Negative Emotions, Positive Outcomes? Exploring the Communication of Negativity in Serious Data Stories

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ABSTRACT

Recent work has highlighted that emotion is key to the user experience with data stories. However, limited attention has been paid to negative emotions specifically. This work investigates the outcomes of negative emotions in the context of serious data stories and examines how they can be augmented by design methods from the perspectives of both storytellers and viewers. First, we conducted a workshop with 9 data story experts to understand the possible benefits of eliciting negative emotions in serious data stories and 19 potential design methods that contribute to negative emotions. Based on the findings from the workshop, we then conducted a lab study with 35 participants to explore the outcomes of eliciting negative emotions as well as the effectiveness of the design methods. The results indicated that negative emotions mainly facilitated contemplative experiences and long-term memory. Besides, the design methods showed varied effectiveness in augmenting negative emotions and being recalled.

CCS CONCEPTS

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

KEYWORDS

data storytelling, affective design, user experience

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1 INTRODUCTION

Data stories, as a visual form that combines data visualization with narratives, interaction, embellishment, or animation [96, 104], are increasingly embraced by content producers and disseminators to communicate data to viewers. Among various communication intentions, *serious data storytelling* is a common goal pursued by storytellers. Unlike stories that aim to entertain the audience [103, 113], serious data stories are based on serious topics (e.g., well-being and environment) whose messages to be communicated are often negative (e.g., inequality and pollution) [64]. Therefore, these stories often seek to elicit negative emotions such as sadness and fear from viewers [5, 59]. Besides, there is a growing agreement that negative emotions can be useful in triggering reflective thoughts and long-lasting memory, or lead to a richer storytelling experience [9, 14, 47, 71]. For example, during the COVID-19 pandemic, many data journalists discussed how to communicate negativity emotionally to viewers, in order to fight against the *fatigue with data* (feeling bored and numb with numbers) and make people aware of the tragedy and care about their own health [34, 37, 48]. *Iraq's bloody toll* (Fig. 1) deliberately uses a "bloody" bar chart to create a striking visual and connect viewers with the horrible war [93].

In the visualization community, there is also an increasing interest in people's emotional experiences with data stories [92, 113]. Researchers have attempted to understand the spectrum of emotions in data stories or explore certain types of emotions. For example, Bartram et al. [6] proposed 8 color palettes that convey emotions such as playfulness and disturbingness. Lan et al. [59] identified 12 typical emotional responses to infographics, such as happiness and sadness. Boy et al. [16] examined whether the use of anthropographics can enhance viewers' empathy towards human rights-related stories and increase the willingness to donate. Similarly, Morais et al. [72] investigated how anthropographics influence empathy and prosocial behaviors. Diakopoulos et al. [31] explored playable interaction in data stories, and Wang et al. [114] measured the feeling of fun and aesthetics when comparing the design of infographics with data comics. The above work has suggested that both positive and negative emotions can be triggered by data stories. However, more efforts have been put into studying emotions such as fun and empathy while the value of negative emotions is less recognized nor explored systematically. To fill this gap, this work focuses on serious data stories and explores what

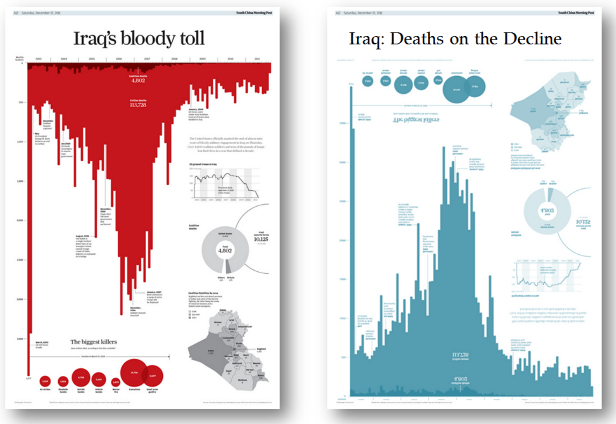

Figure 1: *Iraq's bloody toll* [93] is an infographic about soldiers' deaths in the Iraq war. Cotgreave [29] compares this work (left) with an alternative design (right) to demonstrate how the original work conveys a strong sense of negativity.

benefits negative emotions may bring and which design methods may contribute to negative emotions.

To tackle these problems, we conducted two studies, one with storytellers and the other with viewers. First, we conducted a workshop with 9 data story experts. From the workshop, we collected a corpus of 72 serious data stories that communicate negativity and identified 3 possible benefits of eliciting negative emotions in serious data stories, as well as 19 potential design methods that the experts thought may augment negative emotions. The second study investigated viewers' perceptions on the possible benefits of negative emotions as well as the effectiveness of the 19 design methods. Specifically, we used 13 stories from the corpus as the stimuli and conducted a lab study with 35 participants. The results showed that negative emotions were significantly related to contemplative experiences such as reflective thinking and made a long-term impression on the participants. Besides, the design methods proposed by the experts showed varied effectiveness in augmenting negative emotions and being recalled. Methods such as *tough task* were evaluated as the most effective by the participants in the lab study, while methods such as *picture with negative semantics* and *role-playing game* performed best in the long-term recall. The corpus we collected as well as a summary of the design methods can be accessed at https://negativity.idvxlab.com.

2 RELATED WORK

This section looks back to previous work about the benefits of negative emotions, serious data stories, and emotion in data stories.

2.1 The Benefits of Negative Emotions

Although negative emotions are often viewed as the dark side of human beings, they can function in a positive way [50]. For example, sad music can be attractive and engaging [51], and horror films can lead to enjoyment and gratification [118]. The notable literature, from ancient Greek theatre to the masterpieces of Shakespeare, comprises mostly tragedies. Since negative emotions function positively in these circumstances, researchers have coined terms such as *positive negative experience* [71], *tragic entertainment* [8], and *valance transformation* [94] to describe such emotional experiences. In recent years, a growing body of research has investigated the benefits of negative emotions in storytelling-related media, such as films [7, 9, 75] and digital games [15, 19, 36, 71]. For example, Gowler and Iacovides [36] found that the discomfort experienced in digital games may stimulate self-reflection and lead to a richer play experience. Oliver and Bartsch [74] found that negative emotions in films contribute to the feelings of fun, suspense, and being moved. Some researchers also emphasized the enduring effects of negative emotions such as enlightenment, long-term gratification, and the improvement of sociality [12, 74]. Besides, the role of design in the arousal of negative emotions has also been examined. For example, Benford et al. [12] proposed four tactics for *uncomfortable interaction*, including visceral discomfort, cultural discomfort, discomfort through control, and discomfort through intimacy. Bopp et al. [14] found that in games, negative emotions can be triggered by aspects such as loss, character attachment, and atmosphere. Bartsch et al. [9] found that audio effects in films can be associated with negative emotions.

Data stories, as the combination of multimedia elements such as graphics, interaction, and music, have many shared features with the media discussed above. Therefore, in this work, we take serious data stories as an example and investigate them through the lens of negative emotions.

