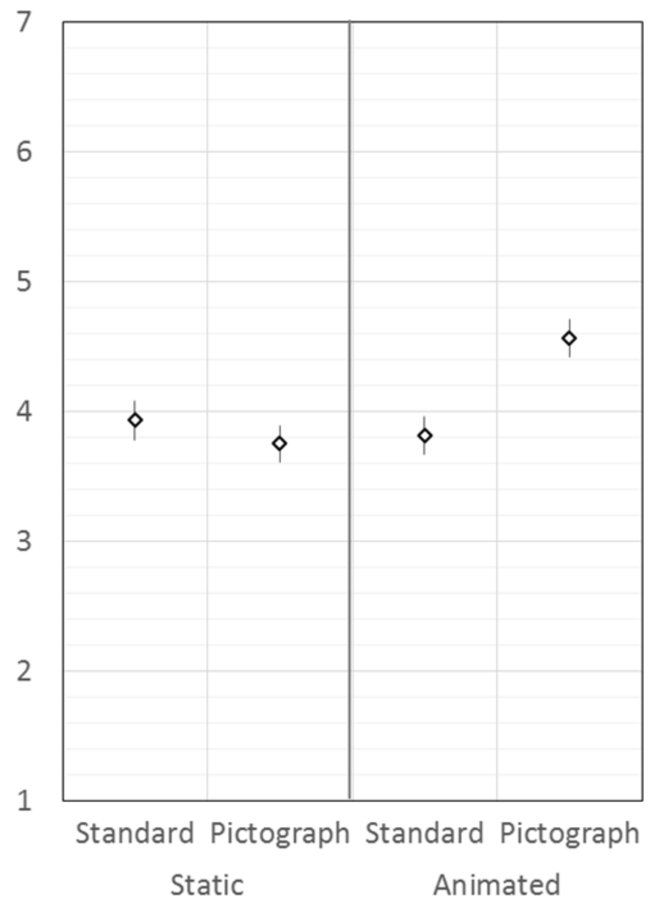

Figure 31. Estimated marginal means for the ratings in the engagement scale.

Engagement Questionnaire Ratings

To calculate the engagement level for each participant, I aggregated across all seven items in the engagement questionnaire. This was done by creating a derived column for the mean ratings given to each item. My analysis revealed significant overall effect of both AnimationStatus ($F(1,118) = 8.23$, $p = .005$) and ChartType ($F(1,118) = 4.48$, $p = .036$).

The results indicate significantly higher viewer engagement levels for animated clips as well as clips including pictographic representations compared to the baselines. I also observed significant interaction effect of AnimationStatus and ChartType, ($F(1,118) = 8.10$, $p= .005$). As depicted in Figure 31, viewers gave significantly higher scores to clips with pictographs when animated ($F(1,118)= 15.15$, $p < .001$).

Regarding the effects of the covariates, I found that average daily online viewing was associated with higher viewer engagement levels in clips that included animated visualizations. Additionally, viewers reporting higher level of education and experience with excel-like charts were less engaged with pictographs. Results controlling for other covariates (e.g., age, gender) did not substantially differ between the ANCOVA and simple ANOVA models.

In subsequent analyses, I submitted participants' ratings for each of the five engagement dimensions to repeated-measures ANOVAs, treating AnimationStatus and ChartType as within-subjects factors. Figure 32 shows the mean ratings collected for each engagement factor separated by data clip condition.

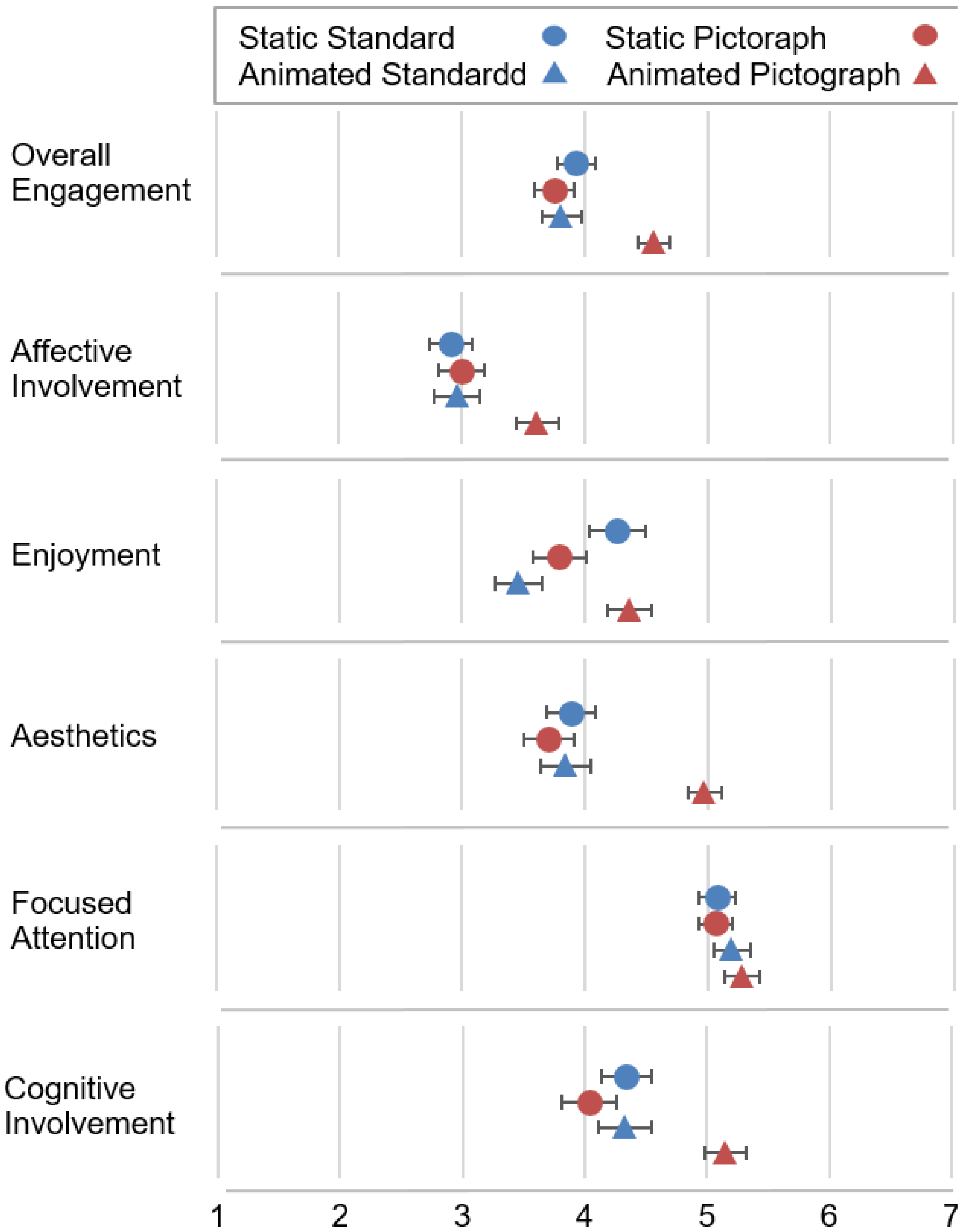

Figure 32. Estimated marginal means of different engagement scale ratings showing interaction between AnimationStatus and ChartType. Error bars represent the standard error of participants' mean ratings for that condition.

1. ***Affective Involvement:*** I found a significant main effect of both AnimationStatus ($F(1,118) = 5.134$, $p = .025$) and ChartType ($F(1,118) = 5.097$, $p = .026$), in that ratings of affective involvement were higher for data clips that contained either animations or iconbased data visualizations. I also found a significant interaction effect of AnimationStatus and ChartType ($F(1,118) = 9.52$, $p = .003$). Similar to the overall engagement levels, affective involvement ratings were significantly higher for clips containing pictographs in the animated condition ($F(1,118) = 9.54$, $p = .002$).

2. ***Enjoyment:*** I calculated the overall enjoyment score as a mean of scores given to the two complementary statements for measuring the enjoyment factor (Table 5). The analysis yielded no main effects of either AnimationStatus or ChartType. However, the analysis revealed a significant interaction effect of AnimationStatus and ChartType ($F(1,118) = 9.828$, $p = .002$). With setup animation, data clips containing pictographs received significantly higher ratings than the ones containing standard charts ($F(1,118) = 9.33$, $p = .003$). I was surprised to see significantly higher enjoyment ratings for data clips with standard charts in the static condition compared to pictographs ($F(1,118) = 6.35$, $p = .01$).

3. ***Aesthetics:*** Using the aggregated aesthetics preference score from the two complementary statements (Table 5), I obtained significant main effects of both AnimationStatus, $F(1,118) = 11.119$, $p = .001$ and ChartType, $F(1,118) = 6.358$, $p = .01$. As expected, participants viewed data clips containing animations and icon-based data visualizations as more aesthetically appealing. I also found significant main effect of AnimationStatus x ChartType interaction, $F(1,118) = 10.809$, $p = .001$. Data

clips containing pictographs were aesthetically perceived significantly more appealing than standard charts when animated, ($F(1,118) = 24.7$, $p < .001$). ***Focused Attention:*** I measured focused attention through a negative attribute by measuring viewers' attention drift while watching a data clip. Therefore, I reverse coded the ratings for this item. Analysis of scores given for this item revealed a significant main effect of AnimationStatus ($F(1,118) = 4.637$, $p = .03$). Participants rated their attention as drifting less when data clips included setup animation techniques. By contrast, the main effect of ChartType was not significant and there was no significant interaction effect.

