Hooked on Data Videos: Assessing the Effect of Animation and Pictographs on Viewer Engagement

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ABSTRACT

Pictographic representations and animation techniques are commonly incorporated into narrative visualizations such as data videos. General belief is that these techniques may enhance the viewer experience, thus appealing to a broad audience and enticing the viewer to consume the entire video. However, no study has formally assessed the effect of these techniques on data insight communication and viewer engagement. In this paper, we first propose a scale-based questionnaire covering five factors of viewer engagement we identified from multiple application domains such as game design and marketing. We then validate this questionnaire through a crowdsourcing study on Amazon's Mechanical Turk to assess the effect of animation and pictographs in data videos. Our results reveal that each technique has an effect on viewer engagement, impacting different factors. In addition, insights from these studies lead to design considerations for authoring engaging data videos.

CCS CONCEPTS

• **Human-centered computing** → *Visualization design and evaluation methods*;

KEYWORDS

Information Visualization, Narrative Visualization, Data Video, Animated Infographic, Animation, Pictograph, Engagement.

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1 INTRODUCTION

Data videos and animated infographics have gained new prominence among journalists, marketers, and government agencies as a compelling way for communicating data-driven facts to a broad audience. This has resulted in efforts for designing and developing authoring tools to further facilitate their creation [3, 4]. The building blocks of data videos are individual data-driven clips (or data clips), each targeting a specific insight [3]. These videos heavily rely on data visualizations, and various creative design techniques are incorporated into the visualizations to engage the viewers and sustain their attention [2]. Designers often use animation techniques to attract viewers' attention and keep them engaged [11]. 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 [12, 15, 20], researchers have drawn contradictory conclusions regarding their effectiveness. While there is strong intuition about the usefulness of motion to communicate [16], studies have shown that animation can be distracting and challenging to interpret [31]. Similarly, researchers have argued that pictographs and icon-based representations may distract from the data itself, merely contributing to an accumulation of "chart junk"[36]. On the other hand, empirical work has shown that including pictures and illustrations in data visualizations positively affects memorability [6] and can lead to better recall [8]. More recently, Haroz et al. [18] 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 [24]. To this aim, we 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, we used our 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, our 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.

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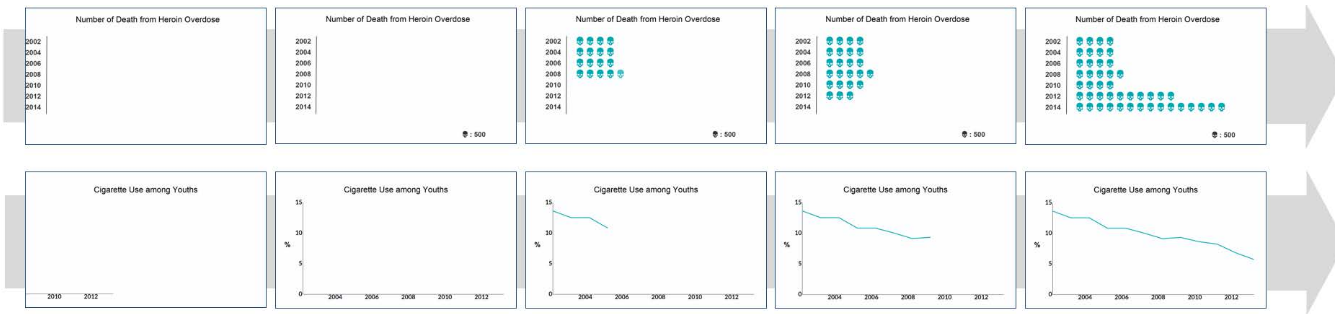

Figure 1: Example use of setup animation to build trend visualization: pictograph (top), standard line chart (bottom).

Our research contributions are threefold: (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.

2 RELATED WORK

2.1 Data Videos

Technological advances have facilitated the design and creation of new forms of media and innovative techniques for communicating insights extracted from data. Film and video-based data stories (e.g., data videos) are recognized among the seven genres of narrative visualization [33]. Their ability to appeal to mass audiences and communicate a wide range of data insights in a short period of time, has made them popular among data journalists and has attracted the attention of researchers in the field. Data videos have also been studied from the perspective of film narratives, a medium that bears significant similarity with data videos. Amini et al. [2] examined 50 data videos and teased apart the various dimensions of data videos with respect to narratives in film or cinematography. Their results show that data videos use various presentation styles to attract and maintain viewer attention. The growing interest in data videos has also inspired efforts for design and development of authoring tools to further facilitate their creation [3, 4]. While prior work has shed light on the possibilities of data videos, their structural constituents, and design techniques, their effects on viewer engagement and communication of data has not been studied. In particular, it is not clear whether incorporating animation and icons in the data visualizations can elicit viewer engagement and help with comprehension of data insights being communicated.