2.2 Serious Data Stories

Data stories combine data visualization with narratives, interaction, embellishment, or animation to communicate data and insights [55, 62]. Data stories are created for various purposes. In casual contexts, data stories are often created to entertain people [103, 113] or boost web traffic [61]. Alternatively, storytellers may look beyond entertainment and use data stories to communicate serious issues such as poverty, social injustice, and pollution, and such practice is called serious storytelling [64]. According to the corpora collected by previous studies about data stories [2, 45, 96, 98–100, 117], a considerable proportion of the data stories in the wild are serious data stories. Besides, many winners of data storytelling awards (e.g., the Information is Beautiful Awards [49], the Sigma Awards [105]) are serious data stories. Given their wide application, researchers have studied serious data stories from various aspects. For example, Pandey et al. [76] used stories about taxing, incarceration, and violence to examine how data visualization helps persuade attitude changes. Heyer et al. [43] studied how the elicitation of prior beliefs affects the persuasiveness of serious data stories about drug overdose. Kong et al. [54] found that the phrasing of titles may induce bias in serious data storytelling (e.g., refugee problem). In addition, some researchers [16, 72] have found that using anthropomorphized visualization in serious data stories (e.g., poverty, the migrant crisis) did not promote prosocial behavior significantly.

However, we notice that limited work has been done to understand serious data stories from the perspective of negative emotions.

Thus, this work explores how to facilitate serious data storytelling by leveraging negative emotions.

2.3 Emotion in Data Stories

As data stories are increasingly used to communicate with a broad audience, investigating people's emotions towards data stories is emerging as a research trend [59, 92]. For example, Figueiras [33] stated that a key benefit of data storytelling is to create an emotional connection between the data and the audience. When evaluating data stories, many researchers agree that emotion is key to user engagement and should be taken into consideration [46, 52, 58, 60, 113]. So far, existing research has studied the elicitation of emotion in data stories from various aspects, such as visual design and interaction. For example, Bartram et al. [6] and Anderson et al. [3] explored how color palettes help express emotions. Boy et al. [16] found that human-shaped pictograms in data stories about human rights have limited contribution to evoking empathy from viewers, which was recently reconfirmed by Morais et al. [72]. Lan et al. [59] studied 976 infographics and found that both the usability and expressiveness of graphic design can lead to emotions such as happiness and shock. Diakopoulos et al. [31] investigated how to make data playable through game-like interaction.

While emotions such as fun and empathy have been frequently explored, the value of negative emotions is less recognized nor researched. Thus, we still lack knowledge about the role of negative emotions in data stories and how to leverage their benefits. To fill this gap, this work aims to investigate negative emotions in the context of serious data storytelling and explore how to design for such emotions.

3 WORKSHOP WITH STORYTELLERS

This section aims to address our research questions from the perspective of storytellers. Our main goal was to understand storytellers' motivations for eliciting negative emotions in serious data stories, how they communicate such emotions using design, and the pitfalls of such practice. Therefore, we conducted a workshop in this section and posed three questions to guide our research: (i) the possible benefits of eliciting negative emotions in serious data stories, (ii) the potential design methods that contribute to negative emotions, and (iii) the controversial issues concerning eliciting negative emotions.

3.1 Method

To explore the above research questions, we conducted a workshop with 9 data story experts. We chose this method since it is effective in identifying needs, collecting in-depth opinions, facilitating idea exchanges, and generating design solutions collaboratively and efficiently [24, 35, 53, 63, 69].

3.1.1 Participants. To recruit participants for the workshop, we published an invitation poster on social media platforms. In the poster, we introduced the theme of the workshop and informed that we were looking for participants who had more than 3 years experience in creating data stories. When selecting the participants, we referred to the guidelines for qualitative research [56, 63]. For example, to facilitate effective discussion and in-depth collaboration, the number of participants should be controlled (typically less than 12) and their backgrounds should be diverse. To create an environment for the participants to speak and share, power differentials among the participants should be avoided. With these issues in mind, we finally recruited 9 data story experts (6 female) with no power differential and have diverse backgrounds (more details can be seen in Table. 1).

ID	Age	Job	Experience	Affiliation
E1	26	Data journalist	3 years	Government-owned news agency
E2	25	Data journalist	4 years	Commercial news agency
E3	27	Data journalist	3 years	Media department in a commercial company
E4	38	Visualization designer, interaction designer	3 years	Freelancer, Tableau Zen Master
E5	29	Data analyst, visualization developer	4 years	Non-profit organization
E6	29	Data journalist, visualization developer	3 years	Government-owned news agency
E7	32	Visualization designer & developer	5 years	Freelancer
E8	25	Visualization designer & developer	3 years	UX department in a commercial company
E9	27	Data journalist, visualization designer	6 years	Government-owned news agency

Table 1: The background information of the 9 experts that participated in our workshop.

3.1.2 Procedure. Inspired by [63], the workshop consisted of two stages: the pre-workshop stage and the workshop stage. The pre-workshop stage was placed one week before the workshop stage, in which we introduced the theme of the workshop (i.e., negative emotions in serious data stories) to the experts and asked them to prepare a 10 to 15-minute case-sharing presentation around the theme of the workshop, that is, to share serious data stories they thought elicit negative emotions effectively and explain which design methods augment the negative emotions. To help the experts better understand this task, we presented them with 5 example stories that are regarded by visualization researchers and professional practitioners as successful examples of eliciting negative emotions [5, 21, 29, 59], including *Gun Death in the U.S.* [83], *the Fallen of World War II* [41], *Iraq's bloody toll* [93], *One LGBT+ person is killed every day in Brazil* [30], and *Do you know who's watching you?* [116]. To collect as varied data stories as possible during the workshop, we also encouraged the experts to register the data stories they would like to present in a shared folder before the workshop to avoid the presentation of the same cases.

In the second stage, we conducted the workshop online with the 9 experts via video meeting software. In the opening session, we gave a 10-minute introduction to the workshop and used one ice-breaking game to make the experts more familiar with each other. In the second session, the experts presented the serious data stories they had found to elicit negative emotions one by one and explained what design methods contribute to arousing negative emotions. This session lasted about 2 hours, including a 10-minute break. In the third session, we held a focus group discussion with all the experts, aiming to explore our research questions further through iterative discussions. The first author led the focus group with a set of prepared questions, which were crafted following the methodology in [56, 57], including 1 opening question that worked to warm up the discussion and guide the experts to recall the shared cases (i.e., "Which data story impressed you most?"), 1 introductory question to foster interaction among the experts and transit the focus to our research questions (i.e., "Do you think it is necessary to elicit negative emotions for serious data stories?"), and 3 key questions ("Why do you think these stories intend to elicit negative emotions from viewers?", "What design methods do you think contribute to eliciting the negative emotions?", and "What are the possible pitfalls of using such methods?"). During the discussion around these issues, we asked follow-up questions if we wanted the experts to clarify their opinions. This session lasted about 1.5 hours. The whole workshop lasted about 4 hours and was audio-recorded.