4. ***Cognitive Involvement:*** In this category, I sought to determine, to what degree, viewers felt comfortable processing the information and understanding the data insights being communicated. I found a significant main effect of AnimationStatus ($F(1,118) = 7.15$, $p = .009$). Participants rated data clips as easier to understand when they contained animation. However, the main effect of ChartType was not significant. I also found a significant interaction effect of AnimationStatus and ChartType ($F(1,118) = 5.81$, $p = .017$). Data clips containing animated pictographs received significantly higher ratings than all other conditions ($F(1,118) = 14.64$, $p < .001$).

Comprehensibility

To further investigate whether participants successfully understood the facts presented, I asked questions about the content immediately after viewing ended for each clip. Analysis of correct answers provided by the viewers did not show significant effects of

AnimationStatus or ChartType. I found significant interaction effects, ($F(1,118) = 17.142$, $p < .001$), matching similar patterns found previously. Viewers provided significantly higher percentage of correct answers for clips having animated pictographs than clips with animated standard charts or clips containing static pictographs. Furthermore, clips in the static standard condition resulted in significantly higher percentage of correct answers compared to static pictographs. This evidence suggests congruent conditions through successful grouping of AnimationStatus and ChartType. Percentage of correct answers provided under each condition is shown in Figure 4-left.

Overall Preference

As an additional measure, I asked participants to pick one data clip over the other through separate blocks with pairs of clips in the survey. Each condition (C1 to C4) was presented two times over two separate blocks. For example, data clip containing static standard chart was once compared with a clip with static pictograph and again, albeit communicating a different insight type, with a clip including animated standard chart in another survey block. Figure 4-right shows the mean number of times a clip under each condition was selected across participants ranging from 0 to 2 times selected.

I found a significant effect of AnimationStatus on clip preference by the viewers, ($F(1,118) = 5.116$, $p = .02$). No significant effect of ChartType was found. I also found a significant interaction effect of AnimationStatus and ChartType ($F(1,118) = 13.12$, $p < .001$). As shown in Figure 3, the pattern matches that of overall viewer engagement levels. Clips containing animated pictographs were selected significantly more number of times across all participants and conditions. Once again, we can see that static standard charts

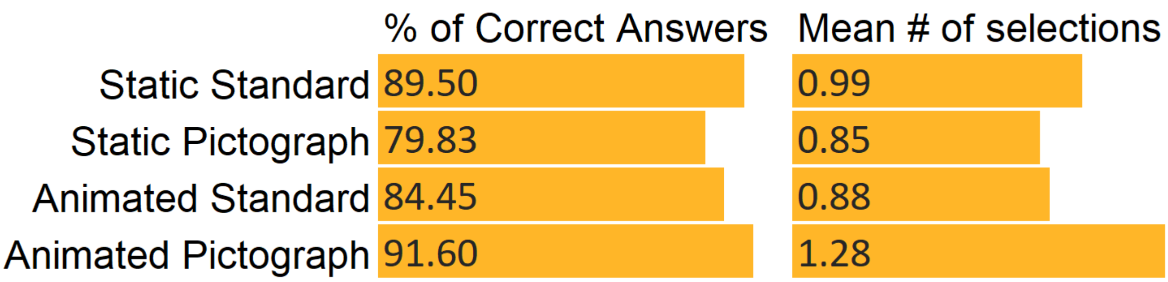

Figure 33. Percentage of correct answers provided (left); mean number of times selected (right).

were favored over static pictographs and animated standard charts. I also looked at the differences between number of selections between congruent conditions (i.e., static standard and animated pictograph) versus conditions not deemed congruent (i.e., animated standard and static pictograph). My analysis indicated that the congruent group is significantly preferred over its non-congruent equivalent ($F(1,118) = 17.142$, $p < .001$).

Viewer Comments

I asked participants to provide the reasons why they selected one data clip over the other on the pairwise comparisons. Here, I highlight interesting findings that emerged from analysis of these open ended comments.

Participants generally liked the movement in the animated clips and thought it made the clip more engaging and enjoyable. In the case of the trend data insight, the animation gave the participants a sense of time: "*I like the way it populated slowly to show progression of time.*" Among viewers preferring static clips, a few mentioned that "*the information was presented quickly*" in the static conditions implying the lack of delay introduced by animation.

The majority of participants selecting clips with standard charts indicated that they were easier to interpret and understand. Some referred to their designs as simple and clear but perhaps the most interesting reason provided by several participants was that they know, are used to seeing, and are familiar with the standard charts. I also saw several comments praising pie and bar charts for comparison tasks. Two comments referred to clips with standard chart as a more "*professional*."

Clips with pictographs were perceived to catch attention right away. Participants referred to them as fun. A reason shared by multiple participants was the icons make the data more relatable and human-like. Some commented on the connection between the topic and graphic choices and how the icons make it easier to view.

Animated Pictographs clips were the most preferred clips under all engagement factors, and received all positive comments (e.g., interesting way of presenting information). While participants pointed out the emotion provoking effects of icons, several comments implied that the added animation brought icons to life. One participant commented, "*the fact that you see people makes it seem more real*," and another mentioned, "*it made me feel something*." In fact, participants' comments included a variety of adjectives to describe the data being communicated (e.g., frightening, serious, crisis, striking, and emotional). Some participants noticed the animation-icon pairing, stating that "*it is much more impactful to use movement and figures to represent real people*."

6.8 Discussion

The results of this experiment confirm that incorporation of setup animation and pictographic representations in the design of data videos can significantly impact different attributes of viewer engagement. Here, I discuss some of the important findings, suggestions for designing engaging data videos, and limitations & future work.

Role of Animation and Pictographs

Addition of animation significantly improved viewer engagement according to the results in the overall engagement scale. Likewise, replacing standard charts with their equivalent pictographic representations significantly boosts viewer engagement. An interesting exception becomes apparent when I take a closer look at the ratings gathered for each engagement attribute. Compared to the standard charts, pictographs do not increase sustained attention nor do they impact comprehensibility of communicated data insights. Incorporation of animation in data clips, however, significantly boosts understandability and decreases attention drift. This might be due to differences in the perception of animation and pictorial representations. Pictographic representations tap into "reservoirs" of collectively held knowledge and cultural associations and engage the reader's imagination, however, this does not translate into more sustained attention. On the other hand and aligned with previous research [113], cleverly designed animate motion does indeed capture and maintain attention.

The results revealed a possible interaction role for congruent combinations of pictographs and animations in stimulating viewer engagement and viewer comprehension of video content. In particular, data clips with animated pictograph received significantly higher ratings in the overall engagement scale compared to all other conditions. These clips elicited higher emotional reactions from the viewers and were perceived as a lot more enjoyable and more appealing. Viewers also gave more percentage of correct answers and found them to be substantially easier to understand.

To my surprise, standard chart clips received higher ratings in several engagement attributes and significantly higher in cognitive involvement and enjoyment compared to clips in the presence of one of the two design strategies (i.e., static pictographs and animated standard charts). A possible explanation based on viewer comments is the ubiquity of static standard charts in data analysis and presentation tools. People find them more professional and suitable for communicating data-driven insights without any delays introduced through the addition of setup animation.

Design Suggestions

Based on the results of the engagement study, I suggest the following considerations for incorporating setup animation and icon-based visualizations in data videos:

1. ***Know Your Audience***: Data videos and animated pictographs are commonly created to appeal to broad audiences. If, however, they are intended for a more specific group of viewers, paying attention to their information consumption habits, level of education, sets of skills, and experiences can go a long way. This finding agrees with prior work on audience research in which contextual, social and cultural factors have been shown to affect users' engagement with data visualizations [91]. For example, if a data video is to be consumed by online viewers with broad backgrounds, combination of animation and pictographs can be an effective

candidate for engaging more viewers. Whereas, pictographic representations are less impactful in data videos created and shared within a more professional organization, in which viewers would have more experience with commonly used data analysis and presentation tools.

2. ***Leverage Static Standard Charts' Strength***: Despite the fact that we see evidence in positive effects of both animation and pictographs on viewer engagement, static standard charts can still engage the viewers. Data clips with static standard charts appear to be as engaging or more engaging than their animated or pictographic representations through several of the engagement dimensions. Therefore, by incorporating such standard charts even without the addition of animation features, designers can take advantage of viewers' learned skills in reading and interpreting these charts.
3. ***Use Setup Animations with Care***: When the information being communicated through data videos requires focused attention from the viewers, I suggest incorporation of setup animation to avoid attention drift. Gradual building of the visualization scene in data clips showed to also help viewers comprehend the information better. On the other hand, beware of the delay introduced as a result of such animations and avoid their excessive use. Viewers may potentially perceive them as annoying.
4. ***Connect to Viewers with Pictographs***: Pictographic representations can provoke viewers' emotions by bringing data to life. Animating pictographs results in a congruent combination that can significantly boost viewer engagement.

6.9 Limitations and Future Work

In this study, I targeted elemental video segments or data clips designed to communicate a single data-driven insight. This decision was made based on the lesson learned from the pilot study for the engagement development scale. By focusing on these smaller units, I sought to avoid potential confounding effects due to the sequencing strategy or narrative structure employed in the data videos. The drawback associated with this design is that the results may not be generalizable to data videos, in which multiple data clips are sequenced together. Future studies are needed to further explore the effects of sequencing strategies or narrative structure on viewer engagement.