2.2 Animated Data Visualizations

Animation in data visualization can take many different roles [11]. Most commonly, it has been used to facilitate the perception of different changes in data visualization [16]. Researchers have questioned the benefits of animation [37], whereas, others have showed its effectiveness [39]. Heer and Robertson [19] investigated the effectiveness of animated transitions between common statistical data graphics, finding that animated transitions can improve graphical perception. Robertson et al. [31], 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 paper, we 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 [3]. We refer to this subset of animation techniques as setup animation. Figure 1 shows examples screenshots demonstrating such animation technique.

2.3 Phictographs and Icon-Based Visualizations

Simple pictographic elements have been used to encode various types of information including numerical data [10, 20]. For example, unit pictographs include symbols, each representing a fixed quantity, that are stacked to provide an intuitive representation of a total amount (Figure 1-top). Amini et al. [3] have identified several different icon-based representations commonly used in the data videos. We consider icon-based representations included in their taxonomy to design the data clips used in our study. The uses and benefits of icon-based visualizations have been debated. Some considered visual embellishments as chart junk [36]. Boy et al. [9] 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. [6] reported an empirical study showing that visual embellishments could improve long-term recall. Similarly, Borkin et al. [8] found that people can better recall pictorial visualizations. Borgo et al. [7] 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 [34] as well as benefits of pictographs representing data through enticing people to inspect visualizations more closely [18].

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

2.4 Viewer Engagement

In HCI, user engagement has been viewed in the context of flow and fluid interaction, leading to satisfying and pleasurable emotions [35]. It has also been defined as the emotional, cognitive, and behavioral connection that exists between a person and an object [5, 32]. Engagement is also believed to be the positive user experience associated with being captivated and motivated to use an interface

Attribute	Description	#. Items	Example Statements
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 interest in learning and thinking about the information communicated through the stimulus	3	I found the content easy to understand.

Table 1: The description of five engagement attributes with example questionnaire statements, which are used in our study (Section 4). The complete list of items is available at our website, datavideo-engmtscale.github.io.

[27]. Additionally, terms such as flow, presence, transportation, immersion, enjoyment, and playfulness are closely related to the concept of viewer engagement [13, 17, 22, 23]. Our scope of engagement is in the context of data videos as the combination of viewer's subjectively reported levels for different attributes of engagement.

Several approaches for assessing engagement have been proposed in various disciplines. O'Brien and Toms [28] 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 users' 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 [9, 32]. Saket et al. have explored subjective reaction cards to capture user feelings [32]. Mayer [25] has looked at audience engagement from the perspective of journalists and newsrooms. Drawing on empirical research with users of data visualizations, Kennedy et al. [21] identify six social and contextual factors that affect engagement. Our study focuses on audience engagement at the data story dissemination phase. We consider different viewer characteristics as possible variables influencing viewer engagement with data videos.

3 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.

3.1 Initial Engagement Scale

We first looked into existing questionnaires from related disciplines such as game design, user interface design, psychology, HCI, communication and marketing, storytelling, and multimedia design [22, 26, 28, 38]. We 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., Parasocial interaction in game design). We identified 53 statements (available at datavideo-engmtscale.github.io), covering the five engagement attributes (Table 1).

3.2 Refining Engagement Scale

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

3.2.1 Study Design. We designed two drastically different data videos on the topic of drug use including or lacking animation and pictographic representations. We 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. We ran a between-subject study, where participants view a single video and fill out the engagement questionnaire. We recruited 50 undergraduate students (aged 18-27) from a university's psychology department.

3.2.2 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. We 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. We 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.