3.2 Results

Together with the 5 example data stories, we collected a corpus of 72 serious data stories that the experts thought trigger negative emotions. These stories were created by notable news agencies such as Reuters and The New York Times, as well as individuals. The topics of the stories are also diverse (e.g., wealth inequality, health, education). Among these stories, 62 are web pages, 8 are infographics, and 2 are data videos.

We also collected a large amount of qualitative data. We transcribed the audio recordings and then coded the texts with the goal of identifying the answers to our research questions (i.e., benefits, design methods, controversies) using thematic analysis [18]. Two authors were in charge of the coding process. First, we coded the transcriptions independently and marked the sentences related to our research questions. Then, for each of the research questions, we read through all the marked sentences, generated codes from the sentences, and grouped similar codes. For example, we found that several experts talked about "*photograph of the funeral*" and "*illustration of a sad guy*" as triggers of negative emotions. Thus, we used the code, "*picture with negative semantics*" to summarize these design methods. After independent coding, we met and compared our codes and discussed mismatches until reaching an agreement. Then, we coded all the transcriptions using the latest codes. For design-related codes, we also grouped the low-level codes into the high-level strategies they serve. When identifying high-level design strategies, we referred to (i) the relevant comments from the experts during the workshop (e.g., "*We can evoke negative feelings by challenging people's sensations*"), and (ii) previous literature that summarizes the strategies of eliciting negative emotions [12, 14, 36]. Our findings are as follows.

3.2.1 Benefits. We identified 3 possible benefits of eliciting negative emotions for serious data stories.

<u>B1: Lead to contemplative experiences.</u> Seven experts (E1, E2, E3, E5, E7, E8, E9) stated that eliciting negative emotions for serious data stories is meant to trigger contemplative experiences, namely, making the viewers think and reflect [7]. For example, E7 said that "*negative emotions may spark people's willingness to discuss serious issues and finally deal with them.*" E8 agreed that "*negative emotions can push you to think and act.*" E3 complemented that "*we journalists not only create 'stories you want to know', but also 'stories you should know'. Serious data stories are often the latter type. Such stories may be disturbing to look at, but they will guide you to reflect on yourself and society.*"

<u>B2: Enhance user engagement.</u> Four experts (E1, E2, E4, E6) mentioned that negative emotions can serve as a device for attracting attention and interest to read serious content. For example, E6 said that "*creating a negative atmosphere is a good way to grab attention.*" E1 complemented that "*since the public can easily get bored by statistics, emotional design is used to interest people in consuming serious data.*"

<u>B3: Leave a long-term impression.</u> E2, E8, and E9 mentioned that negative emotions can leave an aftertaste and make people remember their storytelling experience better. E2 said that "*negative feelings may stick in your mind for a long time.*" E9 complemented that "*we are living in an era of entertainment. Fun experiences are common and short-lived. However, negative experiences can be deep and unforgettable.*"

3.2.2 Design Methods. As shown in Fig. 2, we identified 19 potential design methods that may augment negative emotions. These design methods are grouped into 6 strategies.

<u>S1: Sensory challenge.</u> This strategy appeals to people's sensations (e.g., vision, hearing) to stimulate negative emotions intuitively. Many identified design methods in this category resonate with previous psychological findings. For example, **shrill/deep/pressing sound** is a viable approach since audio effects have a strong impact on emotions [51]. As one case, Fig. 2-1 [77] uses sound to express the emotions of the text written by a melancholiac. Besides, the use of **big size** was also recommended. For example, Fig. 2-2 [13] lets the visualization spread over the screen to "*shock you immediately and achieve an overwhelming feeling*" (E1). **Dense texture**, as another mentioned method, "*can also be used to challenge the eyes*" (E9). For instance, Fig. 2-3 [20] uses crowded marks on the map to augment an intense feeling. Besides, in line with color research [111], many experts recognized the usefulness of the **dark background** or **heavy use of red** in arousing negative emotions. For example, Fig. 2-4 [88] uses a black background "*to make you feel heavy-hearted throughout the reading process*" (E1). Fig. 2-5 [68] uses red massively to "*convey a strong sense of of anger and anxiety*" (E1). **Fade-out effect** (e.g., Fig. 2-6 [78]), as recommended by E2, "*helps create a negative sense that someone/something is disappearing*". Lastly, the **sharp/distorted shape** (e.g., Fig. 2-7 [66]), which usually implies abnormality and strangeness [4], was thought to "*trigger anxiety or uneasiness through the freak shape*" (E4).

<u>S2: Attachment to reality.</u> This strategy links viewers with the real scenes and real characters behind data. The first design method recommended by the experts is the **role-playing game**, which lets people experience the life of a certain character. For example, Fig. 2-8 [86] asks people to play the role of a lifesaver so as to experience the difficulty of first aid. Besides, many experts highlighted the necessity to show the **details behind data** [5]. For example, in Fig. 2-9 [87], each circle represents a mother who died during childbirth. Viewers can hover on the circles and view the detailed profiles of the mothers. Third, the **picture with negative semantics** such as death, violence, or dangerous objects was also frequently recommended by the experts since it directly exposes

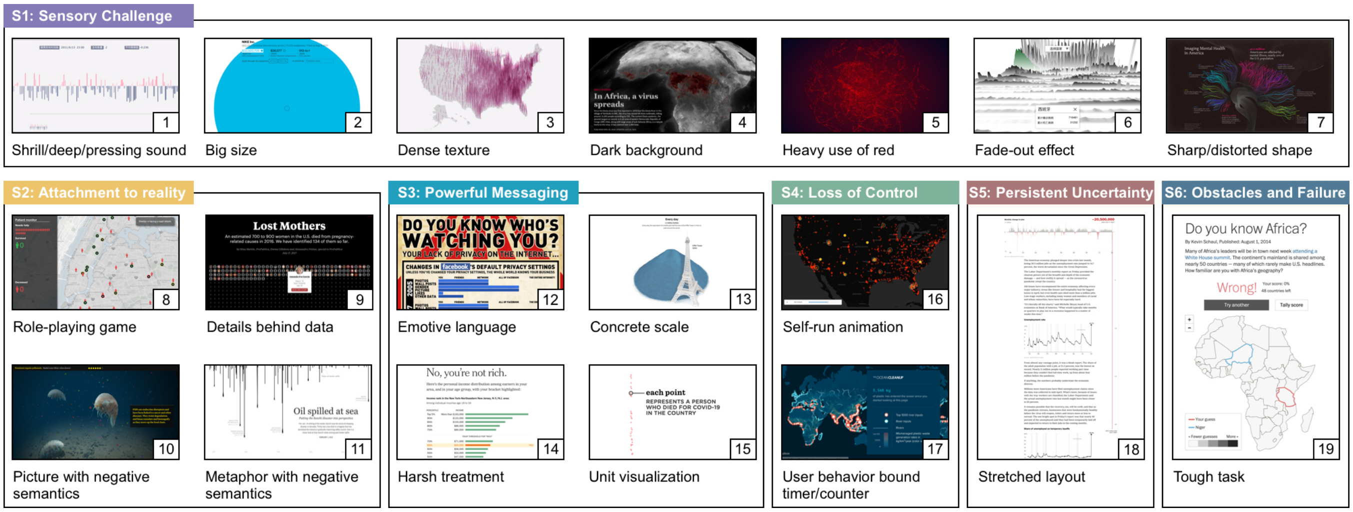

Figure 2: Examples of the 19 design methods identified from the workshop, categorized by 6 design strategies. Image sources: [13, 20, 27, 39, 66, 68, 73, 77, 78, 84, 86–90, 102, 106, 107, 116].

viewers to negative scenes (e.g., Fig. 2-10 [39]). The last design method is the **metaphor with negative semantics**, which integrates negative imagery with data visualization but "*in a more implicit way, trying to trigger synesthesia among the audience*"(E3). An example is Fig. 2-11 [89], which creates a bar chart using the metaphor of dripping oil.