I also acknowledge limitations in the stimuli design. I decided to vary the types of data insights communicated through video clips to cover a wide range of data clips. We, however, opted not to control for this factor since counterbalancing the conditions would explode the number of required data clips. Another limitation is the amount of viewer exposure to each stimulus. As I kept the auto playback of the video clips to 10 seconds, data clips with static visualizations had the advantage of longer exposure to all visualization components, whereas in the animated clips, viewers had to wait for the visualizations to get built. Lastly, I ignored potential effects as a result of topic familiarity and preference. A few comments from the viewers, indicated that they picked a data clip because they related to the topic more. For example, one participant picked the clip with data on marijuana and wrote "*I smoke marijuana*". Future studies can investigate effects of topic choice by possibly controlling for this factor based on gathered knowledge on viewer's topic familiarity and topic preferences.

Finally, I have collected initial data to refine the scale and ensure that it provided an efficient and discriminating basis for evaluating differences in participants' views on data videos with or without setup animations and icon-base visualizations. The scale has shown to be inherently effective to the extent that it revealed differences in participants' judgments about the data videos as I reported in the results section. As next steps, we can run studies based on findings from established research on other effective factors impacting viewer engagement and further validate the engagement scale.

6.10 Summary

In this chapter, I identified two design techniques commonly incorporated into data videos to engage viewers: (1) animation to setup and build a data visualization scene and (2) pictographic representations replacing standard charts. Through a crowd-sourced online study, I explored the effects of these two techniques on viewer engagement and understandability of data-driven clips. I found that both animation and pictographic representation can boost understandability of data insights, and significantly impact different attributes of viewer engagement. While pictographs elicited viewer engagement by triggering more emotions and were significantly more appealing compared to standard charts, addition of animation to pictographs intensified such effects. Furthermore, animation as a design technique was successful in increasing focused attention, which is key in keeping the viewers engaged throughout the viewing of data video. I also highlighted results suggesting possible effects of viewers' expertise, education, and online viewing patterns and concluded with discussion and summary of design suggestions for designing more engaging data videos.

"We shape our tools and thereafter our tools shape us."

John Culkin (1967)

7 CONCLUSION

Data videos are a relatively new yet popular medium for storytelling with data. Our research community can benefit from in-depth studies that help to catalog our knowledge on this exciting medium. Such knowledge can also inform the design of tools to make it possible for a broader audience to craft compelling ones. My research goal was to investigate the design aspects of data videos and support authoring of engaging narratives to communicate data insights to broad audiences. To attain this goal and develop an understanding around data videos and their design implications, I conducted a series of exploratory studies. Through the lens of established disciplines involving storytelling such as film theory and cinematography, I identified the high-level narrative structures found in professionally created data videos and exposed their key components.

Despite the viewers' general impression that data videos each feature diverse custom visualizations, most videos rely on only a few types of well-known visualizations (e.g. bar charts, pictographs, and maps). Limiting novice designers to a small set of commonly used visualization types but giving them the flexibility to customize their rendering options and color palette would appear as a good strategy to enable the creation of data videos that may be comprehensible to a large audience. Along this line, one of the most powerfully customizable, yet easily understood visual representations is certainly the pictograph, composed of icons representing data units. While most visual analytics tools and commercial charting tools do not offer much support to create these visualizations, they are heavily present in data videos and certainly should feature in data video authoring software.

Attention cues are used throughout data videos to guide viewer attention, highlight specific parts of the data, or help a seamless transition between different aspects of data. By guiding authors into using an explicit narrative structure for their videos, hints on the type, frequency and strength of attention cues they can use, based on concrete examples as from my sample list, can help authors achieve the right balance.

My observations in both studies indicated that the audience is more engaged if facts told in the story relate to something they know. Observations from workshops hinted at several degrees of personification. Supporting authors in finding such assets and enabling them to tightly couple them with visualizations would ease one of the most tedious part of visual editing.

I observed that there are many different arrangements for the units composing the narrative in data videos. Thus, it seems important to provide flexible narrative structure, allowing authors to generate their own patterns. It would be also useful to provide sample templates based on our observations that guide the author through a selected narrative structure by making sure the right narrative units are defined and sequenced according to common practices. In particular, showcasing patterns that tend to be associated with different types of videos (e.g., "call-to-action" or "educational" videos) may guide authors in making well-structured videos for their intended messages. For example, a call-to-action could benefit from building tension through repeating several units of the Initial narrative category, concluding with a single Peak unit. Educational data videos, on the other hand, may have multiple Peak units for teaching about different aspects of the topic.

There is a trade-off between encouraging novices to follow common practices and enabling them to create a one-of-a-kind engaging and memorable data video. I believe that a successful authoring tool will limit authors in some dimensions (e.g., types of visualizations, narrative categories) to ensure they create comprehensible narratives; while enabling them to customize other dimensions (e.g., visual rendering, narrative structure pattern) to create unique one-of-a-kind videos.

In addition, I gained valuable insights through a series of workshops I conducted with experienced storytellers, such as screenwriters, video makers, and motion graphics designers. I collected evidence that crafting data video storyboards is a non-linear and iterative process and requires going back to the data throughout the process. This process is also dependent on the authors' background and work practices. An authoring tool with storyboarding facilities based on rapid sketching may help in capturing the authors' initial vision and allow iterative refinement. Such a tool can also integrate features to enable authors to easily go back and forth between different storyboarding activities.

My examination of over 70 professionally crafted data videos revealed the presence of seven major types of elemental video sequences necessary for creating compelling data videos. This includes a significant library of data clips, which allow presenting data-driven insights using different visualization styles (including pictographs) as well as different methods for engaging viewers through the use of motion graphics.

I learned that crafting data videos is not an easy task. It requires a significant amount of time and effort, a broad set of skills, dedicated software or programming capabilities, and often involves a plethora of tools. A main goal of this thesis work was to consolidate the creation of data videos through the major use of one tool and by lowering the skill level required to create data videos using common data visualizations and animations. This led to the development of DataClips— a web-based tool allowing data enthusiasts to compose, edit, and assemble data clips to produce a data video without possessing programming skills. I demonstrated that DataClips covers a wide range of data videos contained in my corpus, albeit limiting the level of customization of the visuals and animations. I also report on a qualitative user study with 12 participants comparing DataClips to Adobe Illustrator/After Effects software, commonly used to create data videos. I found that non-experts can create data videos having the same visual caliber as those created using commercial animation tools (not necessarily for data videos) but also can create more videos in a limited time than tools currently used for creating such videos. An interesting direction for future work would be enabling non-experts to craft compelling narratives for data-driven videos by offering a set of templates geared toward different styles of insights based on the intended message.

To deepen the understanding of what makes compelling data videos. I explored different evaluation methods and metrics to attempt to better capture the characteristics that make quality narrative visualizations. Evaluation is a wide-reaching concept, and the term evokes different meanings in different domains: evaluation of a data-driven story in a newsroom will be very different from the evaluation of a novel storytelling technique in an academic research setting. I outlined the diverse set of goals of storytellers, publishers, readers, tool builders, and researchers (Figure 27). Given these goals, I highlighted evaluation methods and metrics that approximate these goals in the context of data videos and took on the challenge of evaluating viewer engagement.

To assess the quality of data videos, I studied the effect of several design strategies incorporated into the visualizations to engage the viewers and sustain their attention. In chapter 6, I identified two design techniques commonly incorporated into data videos to engage viewers: (1) animation to setup and build a data visualization scene and (2) pictographic representations replacing standard charts. Through a crowd-sourced online study, I explored the effects of these two techniques on viewer engagement and understandability of data-driven clips.

Addition of animation significantly improved viewer engagement according to the results in the overall engagement scale. Likewise, replacing standard charts with their equivalent pictographic representations significantly boosts viewer engagement. An interesting exception becomes apparent when I take a closer look at the ratings gathered for each engagement attribute. Compared to the standard charts, pictographs do not increase sustained attention, nor do they impact comprehensibility of communicated data insights. Incorporation of animation in data clips, however, significantly boosts understandability and decreases attention drift. This might be due to differences in the perception of animation and pictorial representations. Pictographic representations tap into "reservoirs" of collectively held knowledge and cultural associations and engage the reader's imagination, however, this does not translate into more sustained attention. On the other hand and aligned with previous research, cleverly designed animate motion does indeed capture and maintain attention.

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I have collected initial data to refine the scale and ensure that it provided an efficient and discriminating basis for evaluating differences in participants' views on data videos with or without setup animations and icon-base visualizations. The scale has shown to be inherently effective to the extent that it revealed differences in participants' judgments about the data videos. As next steps, we can run studies based on findings from established research on other effective factors impacting viewer engagement and further validate the engagement scale.

8 REFERENCES

[1] Adobeaftereffects cc. http://www.adobe.com/ca/products/aftereffects.html/, Adobe AfterEffects. [Online; accessed on 2019-10-20].

[2] Backbone.js. http://backbonejs.org/, Backbonejs. [Online; accessed on 2019-10-20].

[3] 85 percent of facebook video is watched without sound. https://digiday.com/-media/silent-world-facebook-video. [Online; accessed on 2019-10-20].

[4] FLOWINGDATA. http://flowingdata.com/. [Online; accessed on 2019-10-20].

[5] The Guardian Datablog. http://www.theguardian.com/data/. [Online; accessed on 2019-10-20].

[6] Adobe illustrator cc. http://www.adobe.com/ca/products/illustrator.html/, AdobeIllustrator. [Online; accessed on 2019-10-20].