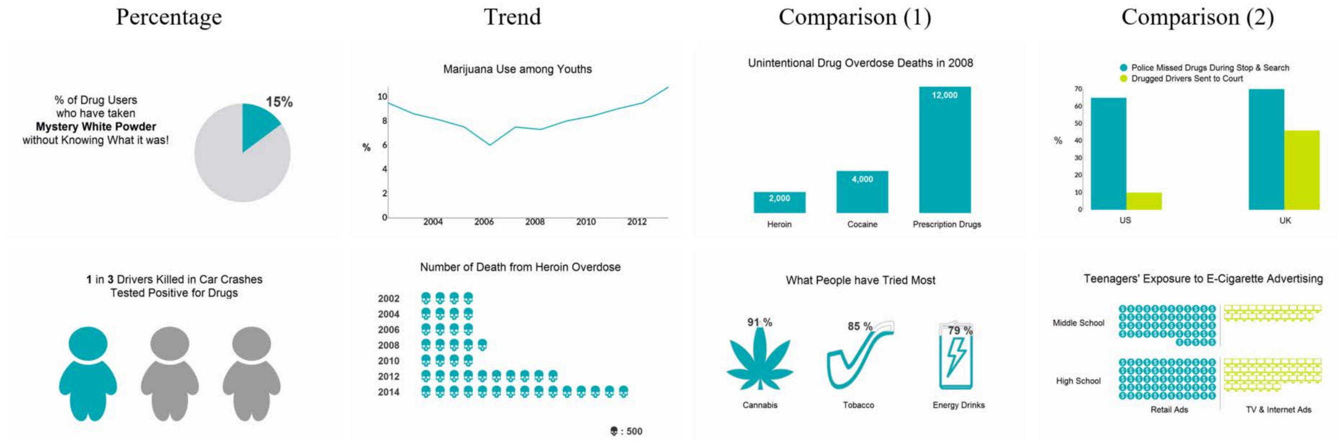

Figure 2: Example last frame screenshots of clips for different insight types: standard charts (top) and pictographs (bottom).

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

We performed an independent-samples t-test to compare the mean engagement scores between the two video conditions. Based on our initial assumption regarding the level of engagement for the two drastically different conditions, we opted to only keep survey items with significant and marginally significant differences between their mean scores. After determining that the sample was factorable, we ran factor analysis on the remaining items. Using reliability analysis, we 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 α > .86. Table 1 shows example questionnaire statements for the five engagement attributes (visit our website, datavideo-engmtscale.github.io, for the complete list of items).

4 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. We 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, we asked them to pick their favorite clip in a series of paired-sample comparisons.

4.1 Study Design, Participants, & Procedure

We conducted the experiment as a within-subject design; pairs of data-driven clips were presented to participants in four different blocks. We counter balanced 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.

We used the Qualtrics survey platform [30] 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). We 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 our 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, we included a practice block. At the beginning of each block, we 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. We repeated the same steps for the second data clip in the block. At the end of each block, participants were 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.

4.2 Experiment Treatment Conditions

The independent factors in our 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. We considered four main insight types [3]: (1) Single value percentage, (2) Trend, (3) Single value comparison, and (4) Multiple attributes comparison. Figure 2 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. We describe the measures we took to achieve treatment equivalency as follows:

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

Data Visualizations: The types of standard charts and pictographs we 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 we used (from the DataClips tool) contained seven distinctly different colors and accounted for color blindness.

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, we 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.

Look and Feel: We 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 2). For all data clips, we used the same font style and size (Times New Roman, 12 pt, black) with white background to guarantee legibility.

4.3 Study Material and Measures

For this study, we 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, we sought to avoid potential confounding effects as a result of sequencing strategy or narrative structure employed in data videos.

The dataset we 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 [14] on drug use. The selected topic was of general interest and included several different insights on different aspects of drug use. Due to our within-subject design, we had to vary data insights for each clip. To account for possible bias as a result of topic preference, we 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.

We created a total of 16 data clips using DataClips [3], a web-based data clips authoring tool. To best fit the 16:9 aspect ratio of the video player used in Qualtrics, we rendered all video clips with 720p at 1280x720 resolution. All materials used in the study can be found in our accompanying website.

We selected seven items (Table 1) from the 15-items engagement questionnaire we have developed (Section 3). In addition to keeping the questionnaire short, we 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. We 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.

4.4 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 our analysis of the results.

We conducted a series of repeated-measures ANCOVA models that included variables from the demographic questionnaire (e.g., age, online viewing, learning style) as covariates. The first model tested the effects of pictographs and setup animation on each engagement factor. Similarly, we tested the effects of each condition on viewers' overall preference. To do so, we analyzed participants selections in the pairwise comparison question. Furthermore, we performed a qualitative analysis on participants' comments provided for justifying their selection. Finally, we 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 our analysis, we investigated the source of possible interaction effects by submitting participants' scores for the two ChartType conditions to separate ANOVAs, treating AnimationStatus as a within-subject factor. Table 2 summarizes the significant main and interaction effects we found in the statistical analysis.

4.4.1 Engagement Questionnaire Ratings. To calculate the engagement level for each participant, we aggregated across all seven items in our engagement questionnaire. This was done by creating a derived column for the mean ratings given to each item. Our 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. We also observed significant interaction effect of AnimationStatus and ChartType, ($F(1,118) = 8.10$, $p = .005$). As depicted in figure 3, viewers gave significantly higher scores to clips with pictographs when animated ($F(1,118) = 15.15$, $p < .001$).