S3: Powerful messaging. This strategy elicits negative emotions by using punchy or forceful language to inform viewers of something bad. In our workshop, some experts emphasized that **emotive language** can be used to express the negative attitude of the storyteller. Fig. 2-12 [116], for example, "*tries to frighten the audience using an emotional telling tone*" (E5). Another method is using a **concrete scale** [26] to help people better understand what a quantity means. For example, Fig. 2-13 [90] "*shows the huge amount of plastic bottles we consume by comparing the volume of the bottles with that of famous architecture*" (E6). Besides, designers may use **harsh treatment**, such as rejecting, warning, and assigning responsibility to viewers to put viewers in a disadvantageous position. For example, Fig. 2-14 [106] questions the viewers with "are you rich?" and asks the viewers to fill out their income. However, the outcome is "no, you're not rich". The last recommended design method is **unit visualization** [79] (e.g., Fig. 2-15 [73]), which uses one mark to represent one person or one tragic event in the dataset to "*lower the data granularity*" (E9) and "*enable the viewers to perceive the data more intuitively*" (E8).

S4: Loss of control. This strategy triggers negative emotions by removing people's ability to control the things happening during their viewing process. One typical design method is **self-run animation** that plays the animation automatically so that the viewers have to wait and watch something occur. For example, Fig. 2-16 [102] animates the map about police violence automatically once the viewer enters the web page, "*hence you are not totally controlling your reading process*" (E8). Another design method is called **user behavior bounded timer/counter**. For instance, Fig. 2-17 [27] puts a real-time counter in the corner, showing how much plastic has been thrown into the ocean since the viewer enters the page, which "*gives you a helpless feeling since bad things are inevitable, and they are related to you*" (E4).

S5: Persistent uncertainty. This strategy puts people in an uncertain position for a relatively long time and thus triggers negative emotions. The typical design method that belongs to this category is the **stretched layout**, which deliberately increases the length of a visualization so that viewers have to scroll for a while to view it completely. For example, Fig. 2-18 [107] stretches the scale of the jobless rate exaggeratedly so that "*viewers have to scroll all the way to the bottom of the page to see how shocking the latest rate is*" (E1).

S6: Obstacles and failure. This strategy elicits negative emotions by setting a trap for viewers and enticing them to fail. To achieve this goal, in serious data stories, designers can intentionally set a **tough task** for the viewers and make them struggle. For example, Fig. 2-19 [84] is a game that presents the names of African countries randomly to viewers and asks them to select the locations of these countries on the map. "*It is likely that people will fail again and again. By experiencing frustration or embarrassment, they will understand they do not know Africa at all*" (E3).

3.2.3 Controversies. We identified 3 controversial issues about eliciting negative emotions in serious data stories.

C1: The acceptance level of negative emotions. Four experts (E2, E4, E6, E8) expressed their worry that negative emotions may not be enjoyed by everyone. "*The viewers may not continue reading if the story is negative*", said E4. E2 complemented that "*sometimes we have to lower the negative degree of the design when dealing with topics like violence and suicide, in case the story becomes too uneasy to look at.*" E8 added that "*serious data stories should neither be too positive nor too negative, and we need to achieve a balance between the two states.*"

C2: The effectiveness of design methods. The experts debated the effectiveness of several design methods in eliciting negative emotions. For example, E2 and E1 had opposing attitudes towards the use of *unit visualization*. While E1 thought that "*showing people a large number of dots representing deaths can be striking*", E2 said that "*a large number of dots is not more touching than a single vivid story*". E4 referred to several game-playing cases mentioned in the workshop and questioned their ability to elicit negative emotions, and E8 agreed that it was still unclear how gamification can facilitate serious data storytelling. E9 expressed her worry about using metaphor in data visualization: "*visual metaphor usually uses an artistic expression which is more implicit and may require higher visual literacy.*"

C3: The self-expression of storytellers. Four experts (E1, E2, E4, E7) discussed whether it is acceptable for storytellers to express their own negative emotions in serious data stories. E1, an expert who works for a traditional news agency, said that "*the news reporting ethics command us to be as objective as possible and avoid integrating our own emotions into stories.*" However, in commercial companies, expressing emotions seems to be more tolerable: "*design methods such as using an angry title is acceptable in my company since emotional content attracts people better*"(E2). E7 also supported the inclusion of subjective expressions. She mentioned the idea of *data feminism* [32] and argued that "*data is often thought of as rational and objective, sort of masculine, but data can also be feminine, which is full of emotions.*" E9 said, "*We can have our own attitudes and emotions, but we have to communicate them appropriately. You can express emotions but should not incite emotions.*"

4 LAB STUDY WITH VIEWERS

Based on the findings from the workshop, this section aims to examine the communication of negative emotions in serious data stories from viewers' perspective, including (i) what are the outcomes of eliciting negative emotions in serious data stories, and (ii) how effective are the identified design methods in augmenting negative emotions. The study materials can be accessed at https://osf.io/c6vnu/.

4.1 Method

Previous studies about the negative emotions triggered by media were mostly conducted in an exploratory or ethnographic manner, such as asking participants to recall and describe their negative experiences [14, 15] and conducting laboratory observations and interviews [36, 47, 70]. The advantage of such a method is that the participants are presented with stimuli from the real world so they can read or interact with the stimuli as they are in their everyday lives rather than being strictly constrained to limited conditions. Besides, using this method, researchers can obtain abundant qualitative data that shows viewers' thoughts and opinions in-depth, which is important to a user experience study. Given these considerations, we also conducted this study in an exploratory manner.

4.1.1 Stimuli. We selected the stimuli used in this study from the corpus collected in Section 3, which contains 72 serious data stories that the experts thought elicit negative emotions. To control the amount of the stimuli while reducing the noises brought by story content, we presented the participants with stories with the same topic, following the methodology in [80]. Besides, to facilitate the assessment of design, the stories should cover as many identified design methods as possible. With these issues in mind, we extracted 17 stories whose topic is COVID-19 from the corpus. Among these stories, 3 are not English stories, and 1 (i.e., the Johns Hopkins Dashboard [25]) is controversial as some experts did not think it should be counted as a data story. Therefore, we removed these 4 cases from the list and kept 13 data stories about COVID-19 as the stimuli (see Fig. 3).