[7] iMovie. https://www.apple.com/mac/imovie/. [Online; accessed on 2019-10-20].

[8] Intro.js. http://introjs.com/, Introjs. [Online; accessed on 2019-10-20].

[9] The New York Times. http://www.nytimes.com/. [Online; accessed on 2019-10-20].

[10] Divorces in 2012. http://www.ons.gov.uk/ons/rel/vsob1/divorces-in-england-and-wales/index.html. [Online; accessed on 2019-10-20].

[11] Oxford online dictionary. http://www.oxforddictionaries.com. [Online; accessed on 2019-10-20].

[12] Use a picture. it's worth a thousand words. *Speakers Give Sound Advice*, Syracuse Post Standard (page 18), March 28, 1911. [Online; accessed on 2019-10-20].

[13] Qualtrics: The leading research & experience software. https://www.qualtrics.com. [Online; accessed on 2019-10-20].

[14] The general (1926). http://explore.bfi.org.uk/4ce2b6aae85f3. [Online; accessed on 2019-10-20].

[15] 200 years that changes the world. http://www.gapminder.org/videos/200-years-that-changed-the-world/, GapMinder, 2009. [Online; accessed on 2019-10-20].

[16] Global air traffic. https://www.youtube.com/user/Rightcolours/, RightColors, 2012. [Online; accessed on 2019-10-20].

[17] 99% v 1%: the data behind the occupy movement. http://www.theguardian.com/-news/datablog/video/2011/nov/16/99-v-1-occupy-data-animation, The Guardian, 2012. [Online; accessed on 2019-10-20].

[18] Racing against history. http://www.nytimes.com/interactive/2012/08/01/sports/-olympics/racing-against-history.html?_r=0, The New York Times, 2012. [Online; accessed on 2019-10-20].

[19] Will taxing the rich fix the deficit? https://youtu.be/FC5Gkox-1QY/, Learn Liberty, 2012. [Online; accessed on 2019-10-20].

[20] Four-in-ten couples are saying i do, again. https://www.youtube.com/-watch?v=EKYOWHtaPQE, 2014. [Online; accessed on 2019-10-20].

[21] An infographic exploration of online video. http://www.shutterstock.com/blog/an-infographic-exploration-of-online-video, Shutterstock, 2014. [Online; accessed on 2019-10-20].

[22] Children of recession. http://rightcolours.com/portfolioï¿½unicef-innocenti-report.html, RightColors, 2014. [Online; accessed on 2019-10-20].

[23] Home - VisLit. http://visualizationliteracy.org, 2014. [Online; accessed on 2019-10-20].

[24] Data videos project. http://hci.cs.umanitoba.ca/Publications/details/data-videos, DataVideos, 2015. [Online; accessed on 2019-10-20].

[25] Data-driven storytelling. https://www.dagstuhl.de/en/program/calendar/semhp/-?semnr=16061/, Dagstuhl Seminar, 2016. [Online; accessed on 2019-10-20].

[26] Dataclips project. http://hci.cs.umanitoba.ca/projects-and-research/details/-dataclips, DataClips, 2016. [Online; accessed on 2019-10-20].

[27] Use bookmarks to share insights and build stories in Power BI. https://-docs.microsoft.com/en-us/power-bi/desktop-bookmarks, 2018. [Online; accessed on 2019-10-20].

[28] Tableau stopry points. https://tabsoft.co/2jxghOC, 2018. [Online; accessed on 2019-10-20].

[29] Evaluating data videos project. datavideo-engmtscale.github.io, 2018. [Online; accessed on 2019-10-20].

[30] Dictionary, o.e. oxford living dictionaries. http://www.oxforddictionaries.com/-definition/english/memory, 2019. [Online; accessed on 2019-10-20].

[31] Nancy E Adams. Bloomï¿½s taxonomy of cognitive learning objectives. *Journal of the Medical Library Association: JMLA*, 103 (3): 152, 2015.

[32] Fereshteh Amini, Nathalie Henry Riche, Bongshin Lee, Christophe Hurter, and Pourang Irani. Understanding data videos: Looking at narrative visualization through the cinematography lens. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 1459–1468. ACM Press, 2015.

[33] Fereshteh Amini, Nathalie Henry Riche, Bongshin Lee, Andres Monroy-Hernandez, and Pourang Irani. Authoring data-driven videos with dataclips. *IEEE transactions on visualization and computer graphics*, 23 (1): 501–510, 2017.

[34] Fereshteh Amini, Mathew Brehmer, Gordon Boldun, Christina Elmer, and Benjamin Wiederkehr. *Evaluating data-driven stories & storytelling tools*, chapter 11. CRC Press, March 2018.

[35] Fereshteh Amini, Nathalie Henry Riche, Bongshin Lee, Jason Leboe-McGowan, and Pourang Irani. Hooked on data videos: assessing the effect of animation and pictographs on viewer engagement. In *Proceedings of the 2018 International Conference on Advanced Visual Interfaces*, page 21. ACM, 2018.

[36] Simon Attfield, Gabriella Kazai, Mounia Lalmas, and Benjamin Piwowarski. Towards a science of user engagement (position paper). In *WSDM workshop on user modelling for Web applications*, pages 9–12, 2011.

[37] Benjamin Bach, Natalie Kerracher, Kyle Wm Hall, Sheelagh Carpendale, Jessie Kennedy, and Nathalie Henry Riche. Telling stories about dynamic networks with graph comics. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 3670–3682. ACM, 2016.

[38] Benjamin Bach, Nathalie Henry Riche, Sheelagh Carpendale, and Hanspeter Pfister. The emerging genre of data comics. *IEEE computer graphics and applications*, 37 (3): 6–13, 2017.

[39] Benjamin Bach, Zezhong Wang, Matteo Farinella, Dave Murray-Rust, and Nathalie Henry Riche. Design patterns for data comics. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, page 38. ACM, 2018.

[40] Donia Badawood and Jo Wood. A visual language to characterise transitions in narrative visualization. In *Posters Compendium of InfoVis*, 2013.

[41] Donia Badawood and Jo Wood. The effect of information visualization delivery on narrative construction and development. In *Eurographics Conference on Visualization (EuroVis)*, 2014.

[42] John A Bateman and Janina Wildfeuer. A multimodal discourse theory of visual narrative. *Journal of Pragmatics*, 74: 180–208, 2014.

[43] Scott Bateman, Regan L Mandryk, Carl Gutwin, Aaron Genest, David McDine, and Christopher Brooks. Useful junk?: the effects of visual embellishment on

comprehension and memorability of charts. In *Proc. CHI*, pages 2573–2582. ACM Press, 2010.

[44] Robert M Bond, Christopher J Fariss, Jason J Jones, Adam DI Kramer, Cameron Marlow, Jaime E Settle, and James H Fowler. A 61-million-person experiment in social influence and political mobilization. *Nature*, 489 (7415): 295, 2012.

[45] David Bordwell. *Narration in the fiction film*. Routledge, 2013.

[46] Rita Borgo, Alfie Abdul-Rahman, Farhan Mohamed, Philip W Grant, Irene Reppa, Luciano Floridi, and Min Chen. An empirical study on using visual embellishments in visualization. *IEEE Transactions on Visualization and Computer Graphics*, 18 (12): 2759–2768, 2012.

[47] Michelle A Borkin, Azalea A Vo, Zoya Bylinskii, Phillip Isola, Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister. What makes a visualization memorable? *IEEE Transactions on Visualization and Computer Graphics*, 19 (12): 2306–2315, 2013.

[48] Michelle A Borkin, Zoya Bylinskii, Nam Wook Kim, Constance May Bainbridge, Chelsea S Yeh, Daniel Borkin, Hanspeter Pfister, and Aude Oliva. Beyond memorability: Visualization recognition and recall. *IEEE Transactions on Visualization and Computer Graphics*, 22 (1): 519–528, 2016.

[49] Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer. D^3 data-driven documents. *IEEE Transactions on Visualization and Computer Graphics*, 17 (12): 2301–2309, 2011.

[50] Jeremy Boy, Francoise Detienne, and Jean-Daniel Fekete. Storytelling in information visualizations: Does it engage users to explore data? In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 1449–1458. ACM, 2015.

[51] Matthew Brehmer, Sheelagh Carpendale, Bongshin Lee, and Melanie Tory. Pre-design empiricism for information visualization: scenarios, methods, and

challenges. In *Proceedings of the Fifth Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization*, pages 147–151. ACM, 2014.

[52] Matthew Brehmer, Bongshin Lee, Nathalie Henry Riche, David Tittsworth, Kate Lytvynets, Darren Edge, and Christopher White. Timeline storyteller: The design & deployment of an interactive authoring tool for expressive timeline narratives. In *proceedings of the the Computation+ Journalism Symposium. https://aka.ms/TSCJ19*, 2019.

[53] Willard Cope Brinton. *Graphic methods for presenting facts*. Engineering magazine company, 1917.

[54] Willard Cope Brinton. *Graphic presentation*. Ripol Classic Publishing House, 1939.

[55] Jeanne H Brockmyer, Christine M Fox, Kathleen A Curtiss, Evan McBroom, Kimberly M Burkhart, and Jacquelyn N Pidruzny. The development of the game engagement questionnaire: A measure of engagement in video game-playing. *Journal of Experimental Social Psychology*, 45 (4): 624–634, 2009.

[56] Dick CA Bulterman and Lynda Hardman. Structured multimedia authoring. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 1 (1): 89–109, 2005.