Regarding the effects of the covariates, we 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 our ANCOVA and simple ANOVA models.

In subsequent analyses, we submitted participants' ratings for each of the five engagement dimensions to repeated-measures ANOVAs, treating AnimationStatus and ChartType as within-subject factors. Figure 3 shows the mean ratings collected for each engagement factor separated by data clip condition.

Affective Involvement: We 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 icon-based data visualizations. We 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).

Enjoyment: We calculated the overall enjoyment score as a mean of scores given to the two complementary statements for measuring the enjoyment factor (Table 1). Our analysis yielded no main effects of either AnimationStatus or ChartType. However, our 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). We were 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).

Aesthetics: Using the aggregated aesthetics preference score from the two complementary statements (Table 1), we 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. We 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).

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

Table 2: Quantitative analysis overview. $*$**:** $p < .05$**,** $**$**:** $p < .01$

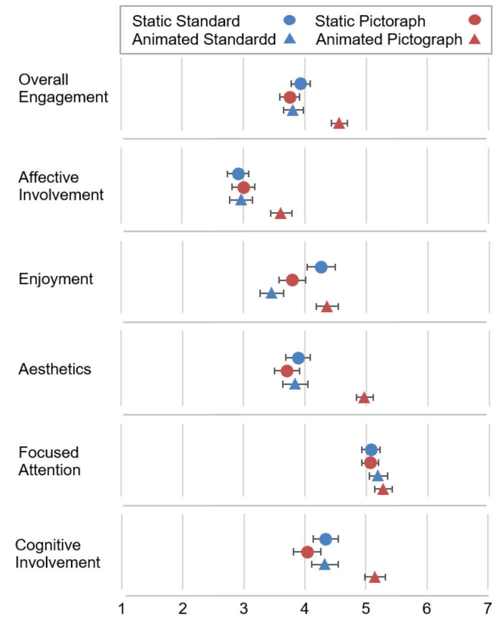

Figure 3: Estimated marginal means of different engagement scale ratings showing interaction between AnimationStatus and ChartType. Error bars represent the standard error of participants' mean ratings for that condition.

Focused Attention: We measured focused attention through a negative attribute by measuring viewers' attention drift while watching a data clip. Therefore, we 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.

Cognitive Involvement: In this category, we sought to determine, to what degree, viewers felt comfortable processing the information and understanding the data insights being communicated. We 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. We also found a significant interaction effect of AnimationStatus and ChartType (F(1,118) = 5.81, p = .017). Data clips containing animated pictograophs received significantly hiegher ratings than all other conditions (F(1,118) = 14.64, p < .001).

4.4.2 Comprehensibility. To further investigate whether participants successfully understood the facts presented, we 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. We 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

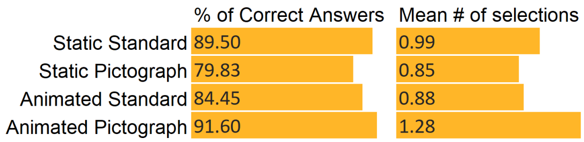

Figure 4: Percentage of correct answers provided (left); mean number of times selected (right).

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.

4.4.3 Overall Preference. As an additional measure, we 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.

We 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. We 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 were favored over static pictographs and animated standard charts. We 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). Our analysis indicated that the congruent group is significantly preferred over its non-congruent equivalent ($F(1,118) = 17.142$, $p < .001$).

4.4.4 Viewer Comments. We asked participants to provide the reasons why they selected one data clip over the other on the pairwise comparisons. Here, we 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. We 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*."

5 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, we discuss some of the important findings, suggestions for designing engaging data videos, and limitations & future work.

5.1 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 we 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 [29], cleverly designed animate motion does indeed capture and maintain attention.

Our 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 our 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.

5.2 Design Suggestions

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

5.2.1 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 [21]. 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.

5.2.2 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.

5.2.3 Use Setup Animations with Care. When the information being communicated through data videos requires focused attention from the viewers, we 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.

5.2.4 Connect to Viewers with Pictographs. Pictographic representations are able to provoke viewers' emotions by bringing data to life. The addition of animation to pictographs results in a congruent combination that can significantly boost viewer engagement.

5.3 Limitations and Future Work

In this study, we 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 our pilot study for the engagement development scale. By focusing on these smaller units, we 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 our 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 used in data videos on viewer engagement.

We also acknowledge limitations in our stimuli design. We 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 we 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, we 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, our work is the first step to develop a scale to evaluate viewer engagement in data videos. We 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 we 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 CONCLUSION

In this paper, we 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, we explored the effects of these two techniques on viewer engagement and understandability of data-driven clips. We 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. We 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.

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