The 13 stories are from diverse authors and cover all the 19 design methods summarized in Section 3. For example, S1 in Fig. 3 uses distorted shapes and massive red to visualize the confirmed COVID-19 cases in Hong Kong. S6 explains the huge amount of deaths by showing viewers how many buses would be needed to load all the dead bodies. S10 uses flowers as a symbol to encode the death toll to show the idea of grief. S7 and S13 ask users to play a role-playing game in the context of COVID-19.

4.1.2 Measurement. First, we measured the emotions of the participants immediately after they finished viewing a stimulus. As many instruments can be used to assess emotions (e.g., the SAM scale [17], the PANAS scale [115]), we chose the most appropriate instrument for our study according to the following considerations. First, as the participants often named discrete emotions they felt in interviews [81], the instrument used in this study should measure emotions in a discrete manner. Second, as the negative emotions mentioned by the experts were quite diverse (e.g., frustration, anxiety), concise instruments such as PANAS are not able to capture the full spectrum of these emotions. Thus, to capture the emotions more comprehensively, we followed [81] and presented the participants with 48 EARL (Emotion Annotation and Representation Language) emotions, including 24 positive emotions and 24 negative emotions. Participants were asked to rate the 48 emotions using a 9-point scale (0 denotes "did not feel even the slightest bit" while 8 denotes "the most you have felt in your life") [38, 81]. If the participants didn't feel any of the 48 emotions, they could select "none of the above". Note that EARL also tags the 48 emotions with 10 subcategories, such as *negative and passive* (e.g., sadness), *agitation* (e.g., stress), *caring* (e.g., empathy), *reactive* (e.g., interest), and *positive and lively* (e.g., amusement). These subcategories were also used in our analysis to examine their mutual correlations.

Besides, we measured the outcomes of eliciting negative emotions. The 3 possible benefits of eliciting negative emotions identified in Section 3.2.1 (B1-B3, i.e., contemplative experiences, user engagement, long-term recall) were included as indicators. In addition, since whether people accept or resist negative emotions seems to be controversial (C1 in Section 3.2.3), we included another indicator called meta-emotion [7], that is, the appraisal of emotion. A series of prompts were used to measure the 4 indicators, and the participants rated the prompts using a 7-point Likert scale (1 denotes "strongly disagree", 7 denotes "strongly agree"). Specifically, there were 4 prompts for contemplative experiences (e.g., "The emotions encouraged me to focus on things that are important to me", "The emotions inspired me to think about meaningful issues"), following [7]. There were 7 prompts for user engagement (e.g., "I think this story holds my attention", "I felt involved when reading this story"), following [60]. There were 3 prompts for meta-emotion (e.g., "I like these emotions", "When I experience these emotions I enjoy them"), following [7]. The long-term recall was gathered 2 to 3 weeks after the lab study [10]. Online interviews were conducted

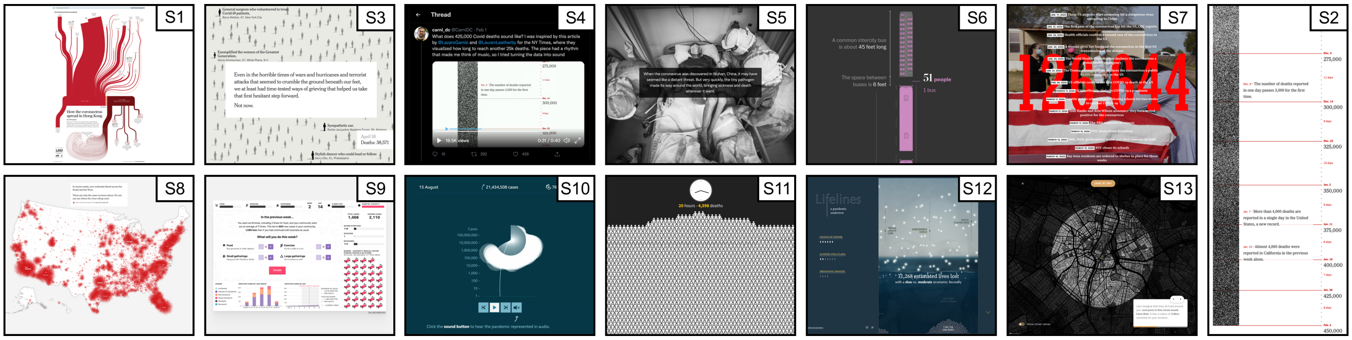

Figure 3: Thirteen serious data stories [11, 20, 23, 65, 82, 85, 91, 95, 101, 108–110, 112] about COVID-19 used as the stimuli (marked from S1 to S13). More descriptions of these stories as well as their design methods can be found at https://negativity.idvxlab.com.

to ask the participants to recall the stimuli they viewed and describe what they remembered.

4.1.3 Participants. 35 participants (20 female) took part in this study. We recruited the participants by posting an advertisement on an academic recruitment platform as well as an event forum. The ages of the participants ranged from 19 to 31 (M = 23.69, SD = 2.48). The educational backgrounds of the participants were diverse (e.g., architecture, politics, medicine, law, design), as well as their education levels (High school diploma: 25.7%, Bachelor's degree: 57.1%, Master's degree: 14.3%, Ph.D.: 2.9%). Most of them had limited expertise in data visualization (novice: 28.6%, advanced beginner: 37.1%, competent: 31.4%, proficient: 0.0%, expert: 2.9%) and their frequencies of reading data stories varied (never: 2.8%, rarely: 8.6%, sometimes: 54.3%, often: 28.6%, always: 5.7%). We paid each participant $25.

4.1.4 Procedure. To begin with, we informed the participants that they would be going to view 3 data stories about COVID-19 and obtained their consent to voice recording. The participants then filled out a brief online questionnaire to provide their gender, age, education level, educational background, expertise in data visualization, and frequency of reading data stories. Next, the participants were presented with 3 data stories about COVID-19 randomly chosen from our stimuli, one at a time. The order of the 3 stories was also random. After ensuring that the participants had not seen the story before, the experimenter went to the next room and came back when the participants stated that they had finished viewing the story. Then, the participants filled out an online questionnaire which asked them to rate: (i) 48 EARL emotions, (ii) 4 prompts about contemplative experiences, (iii) 7 prompts about user engagement, (iv) 3 prompts about meta-emotion, and (v) list all the thoughts that crossed their minds during and after the viewing process [9]. Afterward, the experimenter conducted a semi-structured interview with the participants to further understand their experiences and ratings. The participants were first asked to elaborate their emotional experience with the story ("Could you please walk us through your emotional journey when viewing this story?"), then answered more in-depth questions such as "What happened in the story that made you feel this emotion?", "Why do you like/dislike this emotion?", and "How the design method influenced your emotion?" Next, the participants saw a blank screen for 5 seconds to clear their thoughts and feelings [38] and view the next data story. We iterated the above process (i.e., story viewing, questionnaire survey, interview) until each participant had finished viewing 3 data stories. Last, we informed the participants that there would be an online interview 2-3 weeks later and asked them to schedule their time. To avoid intentional learning, we did not mention the specific reason for the interview (i.e., measure long-term recall). Each participant spent about 1.5 hours completing the lab study.