[57] Stuart K Card, Jock D Mackinlay, and Ben Shneiderman. *Readings in information visualization: using vision to think*. Morgan Kaufmann, 1999.

[58] Sheelagh Carpendale. Evaluating information visualizations. In *Information Visualization*, pages 19–45. Springer, 2008.

[59] Seymour Benjamin Chatman. *Story and discourse: Narrative structure in fiction and film*. Cornell University Press, 1980.

[60] Fanny Chevalier, Romain Vuillemot, and Guia Gali. Using concrete scales: A practical framework for effective visual depiction of complex measures. *IEEE transactions on visualization and computer graphics*, 19 (12): 2426–2435, 2013.

[61] Fanny Chevalier, Nathalie Henry Riche, Catherine Plaisant, Amira Chalbi, and Christophe Hurter. Animations 25 years later: New roles and opportunities. In *Proceedings of the International Working Conference on Advanced Visual Interfaces*, pages 280–287. ACM, 2016.

[62] William S Cleveland and Robert McGill. Graphical perception: The visual decoding of quantitative information on graphical displays of data. *Journal of the Royal Statistical Society: Series A (General)*, 150 (3): 192–210, 1987.

[63] Neil Cohn. Visual narrative structure. *Cognitive science*, 37 (3): 413–452, 2013.

[64] Neil Cohn. The architecture of visual narrative comprehension: the interaction of narrative structure and page layout in understanding comics. *Frontiers in Psychology*, 5: 680, 2014.

[65] Yellowlees Douglas and Andrew Hargadon. The pleasure principle: immersion, engagement, flow. In *Proceedings of the eleventh ACM on Hypertext and hypermedia*, pages 153–160. ACM, 2000.

[66] Graham Dove and Sara Jones. Narrative visualization: sharing insights into complex data. In *Interfaces and Human Computer Interaction (IHCI 2012)*, 2012.

[67] Ryan Eccles, Thomas Kapler, Robert Harper, and William Wright. Stories in geotime. *Information Visualization*, 7 (1): 3–17, 2008.

[68] T Todd Elvins. Visfiles: presentation techniques for time-series data. *ACM SIGGRAPH Computer Graphics*, 31 (2): 14–16, 1997.

[69] Dezheng Feng and Kay L O'Halloran. Representing emotive meaning in visual images: A social semiotic approach. *Journal of Pragmatics*, 44 (14): 2067–2084, 2012.

[70] Danyel Fisher. *Animation for Visualization: Opportunities and Drawbacks*. O'Reilly Media, April 2010. ISBN 9781449379865. URL https://www.microsoft.com/en-us/-research/publication/animation-for-visualization-opportunities-and-drawbacks/.

[71] Gustav Freytag. *Technique of the Drama: An Exposition of Dramatic Composition and Art*. University Press of the Pacific, 1904.

[72] Tong Gao, Jessica Hullman, Eytan Adar, Brent Hecht, and Nicholas Diakopoulos. Newsviews: An automated pipeline for creating custom geovisualizations for news. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 3005–3014. ACM Press, 2014.

[73] Nahum Gershon and Ward Page. What storytelling can do for information visualization. *Association for Computing Machinery. Communications of the ACM*, 44 (8): 31–31, 2001.

[74] Barney G Glaser and Anselm L Strauss. Discovery of grounded theory: Strategies for qualitative research, 2017.

[75] Kristina Gluic. Skype interview. http://rightcolours.com/, 2015, September 22.

[76] Samuel Gratzl, Alexander Lex, Nils Gehlenborg, Nicola Cosgrove, and Marc Streit. From visual exploration to storytelling and back again. In *Computer Graphics Forum*, volume 35, pages 491–500. Wiley Online Library, 2016.

[77] MC Green, TC Brock, and SD Livingston. Transportation and enjoyment. *Unpublished data*, 2004.

[78] Steve Haroz, Robert Kosara, and Steven L Franconeri. Isotype visualization: Working memory, performance, and engagement with pictographs. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 1191–1200. ACM Press, 2015.

[79] Lane Harrison, Fumeng Yang, Steven Franconeri, and Remco Chang. Ranking visualizations of correlation using weber's law. *IEEE transactions on visualization and computer graphics*, 20 (12): 1943–1952, 2014.

[80] Lane Harrison, Katharina Reinecke, and Remco Chang. Infographic aesthetics: Designing for the first impression. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 1187–1190. ACM, 2015.

[81] Jeffrey Heer and George Robertson. Animated transitions in statistical data graphics. *IEEE transactions on visualization and computer graphics*, 13 (6): 1240–1247, 2007.

[82] Jeffrey Heer, Jock Mackinlay, Chris Stolte, and Maneesh Agrawala. Graphical histories for visualization: Supporting analysis, communication, and evaluation. *IEEE transactions on visualization and computer graphics*, 14 (6): 1189–1196, 2008.

[83] Nigel Holmes. Pictograms: A view from the drawing board or, what i have learned from otto neurath and gerd arntz (and jazz). *Information design journal*, 10 (2): 133–143, 2000.

[84] Jessica Hullman and Nicholas Diakopoulos. Visualization rhetoric: Framing effects in narrative visualization. *Visualization and Computer Graphics, IEEE Transactions on*, 17 (12): 2231–2240, 2011.

[85] Jessica Hullman, Eytan Adar, and Priti Shah. Benefitting infovis with visual difficulties. *IEEE Transactions on Visualization and Computer Graphics*, 17 (12): 2213–2222, 2011.

[86] Jessica Hullman, Nicholas Diakopoulos, and Eytan Adar. Contextifier: automatic generation of annotated stock visualizations. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 2707–2716. ACM Press, 2013.

[87] Jessica Hullman, Steven Drucker, Nathalie Henry Riche, Bongshin Lee, Danyel Fisher, and Eytan Adar. A deeper understanding of sequence in narrative visualization. *IEEE Transactions on visualization and computer graphics*, 19 (12): 2406–2415, 2013.

[88] Animoto Inc. Animoto. http://animoto.com/, 2019. [Online; accessed on 2019-10-20].

[89] Martin Jenkins and Jo Lonsdale. Evaluating the effectiveness of digital storytelling for student reflection. In *ICT: Providing choices for learners and learning. Proceedings ASCILITE Singapore*, 2007.

[90] Eser Kandogan. Just-in-time annotation of clusters, outliers, and trends in point-based data visualizations. In *2012 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 73–82. IEEE, 2012.

[91] Helen Kennedy, Rosemary Lucy Hill, William Allen, and Andy Kirk. Engaging with (big) data visualizations: Factors that affect engagement and resulting new definitions of effectiveness. *First Monday*, 21 (11), 2016.

[92] Nam Wook Kim, Nathalie Henry Riche, Benjamin Bach, Guanpeng Xu, Matthew Brehmer, Ken Hinckley, Michel Pahud, Haijun Xia, Michael J McGuffin, and Hanspeter Pfister. Datatoon: Drawing dynamic network comics with pen+ touch interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, page 105. ACM, 2019.

[93] Robert Kosara. Presentation-oriented visualization techniques. *IEEE computer graphics and applications*, 36 (1): 80–85, 2016.

[94] Robert Kosara and Jock Mackinlay. Storytelling: The next step for visualization. *IEEE Computer*, 46 (5): 44–50, 2013.

[95] Randy Krum. *Cool infographics: effective communication with data visualization and design*. John Wiley & Sons, 2013.

[96] Bongshin Lee, Rubaiat Habib Kazi, and Greg Smith. Sketchstory: Telling more engaging stories with data through freeform sketching. *Visualization and Computer Graphics, IEEE Transactions on*, 19 (12): 2416–2425, 2013.

[97] Bongshin Lee, Nathalie Henry Riche, Petra Isenberg, and Sheelagh Carpendale. More than telling a story: A closer look at the process of transforming data into visually shared stories. In *IEEE Computer Graphics and Applications*. IEEE, 2015.

[98] Jane Lessiter, Jonathan Freeman, Edmund Keogh, and Jules Davidoff. A cross-media presence questionnaire: The itc-sense of presence inventory. *Presence: Teleoperators and virtual environments*, 10 (3): 282–297, 2001.

[99] Guardian News & Media Limited. Drug use: 20 things you might not know. http://-www.theguardian.com/society/datablog/video/2012/mar/15/drugs-use-animation-20-facts, The Guardian, 2012. [Online; accessed on 2019-10-20].

[100] Andrés Lucero, Jussi Holopainen, Elina Ollila, Riku Suomela, and Evangelos Karapanos. The playful experiences (plex) framework as a guide for expert evaluation. In *Proceedings of the 6th International Conference on Designing Pleasurable Products and Interfaces*, pages 221–230. ACM, 2013.

[101] Kwan-Liu Ma, Isaac Liao, Jennifer Frazier, Helwig Hauser, and Helen-Nicole Kostis. Scientific storytelling using visualization. *IEEE Computer Graphics and Applications*, 32 (1): 12–19, 2011.

[102] Narges Mahyar, Sung-Hee Kim, and Bum Chul Kwon. Towards a taxonomy for evaluating user engagement in information visualization. In *Workshop on Personal Visualization: Exploring Everyday Life*, volume 3, page 2, 2015.

[103] Jean M Mandler and Nancy S Johnson. Remembrance of things parsed: Story structure and recall. *Cognitive psychology*, 9 (1): 111–151, 1977.

[104] Andrew J Martin and Martin Dowson. Interpersonal relationships, motivation, engagement, and achievement: Yields for theory, current issues, and educational practice. *Review of educational research*, 79 (1): 327–365, 2009.

[105] Joy Mayer. *A culture of audience engagement in the news industry*. University of Missouri-Columbia, 2011.

[106] Daniel K Mayes and James E Cotton. Measuring engagement in video games: A questionnaire. In *Proceedings of the human factors and ergonomics society annual meeting*, volume 45, pages 692–696. SAGE Publications Sage CA: Los Angeles, CA, 2001.

[107] Scott McCloud. *Understanding comics: The invisible art*. William Morrow Paperbacks, 1994.

[108] Sean McKenna, N Henry Riche, Bongshin Lee, Jeremy Boy, and Miriah Meyer. Visual narrative flow: Exploring factors shaping data visualization story reading experiences. In *Computer Graphics Forum*, volume 36, pages 377–387. Wiley Online Library, 2017.

[109] Britta Meixner, Katarzyna Matusik, Christoph Grill, and Harald Kosch. Towards an easy to use authoring tool for interactive non-linear video. *Multimedia Tools and Applications*, 70 (2): 1251–1276, 2014.

[110] Andrew Vande Moere and Helen Purchase. On the role of design in information visualization. *Information Visualization*, 10 (4): 356–371, 2011.

[111] Heather L O'Brien and Elaine G Toms. What is user engagement? a conceptual framework for defining user engagement with technology. *Journal of the Association for Information Science and Technology*, 59 (6): 938–955, 2008.

[112] Heather L O'Brien and Elaine G Toms. The development and evaluation of a survey to measure user engagement. *Journal of the Association for Information Science and Technology*, 61 (1): 50–69, 2010.

[113] Jay Pratt, Petre V Radulescu, Ruo Mu Guo, and Richard A Abrams. Itï¿½s alive! animate motion captures visual attention. *Psychological Science*, 21 (11): 1724–1730, 2010.

[114] Donghao Ren, Matthew Brehmer, Bongshin Lee, Tobias Höllerer, and Eun Kyoung Choe. Chartaccent: Annotation for data-driven storytelling. In *2017 IEEE Pacific Visualization Symposium (PacificVis)*, pages 230–239. IEEE, 2017.

[115] Lyn Richards. *Handling qualitative data: A practical guide*. Sage Publications, 2009.

[116] N Riche et al. Beyond system logging: Human logging for evaluating information visualization. In *Position paper presented orally at the BELIV 2010 conference*. Citeseer, 2010.

[117] George Robertson, Roland Fernandez, Danyel Fisher, Bongshin Lee, and John Stasko. Effectiveness of animation in trend visualization. *IEEE transactions on visualization and computer graphics*, 14 (6): 1325–1332, 2008.

[118] Hans Rosling. Gapminder. *GapMinder Foundation http://www. gapminder. org*, 2009.

[119] Bahador Saket, Carlos Scheidegger, Stephen G Kobourov, and Katy Börner. Map-based visualizations increase recall accuracy of data. In *Computer Graphics Forum*, volume 34, pages 441–450. Wiley Online Library, 2015.

[120] Bahador Saket, Alex Endert, and John T Stasko. Beyond usability and performance: A review of user experience-focused evaluations in visualization. In *BELIV*, pages 133–142, 2016.

[121] Arvind Satyanarayan and Jeffrey Heer. Authoring narrative visualizations with ellipsis. *Computer Graphics Forum (EuroVis '14')*, 33 (3): 361–370, 2014.

[122] Jonathan A Schwabish. An economist's guide to visualizing data. *The Journal of Economic Perspectives*, 28 (1): 209–233, 2014.

[123] Edward Segel and Jeffrey Heer. Narrative visualization: Telling stories with data. *IEEE Transactions on Visualization and Computer Graphics*, 16 (6): 1139–1148, 2010.

[124] Martin EP Seligman and Mihaly Csikszentmihalyi. Positive psychology: An introduction. In *Flow and the foundations of positive psychology*, pages 279–298. Springer, 2014.

[125] Matthias Shapiro. Once upon a stacked time series. *Beautiful Visualization: Looking at Data Through the Eyes of Experts*, pages 15–36, 2010.

[126] Edward Yu-Te Shen, Henry Lieberman, and Glorianna Davenport. What's next?: emergent storytelling from video collection. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 809–818. ACM, 2009.

[127] Drew Skau, Lane Harrison, and Robert Kosara. An evaluation of the impact of visual embellishments in bar charts. In *Computer Graphics Forum*, volume 34, pages 221–230. Wiley Online Library, 2015.

[128] Andre Suslik Spritzer, Jeremy Boy, Pierre Dragicevic, Jean-Daniel Fekete, and Carla Maria Dal Sasso Freitas. Towards a smooth design process for static communicative node-link diagrams. In *Computer Graphics Forum*, volume 34, pages 461–470. Wiley Online Library, 2015.

[129] Alistair Sutcliffe. Designing for user engagement: Aesthetic and attractive user interfaces. *Synthesis lectures on human-centered informatics*, 2 (1): 1–55, 2009.

[130] Justin Talbot, Vidya Setlur, and Anushka Anand. Four experiments on the perception of bar charts. *IEEE transactions on visualization and computer graphics*, 20 (12): 2152–2160, 2014.

[131] James J Thomas and Kristin A Cook. *Illuminating the path: The research and development agenda for visual analytics*. IEEE Computer Society Press, 2005.

[132] Edward R. Tufte. *The Visual Display of Quantitative Information*. Graphics Press, Cheshire, CT, USA, 1986. ISBN 0-9613921-0-X.

[133] Barbara Tversky, Julie Bauer Morrison, and Mireille Betrancourt. Animation: can it facilitate? *International journal of human-computer studies*, 57 (4): 247–262, 2002.

[134] Fernanda B Viegas, Martin Wattenberg, Frank Van Ham, Jesse Kriss, and Matt McKeon. Manyeyes: a site for visualization at internet scale. *IEEE transactions on visualization and computer graphics*, 13 (6): 1121–1128, 2007.

[135] Colin Ware. *Information visualization: perception for design*. Elsevier, 2012.

[136] Wita Wojtkowski and W Gregory Wojtkowski. Storytelling: its role in information visualization. In *European Systems Science Congress*, volume 5. Citeseer, 2002.

[137] Judith Lynne Zaichkowsky. Measuring the involvement construct. *Journal of consumer research*, 12 (3): 341–352, 1985.

[138] Zhenpeng Zhao, Rachael Marr, and Niklas Elmqvist. Data comics: Sequential art for data-driven storytelling. *tech. report*, 2015.

[139] Douglas E Zongker and David H Salesin. On creating animated presentations. In *Proceedings of the 2003 ACM SIGGRAPH/Eurographics symposium on Computer animation*, pages 298–308. Eurographics Association, 2003.

#	Data Video Title	Source	Link
1	200 Countries-200 Years-4minutes	BBC	http://www.gapminder.org/videos/200-years-that-changed-the-world-bbc/#.VB3ChfldXts
2	350.org: Because the world needs to know	350.org	http://350.org/resources/videos/the-350-movement-90-seconds-no-words/
3	99% v 1%: the data behind the Occupy movement - animation	The Guardian	http://www.theguardian.com/news/datablog/video/2011/nov/16/99-v-1-occupy-data-animation
4	A big problem	The Economist	http://www.economist.com/blogs/graphicdetail/2012/12/daily-chart-16
5	ActNow	The Big Ask campaign	https://www.youtube.com/watch?v=-kRP5x2MsAw
6	AdReaction 2014: Marketing in the multiscreen world - infographic	The Guardian	http://www.theguardian.com/media-network/2014/mar/17/milward-brown-ad-reaction-multiscreen-infographic
7	All the Medalists: Men’s 100-Meter Freestyle	The New York Times	http://www.nytimes.com/interactive/2012/08/01/sports/olympics/racing-against-history.html?_r=0
8	Australian Mid-Market in focus	GEAustralia	https://www.youtube.com/watch?v=ewIB5ZgjbhA
9	Drug use: 20 things you might not know - animation	The Guardian	http://www.theguardian.com/society/datablog/video/2012/mar/15/drugs-use-animation-20-facts
10	Fitness Supplement Infographic	SCAD University	http://portfolios.scad.edu/gallery/8159705/Fitness-Supplement-Infographic
11	Global Air Traffic	RightColors: Creative Visualization Agency	http://www.rightcolours.com/portfolio2.html
12	Global Wealth Report 2012-WhatWillTheFutureBring	Suisse Group Research	https://www.youtube.com/watch?v=WX-tEWNL_e0
13	Heart Disease Facts PSA Video	Multimedia Web Content Production	http://digitalsplashmedia.com/2014/04/heart-disease-facts-psa-video
14	How Mariano Rivera Dominates Hitters	The New York Times	http://www.nytimes.com/video/sports/1247468158551/how-mariano-rivera-dominates-hitters.html
15	Inequality: how wealth is distributed in the UK - animated video	The Guardian	http://www.theguardian.com/commentisfree/video/2013/oct/08/inequality-how-wealth-distributed-uk-animated-video