In the long-term recall interviews, we first asked the participants to retell the 3 stories they had viewed in as much detail as possible. This step was done to activate the participants' memory of the stimuli. Then, we asked questions such as (i) "Do you remember any data in this story?", (ii) "Do you remember any emotion you felt while viewing this story?", and (iii) "Do you remember any design methods that helped elicit your emotions?". Each participant spent approximately 20 minutes on the recall task.

4.2 Analyses and Results

All the stimuli elicited negative emotions effectively and the mean score of negative emotions was 1.55 (SD = 1.15, Cronbach's α = .93). The most negative stories were S3 (M = 2.41, SD = 1.22), S5 (M = 2.23, SD = 0.84), and S4 (M = 1.88, SD = 1.08), and the least negative stories were S10 (M = 0.78, SD = 0.61), S2 (M = 0.96, SD = 0.79), and S1 (M = 1.15, SD = 1.30). The mean score of positive emotions elicited by the stimuli was lower than that of negative emotions (M = 0.85, SD = 0.86, Cronbach's α = .90), and a Mann-Whitney U test further showed that the difference was significant with a medium effect size (U = 3327, p < .001, z = -4.965, r = .343). In other words, the stimuli in our study generally leaned towards being negative, which was in line with our expectation.

4.2.1 Outcome Analysis. As Shapiro-Wilk normality tests showed that some variables in our dataset are non-normal, we used Kendall's tau correlation coefficient, a non-parametric measure robust to skewed data [44], to analyze the relationship between the mean scores of negative emotions and the indicators of contemplative experiences, user engagement, meta-emotion, and different categories of positive emotions. Fig. 4 shows the results.

Contemplative experiences. The mean scores of negative emotions showed a significantly positive correlation with the mean scores of contemplative experiences (τ = .443, p < .001), as well as the 4 individual metrics of contemplative experiences, including thinking about important things (τ = .439, p < .001), thinking about meaningful issues (τ = .420, p < .001), thinking about myself (τ = .401, p < .001), and new insights (τ = .352, p < .001). In the interviews, most participants agreed that negative emotions led to thoughts and reflections (e.g., "*If I didn't experience that emotion (helplessness), I wouldn't care about this issue.*", "*Seeing others' misery makes me want to do something.*") On the downside, several participants said that they preferred being calm (e.g., "*I want to stay calm when I'm thinking.*") or that they thought the negative emotions were too strong (e.g., "*I felt so anxious that I couldn't think about anything.*")

To explore the contemplative experiences of the participants more in-depth, we then coded the participants' answers to the thought-listing question in the questionnaire following the codes by Bartsch et al. [9] who proposed four types of contemplative experiences triggered by visual stories: (i) thoughts related to character psychology (e.g., "*It must be sad to lose someone they love*"), (ii) thoughts related to abstract moral messages (e.g., "*We have to cherish every moment in our lives*"), (iii) self-related thoughts (e.g., "*I should not travel at the moment*"), (iv) thoughts related to social reality (e.g., "*What should we do next?*"). Thoughts that merely evaluated the story (e.g., "*Nice design.*"), described formal aspects (e.g., "*This is a well-known news agency.*"), or raised simple questions about the story content (e.g., "*What does this chart mean?*") were not coded. As a result, we identified 181 contemplative thoughts in total. The stimuli elicited 1.72 contemplative thoughts on average (SD = 1.24). Among these thoughts, 14 were about character psychology, 11 were about abstract moral messages, 77 were self-related, and 79 were about social reality. Typical thoughts triggered by negative emotions included an awareness of the danger of COVID-19 (e.g., "*This epidemic is more horrible than I thought.*"), the intention to stay healthy (e.g., "*We should wear masks.*"), and reflections on the actions of governments (e.g., "*The government should react earlier.*") Another interesting finding was that many participants were able to think from others' perspectives (e.g., patients, nurses, governors) in their contemplative thoughts. The correlation analysis between the mean score of negative emotions and caring emotions (see Fig. 4) also showed that the extent of negative emotions was moderately related to how much the participants cared about others (τ = .377, p < .001). Last, to provide an additional context for understanding negative emotions, we also ran correlation tests to examine the relationship between the mean scores of positive emotions and contemplative experiences. While positive emotions also showed significant correlations with contemplative experiences, the coefficient (τ = .224, p = .001) was much lower than that of negative emotions (τ = .443, p < .001).

User engagement. The mean scores of negative emotions showed a low positive correlation with the mean scores of user engagement (τ = .163, p = .015). By looking at the 7 metrics of user engagement separately, we found that negative emotions showed an insignificant correlation with 3 of them (e.g., enjoyment, likability, see Fig. 4). Qualitative feedback showed that while some participants agreed that negative emotions are important reasons for them to engage with data (e.g., "*Sad pictures made me want to learn more.*"), others thought that emotional messages may hinder their engagement (e.g., "*I wish the author would be more objective with the data.*") or that emotion is not the decisive factor of engagement (e.g., "*I think the story content itself influenced my involvement more.*"). On the other hand, the mean scores of negative emotions showed a positive correlation with 4 metrics of user engagement, including the feeling of interest (τ = .256, p < .001), the challenge to thinking (τ = .205, p = .005), focused attention (τ = .187, p = .012), and involvement (τ = .154, p = .035). The main reason was that the participants tended to be more intrigued if they felt an emotional atmosphere when they started viewing the stimuli (e.g., "*It gave me a serious tone, which made me want to read it carefully.*", "*It attracted me because the negative atmosphere suggested that this is not a boring statistical report.*"). The positive correlation between the mean scores of negative emotions and reactive emotions (see Fig. 4) further consolidated the above finding (τ = .305, p < .001). However, in general, in terms of augmenting user engagement, negative emotions did not perform significantly better than positive emotions, as positive emotion also showed a low positive correlation with user engagement (τ = .143, p = .035) and the coefficient was similar to that of negative emotions (τ = .163, p = .015).

Meta-emotion. The mean scores of negative emotion did not show a significant correlation with the mean scores of meta-emotion (τ = .061, p = .378), as well as the 3 metrics of meta-emotion (see Fig. 4). This result was in line with our findings from interviews that some participants resisted experiencing negative emotions, while others did not. Specifically, 24% participants said that they preferred to read positive stories and would resist negative emotions since "*life is hard enough*" and "*I may be drowned in the negative mood for a long time*". 40% participants said that they felt good to experience negative emotions (e.g., "*It's natural to feel sad or scared*", "*It's like watching a thrill. The more you are terrified, the more you enjoy the movie*", "*Feeling painful helps you grow*"). 36% participants said that it would be hard to say they liked or enjoyed negative emotions, but they do not totally resist experiencing negative emotions (e.g., "*I can digest the negative emotion if you feed me one, but I won't intentionally seek it*", "*It's OK for me as long as the negative emotion is not too strong*", "*Although I do not like negative emotions, I have to say they are useful*"). On the contrary, the mean of positive emotions showed a significantly positive relationship with meta-emotion (τ = .151, p = .028), showing that the participants indeed liked and enjoyed experiencing positive emotions more than negative emotions.