16	International Migration	edeos- digital education	https://www.youtube.com/watch?v=lOZmqIwqur4
17	iPadPastPresentNewGeneration	RightColors: Creative Visualization Agency	https://www.youtube.com/watch?v=fXi1YTKEcY0
18	ISSUE_ Trade Justice - why world trade rules need to change	Trade Aid Movement Agency	https://www.youtube.com/watch?v=ldZwGDXTsmk
19	Japan's Debt Problem Visualized	Designer Youtube Channel	https://www.youtube.com/watch?v=Njp8bKpi-vg&list=TL6ZgCranjlWeMXo0NT2dQ_6SF0WOMEzbM
20	Live Chart: Global smartphone shipments	The Economist	https://www.youtube.com/watch?v=ph8F320Bljc
21	Live chart: Media to watch	The Economist	https://www.youtube.com/watch?v=QQM4BfS0G_Y
22	Live chart: The lucky left	The Economist	https://www.youtube.com/watch?v=CtKC2_xiAps
23	One Race, Every Medalist Ever	The New York Times	http://www.nytimes.com/interactive/2012/08/05/sports/olympics/the-100-meter-dash-one-race-every-medalist-ever.html
24	OneTrillionDollarsVisualized	VizWorld	http://www.vizworld.com/2009/07/one-trillion-dollars-visualized-from-mint/#sthash.qpuiOrsU.dpbs
25	Overview: 2014 GE Capital Australian Mid-Market Report	GE Capital	http://www.gecapital.com.au/knowledge-hub/2014/mid-market-overview.html
26	People and Their Cars: America's Love Affair with the Automobile	Blog	http://blog.cjponyparts.com/2014/05/people-and-their-cars-americas-love-affair-automobile/
27	RoadToRecovery	BarackObama.com	https://www.youtube.com/watch?v=jWmUnU7HS-I
28	Shocking Amounts of Sugar People Eat Around The World	Buzzfeed	http://www.buzzfeed.com/brandensueper/shocking-amounts-of-sugar-people-eat-around-the-world#3h2hzr6
29	Show Me Something	Design Blog	http://www.shutterstock.com/blog/an-infographic-exploration-of-online-video
30	Skivers v strivers: the benefits debate explained | Animation	The Guardian	http://www.theguardian.com/society/datablog/video/2013/feb/05/benefits-skiver-striver-animated-video
31	TelanganaAndAndhraPradesh	The Economist	http://www.economist.com/blogs/banyan/2014/06/telangana-and-andhra-pradesh
32	The Facts on Medicare and How to Save It	Government Budget House	http://budget.house.gov/fy2012budget/medicare.htm
33	The largest migration in history	The Economist	http://www.economist.com/blogs/graphicdetail/2012/02/daily-chart-17
34	The Marathon Route's Evolving Neighborhoods	The New York Times	http://www.nytimes.com/interactive/2011/11/05/nyregion/the-evolving-neighborhoods-along-the-marathon.html

35	The shoe-thrower's index	The Economist	http://www.economist.com/blogs/multimedia/2011/02/unrest_arab_world
36	The Snowden files: facts and figures - video animation	The Guardian	http://www.theguardian.com/world/video/2013/dec/02/the-snowden-files-guide-surveillance-industry-video
37	The Status of Aid	Designer Vimeo Channel	http://vimeo.com/10852417
38	The Swing State of Swing States	The New York Times	http://www.nytimes.com/video/us/politics/100000001883681/the-swing-state-of-swing-states.html
39	Examining High Net Worth Individuals from around the world	elitehavenssales.com	http://www.elitehavenssales.com/news/elite-havens/47/The-Wealth-Report-2013-Examining-High-Net-Worth-Individuals-from-around-the-world
40	Time History of Atmospheric Carbon Dioxide	CIRES/NOAA	http://climatestate.com/2014/07/12/time-history-of-atmospheric-carbon-dioxide/
41	Top growers in 2014	The Economist	http://www.economist.com/blogs/graphicdetail/2014/01/daily-chart-3
42	Ukrainian web-revolution	Plus One Web Design Agency	https://www.youtube.com/watch?v=2NpVNWwW2ZU
43	US Energy Outlook 2030	BP Company	https://www.youtube.com/watch?v=PN6Nq_hpUck
44	Videographic: Sidestepping Russia's gas monopoly	The Economist	https://www.youtube.com/watch?v=qaEQQyYkYY8
45	Visualization of the Obama Budget Cuts as Pennies	infosthetics.com	http://infosthetics.com/archives/2009/05/visualization_of_the_obama_budget_cuts.html
46	Waiting For Superman Trailer	Digital Media Content Company	http://www.participantmedia.com/pm-films/waiting-for-superman/
47	Waste to Energy Infographic	The New York Times	http://vimeo.com/34927466
48	We are 7 billion	The Economist	http://www.economist.com/blogs/dailychart/2011/10/world-population
49	Wealth Inequality In America	The Washington Post	http://www.washingtonpost.com/blogs/wonkblog/wp/2013/03/06/this-viral-video-is-right-we-need-to-worry-about-wealth-inequality/
50	What is the true UK cost of the Afghanistan war?	stopwar.org.uk	http://stopwar.org.uk/video/afghanistan-the-cost

1

ID	Title	Video URLs	Publisher
1	Experimental Motion	https://vimeo.com/50348628	Alex Chan
2	The 350 Movement	http://350.org/resources/videos/the-350-movement-90-seconds-no-words/	350.org
3	Japan's Debt Problem Visualized	https://www.youtube.com/watch?v=Njp8bKpi-vg&list=TL6ZgCranjlWeMXo0NT2dQ_6SF0WOMEzbM	Addogram
4	Road to Recovery	https://www.youtube.com/watch?v=jWmUnU7HS-I	BarackObama.com
5	The Status of Aid	http://vimeo.com/10852417	Bjørn Rostad
6	America's Love Affair with the Automobile	http://blog.cjponyparts.com/2014/05/people-and-their-cars-americas-love-affair-automobile/	blog.cjponyparts.com
7	America's Energy Future	https://www.youtube.com/watch?v=PN6Nq_hpUck	BP Company
8	Shocking Amounts Of Sugar People Eat Around The World	http://www.buzzfeed.com/brandensueper/shocking-amounts-of-sugar-people-eat-around-the-world#.oeadnG5QL	Buzzfeed
9	Shocking Amounts Of Sugar People Eat Around The World	http://www.buzzfeed.com/brandensueper/shocking-amounts-of-sugar-people-eat-around-the-world#3h2hzr6	Buzzfeed
10	Time history of atmospheric carbon dioxide	http://climatestate.com/2014/07/12/time-history-of-atmospheric-carbon-dioxide/	CIRES/NOAA
11	Show Me Something	http://www.shutterstock.com/blog/an-infographic-exploration-of-online-video	Design Blog
12	International Migration	https://www.youtube.com/watch?v=IOZmqIwqur4	edeos- digital education
13	Mobile Phone users	http://vimeo.com/50348628	Experimental Motion
14	Will saving poor children lead to overpopulation?	http://www.gapminder.org/videos/will-saving-poor-children-lead-to-overpopulation/	GAPMINDER
15	The River of Myths	http://www.gapminder.org/videos/the-river-of-myths/	GAPMINDER
16	Mid-Market Report Overview	http://www.gecapital.com.au/knowledge-hub/2014/mid-market-overview.html	GE Capital
17	Mid-Market in Focus: Australian Mid-Market in focus	https://www.youtube.com/watch?v=ewIB5ZgjbhA	GEAustralia
18	What is the World's Deadliest Animal?	https://www.youtube.com/watch?v=VzRKxLitti4&list=PLUgRTD1mpwSXQmCShm0FkyJUFNw3CxAwk&index=1	GOOD Magazine
19	Heartbeat During a Marriage Proposal	https://www.youtube.com/watch?v=JcY2_Gzx_TQ&list=PLUgRTD1mpwSXQmCShm0FkyJUFNw3CxAwk&index=2	GOOD Magazine

20	The Facts on Medicare and How to Save It	http://budget.house.gov/fy2012budget/medicare.htm	Government Budget House
21	1 Offshore Natural Gas Platform = 59 Cape Wind Projects	https://www.youtube.com/watch?v=McWBtXr7j28&index=19&list=PL818EA6DFD5293BD6	IERDC
22	Visualization of the Obama Budget Cuts as Pennies	http://infosthetics.com/archives/2009/05/visualization_of_the_obama_budget_cuts.html	infosthetics.com
23	Celebrating Working Women: International Women's Day	https://www.youtube.com/watch?v=eaf_X9qSeVY&list=PL818EA6DFD5293BD6&index=3	kronosinc
24	Are the Poor Getting Poorer?	https://www.youtube.com/watch?v=vDhcqua3_W8	Learn Liberty
25	Will Taxing the Rich Fix the Deficit?	https://www.youtube.com/watch?v=FC5Gkox-1QY	Learn Liberty
26	How to Fix Our Fiscal Crisis	https://www.youtube.com/watch?v=9EnpzrD277E	Learn Liberty
27	Marketing in a Multiscreen World	https://www.youtube.com/watch?v=1GyIoYOLEQ8	Millward Brown Global
28	Heart Disease Facts PSA	http://digitalsplashmedia.com/2014/04/heart-disease-facts-psa-video	Multimedia Web Content Production
29	Drug Use among Young People in England	https://www.youtube.com/watch?v=Wuiqd0SdMno	NatCen Social Research
30	The Health of the Nation	https://www.youtube.com/watch?v=H19WX9oP95Q	NatCen Social Research
31	The Fallen of the world war II	http://www.fallen.io/ww2/	Neil Halloran
32	Looking to 2060: A Global Vision of Long-term Growth	https://www.youtube.com/watch?v=fnIl212tBPk	OECD
33	The Rise of Online Video	https://www.youtube.com/watch?v=mGgBY3yBpYY	Pew Research Center
34	America's Place in the World	https://www.youtube.com/watch?v=tdxhDHcF5Fc	Pew Research Center
35	What is the future of the world's religions?	https://www.youtube.com/watch?v=ZJn6vMjHhCA	Pew Research Center
36	More to the story of the shrinking pay gap	http://www.pewsocialtrends.org/2014/01/09/theres-more-to-the-story-of-the-shrinking-pay-gap/	Pew Research Center
37	Four-in-Ten Couples Are Saying "I Do," Again	https://www.youtube.com/watch?v=EKYOWHtaPQE	Pew Research Center
38	The Lost Decade of the Middle Class	https://www.youtube.com/watch?v=dkpHOwAxJkc	Pew Research Center
39	America's Place in the World	https://www.youtube.com/watch?v=tdxhDHcF5Fc	Pew Research Center
40	Ukrainian web-revolution	https://www.youtube.com/watch?v=2NpVNWwW2ZU	Plus One Web Design Agency

41	Global air traffic	http://vimeo.com/38595224	Rightcolours
42	iPad - Past/Present/New Generation	https://www.youtube.com/watch?v=fXi1YTKEcY0&index=33&list=UUKjMrD0GtDQLn0RfvVHoyJg	Rightcolours
43	UNICEF - A Generation Cast Aside	https://www.youtube.com/watch?v=w5xk2wps-wM	Rightcolours
44	Fitness Supplement	http://portfolios.scad.edu/gallery/8159705/Fitness-Supplement-Infographic	SCAD University
45	What is the true UK cost of the Afghanistan war?	http://stopwar.org.uk/video/afghanistan-the-cost	stopwar.org.uk
46	Climate change, "ACT NOW!"	https://www.youtube.com/watch?v=-kRP5x2MsAw	The Big Ask campaign
47	Future World Populations (2050)	https://www.youtube.com/watch?v=YJjz7LVVl8c	The Daily Conversation
48	Top 10 Immigrant Countries	https://www.youtube.com/watch?v=GeQ2h95Oppw	The Daily Conversation
49	Live Chart: Global smartphone shipments	https://www.youtube.com/watch?v=ph8F320Bljc	The Economist
50	How advertising spending has changed in America	https://www.youtube.com/watch?v=QQM4BfS0G_Y	The Economist
51	Democrats or Republicans?	https://www.youtube.com/watch?v=CtKC2_xiAps	The Economist
52	A big problem	http://www.economist.com/blogs/graphicdetail/2012/12/daily-chart-16	The Economist
53	Two states	http://www.economist.com/blogs/banyan/2014/06/telangana-and-andhra-pradesh	The Economist
54	The largest migration in history	http://www.economist.com/blogs/graphicdetail/2012/02/daily-chart-17	The Economist
55	The shoe-thrower's index	http://www.economist.com/blogs/multimedia/2011/02/unrest_arab_world	The Economist
56	Top growers in 2014	http://www.economist.com/blogs/graphicdetail/2014/01/daily-chart-3	The Economist
57	Sidestepping Russia's gas monopoly	https://www.youtube.com/watch?v=qaEQQyYkYY8	The Economist
58	We are 7 billion	http://www.economist.com/blogs/dailychart/2011/10/world-population	The Economist
59	Drug use: 20 things you might not know	http://www.theguardian.com/society/datablog/video/2012/mar/15/drugs-use-animation-20-facts	The Guardian

60	99 vs 1%	http://www.theguardian.com/news/datablog/video/2011/nov/16/99-v-1-occupy-data-animation	The Guardian
61	Inequality: how wealth is distributed in the UK	http://www.theguardian.com/commentisfree/video/2013/oct/08/inequality-how-wealth-distributed-uk-animated-video	The Guardian
62	Inequality: how wealth is distributed in the UK	http://www.theguardian.com/commentisfree/video/2013/oct/08/inequality-how-wealth-distributed-uk-animated-video	The Guardian
63	Skivers vs. Strivers	http://www.theguardian.com/society/datablog/video/2013/feb/05/benefits-skiver-striver-animated-video	The Guardian
64	The Snowden files: facts and figures	http://www.theguardian.com/world/video/2013/dec/02/the-snowden-files-guide-surveillance-industry-video	The Guardian
65	Racing Against History	http://www.nytimes.com/interactive/2012/08/01/sports/olympics/racing-against-history.html?_r=1&	The New York Times
66	How Mariano Rivera Dominates Hitters	http://www.nytimes.com/video/sports/1247468158551/how-mariano-rivera-dominates-hitters.html	The New York Times
67	One Race, Every Medalist Ever	http://www.nytimes.com/interactive/2012/08/05/sports/olympics/the-100-meter-dash-one-race-every-medalist-ever.html	The New York Times
68	The Marathon Route's Evolving Neighborhoods	http://www.nytimes.com/interactive/2011/11/05/nyregion/the-evolving-neighborhoods-along-the-marathon.html	The New York Times
69	The Swing State of Swing States	http://www.nytimes.com/video/us/politics/100000001883681/the-swing-state-of-swing-states.html	The New York Times
70	Waste to Energy	http://vimeo.com/34927466	The New York Times
71	Stress	http://vimeo.com/60063494	The One Academy
72	Wealth Inequality in America	http://www.washingtonpost.com/blogs/wonkblog/wp/2013/03/06/this-viral-video-is-right-we-need-to-worry-about-wealth-inequality/	The Washington Post
73	Why world trade rules need to change	https://www.youtube.com/watch?v=ldZwGDXTsmk	Trade Aid Movement Agency
74	A Look at Income Taxes	https://www.youtube.com/watch?v=0qd_VTT1cSU	VisualBudget

Engagement Questionnaire (Final items are highlighted in blue & items used in the last study are starred *)

Attribute	Statement	
Cognitive Involvement	During viewing, I reflected on the content of the video	
	During viewing, I got the impression that the video might be important for my own life	
	During viewing, I considered solutions for the problems described in the video	
	During viewing, I hardly thought about the video's content	
	I vividly remember some parts of the video	
	I was able to anticipate what would happen next in response to the facts being presented	
	I learned something new	
	I found the video stimulating	
	I think I have a good understanding of the facts presented	
	At points, I had a hard time making sense of what was going on in the video	
	I found the content easy to understand	*
	My understanding of the facts is unclear	
	I had a hard time recognizing the thread of the video	
Affective Involvement	The video touched me emotionally	
	The video didn't affect me at all	
	The video triggered my emotions	*
	I felt sad that the viewing was over	
	I responded emotionally	
Enjoyment	This video was fun to watch	*
	I enjoyed viewing the video	
	The video was entertaining	
	I found the video boring	
	It is good that the video wasn't even longer	
	The video was typical for ones you generally find online	
	I would have liked the viewing to continue	
	I'd recommend the viewing of this video to my friends	*
	I felt tired	
	The content appealed to me	
Presence, transportation, and focused attention	I felt myself being 'drawn in'	
	I felt involved	
	I lost track of time	
	I paid more attention to the video being played than I did to my own thoughts (eg, daydreams, etc)	
	While viewing, I forgot myself and was fully absorbed	
	% of time attention drifted	
	I found my mind wandering while the video was being played	*

Attribute	Statement	
Presence, transportation, and focused attention	While the video was on I found myself thinking about other things	
	I had a hard time keeping my mind on the video	
	I forgot about my immediate surroundings while watching the video.	
	I was so involved in watching the video that I ignored everything around me.	
	I lost myself in this vieweing experience.	
Experience	I feel that I could construct a story about the facts presented in the video	
	I had an emotional reaction while viewing the video	
	I thought that the facts presented in the video were interesting	
	I was mentally involved in the video while viewing	
Aesthetics	This video was aesthetically appealing	
	I liked the graphics in this video	*
	This video appealed to my visual senses	
	The video was visually pleasing	*
	I found the graphics in the video distracting	

12 APPENDIX D

UNIVERSITY OF MANITOBA | Research Ethics and Compliance
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APPROVAL CERTIFICATE

April 13, 2016

TO: **Pourang Irani**
Principal Investigator [redacted]

FROM: **Lorna Guse, Chair**
Joint-Faculty Research Ethics Board (JFREB)

Re: **Protocol #J2016:028 (HS19609)**
"Authoring Data Clips: Development and Evaluation of a Web based Tool for Creating Animated Data-Driven Visualizations"

Please be advised that your above-referenced protocol has received human ethics approval by the **Joint-Faculty Research Ethics Board**, which is organized and operates according to the Tri-Council Policy Statement (2). **This approval is valid for one year only and will expire on <u>April 13, 2017</u>.**

Any significant changes of the protocol and/or informed consent form should be reported to the Human Ethics Secretariat in advance of implementation of such changes.

Please note:

- **If you have funds pending human ethics approval, please mail/e-mail/fax (261-0325) a copy of this Approval (identifying the related UM Project Number) to the Research Grants Officer in ORS in order to initiate fund setup. (How to find your UM Project Number: http://umanitoba.ca/research/ors/mrt-faq.html#pr0)**

- **if you have received multi-year funding for this research, responsibility lies with you to apply for and obtain Renewal Approval at the expiry of the initial one-year approval; otherwise the account will be locked.**

The Research Quality Management Office may request to review research documentation from this project to demonstrate compliance with this approved protocol and the University of Manitoba *Ethics of Research Involving Humans.*

The Research Ethics Board requests a final report for your study (available at: http://umanitoba.ca/research/orec/ethics/human_ethics_REB_forms_guidelines.html) **in order to be in compliance with Tri-Council Guidelines.**

umanitoba.ca/research