Long-term recall. The participants' memory concerning the stimuli generally faded after 2-3 weeks. Most participants could only remember the overall content of the stories (e.g., "*It is about the spread of the virus*"), the main conclusion drawn by the visualizations (e.g., "*The number of deaths is increasing*"), or the rough appearance of the visualizations (e.g., "*I remember there was a bar chart*"). In 13.33% cases, the participants remembered one or two specific data in the story (e.g., "*500,000 people died for coronavirus*"). However, in most cases, the participants' memory of data values has totally faded. By contrast, in 97% cases, the participants were able to describe the emotions they experienced when viewing the stimuli (e.g., "*This story was pretty sad, I remember it very well*"). We then compared their recalled emotions with the emotions they

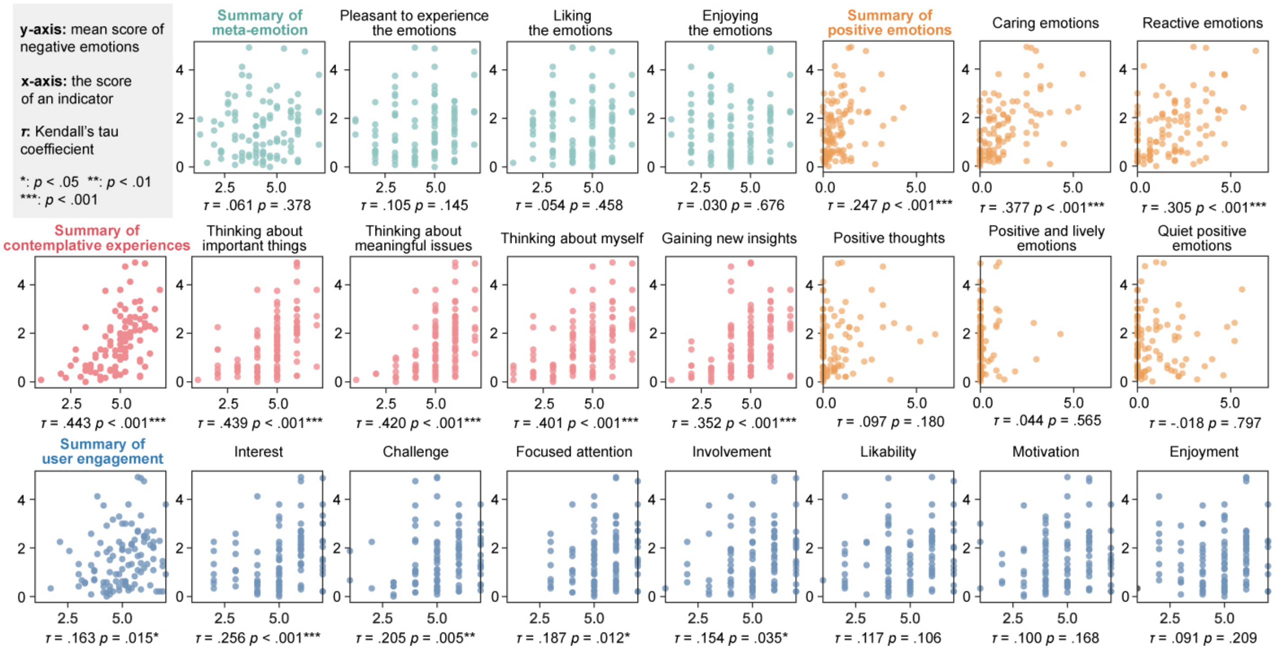

Figure 4: The Kendall's tau correlation coefficients (τ) between the mean score of negative emotions and contemplative experiences (red), user engagement (blue), meta-emotion (green), and positive emotions (orange), along with p-values.

had rated as experienced in the lab (score > 0) to see how many of the experienced emotions have been remembered. As a result, on average, 17.49% negative emotions (SD = 0.19) and 12.98% (SD = 0.20) positive emotions have been accurately remembered. Mann-Whitney U-test further indicated that the recall ratio of negative emotions was significantly higher that that of positive emotions with a small effect size (U = 3948, p = .004, z = -2.918, r = .205).

To conclude, we found that (i) the negative emotions triggered by our stimuli showed a significantly positive relationship with contemplative experiences and (ii) limited aspects of user engagement (e.g., interest, focused attention), (iii) the participants' acceptance levels of negative emotions were different, (iv) although the participants' memory of the data faded away, the negative emotions stuck in their minds more or less and were slightly better remembered than positive emotions.

4.2.2 Design Method Analysis. We collected 105 interview transcriptions from the lab (35 participants × 3 interviews) and 35 interview transcriptions from the long-term recall (35 participants × 1 interview). We noticed that although not all the negative emotions reported in our study were related to design (e.g., some emotions were caused by content only), many negative emotions were augmented by design methods. Therefore, we extracted all the descriptions about design and coded (i) the design methods explicitly mentioned by the participants, (ii) how the participants evaluated the design methods as contributors of negative emotions (i.e., effective or ineffective), and (iii) which specific emotion(s) had been augmented by these design methods.

The coding methodology is similar to that of Section 3. Two authors first coded 20% of the transcriptions independently and then compared and discussed our codes until resolving mismatches. For example, we found that when talking about the effect of a *dark background*, some participants thought it "*creates a serious tone*" or "*matches the theme*" without eliciting obvious emotions. Thus, we came to an agreement that such mentions do not support a design-emotion relationship. After achieving consensus, we coded all the transcriptions using the latest codes.

Effectiveness. First, we found that all the design methods summarized in Section 3 had been mentioned by the participants and we did not identify any additional design methods that contribute to negative emotions. Second, we found that these design methods showed varied effectiveness in augmenting negative emotions. As shown in Fig. 5, the design methods that earned the highest percentage of agreement on their effectiveness in augmenting negative emotions included the *tough task* (100%), *role-playing game* (88%), and *emotive language* (88%). In the interviews, the participants explained why these design methods worked: "*It (S13) asks me to imagine I live there and my neighbors all died. Thinking about this is extremely sad.*", "*This game (S6) is difficult to play. When I saw I had made the circumstance worse, I felt really bad.*" On the contrary, *sharp/distorted shape* (20%), *fade-out effect* (23%), and *metaphor with negative semantics* (29%) were regarded as ineffective in most cases. Most participants failed to receive the messages communicated by these methods since "*their meaning is too implicit*" and the participants "*could not understand how the design is related to the data or the topic*". For example, two participants thought the shape in S1 (see Fig. 3) was funny, and three participants thought the metaphors in S10 and S12 were not negative. Several methods were controversial, including the *stretched layout* (44%), *unit visualization* (48%), *heavy*

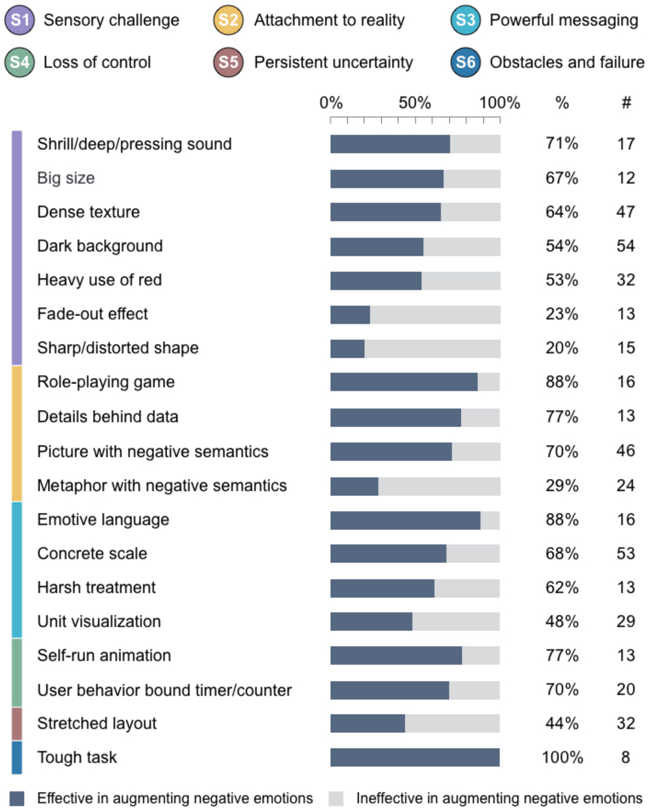

Figure 5: How frequently the 19 design methods were mentioned (#), and the percentages (%) of the mentions that said the design methods augmented negative emotions effectively.

use of red (53%), and *dark background* (54%). For example, while some participants acknowledged that *stretched layout* brought tension or anxiety, some participants disliked it because they had little patience (e.g., "*It's boring for me to scroll for a long time. I want to see the result immediately.*"). Although some participants thought that "*massive red makes me stressful*", others thought that "*red is good for attracting attention, but not that emotional*".

Design-emotion relationship. Next, we analyzed the relationship between design methods and negative emotions by first coding design-emotion pairs from the narratives of the participants, then visualizing all the design-emotion pairs into a node-link diagram and conducting social network analysis on this diagram. In order to reduce the noises caused by occasional cases and increase the clarity of the diagram, we followed [6] and excluded design-emotion pairs that occurred less than 3 times. Fig. 6 shows the result. As we can see, a design method may elicit multiple emotions, and a certain emotion may be triggered by more than one design method. In other words, we did not observe an exclusive relationship between a certain design method and a negative emotion. According to the result in the lab study (Fig. 6 (a)), *concrete scale* (degree = 8), *dense texture* (degree = 7), and *picture with negative semantics* (degree = 6) are design methods that showed the highest degree centrality, that is, elicited most diverse emotions. In addition, the calculation of betweenness centrality showed that *dense texture* (betweenness = 58.46), *concrete scale* (betweenness = 54.52), and *role-playing game* (betweenness = 32.30) showed the strongest capacity to bridge different nodes in the network. Besides, some design-emotion pairs were more empirically observed than others. For example, sadness was mostly related to *picture with negative semantics* and *dark background*, and shock was more related to *concrete scale.*

Fig. 6 (b) shows the network visualized from the recall data. Some design-emotion pairs have shrunk or disappeared with the faded memory (e.g., the mentions about fear). Social network analysis indicated that *picture with negative semantics* (degree = 6), *role-playing game* (degree = 5), and *dense texture* (degree = 5) triggered most diverse emotions in recall, while *picture with negative semantics* (betweenness = 48.51), *role-playing game* (betweenness = 23.61), and *dense texture* (betweenness = 21.51) became the main brokers

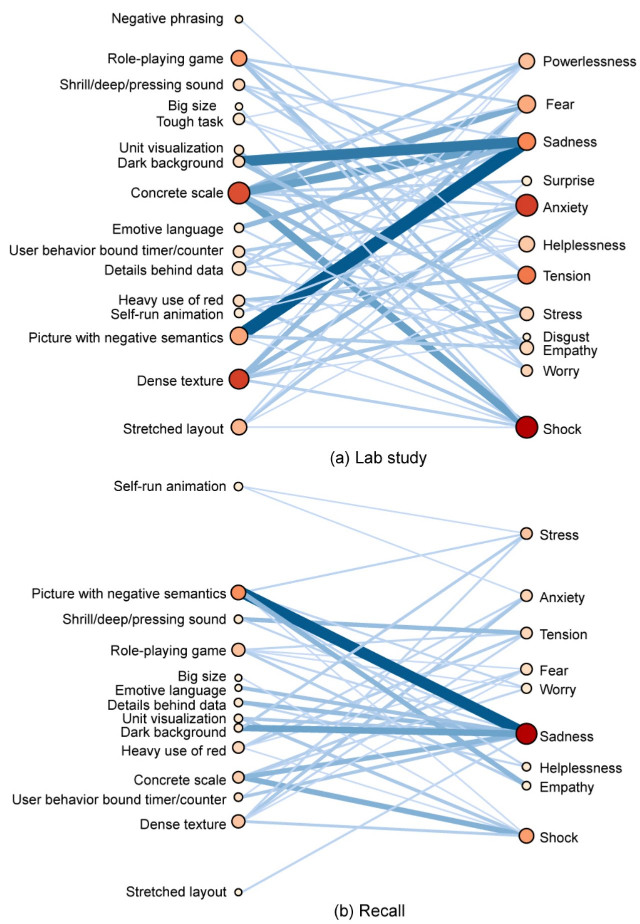

Figure 6: The design-emotion pairs mentioned in the (a) lab study and (b) recall. The width of the links encodes the frequencies of the pairs being mentioned. The node size encodes *degree centrality*, and the darkness of the nodes encodes *betweenness centrality*, calculated from social network analysis. Since negative emotions were found to be significantly associated with caring and reactive emotions, we also included these emotions (e.g., empathy) in the diagram.

in this network. The most recalled design-emotion pairs (e.g., *picture with negative semantics* and sadness) were generally consistent with those mentioned in the lab. In general, the better remembered design methods kept their central positions or became more central in the network (e.g., *concrete scale*, *role-playing game*). By contrast, the less remembered design methods (e.g., *stretched layout*) became more marginalized in the network.

To conclude, by comparing the findings from this study with those from the workshop, we found that while most design methods named by the domain experts effectively augmented the desired negative emotions from the participants, some did not. Therefore, there may be a gap between the expectations of storytellers and the real experience of viewers. Besides, the varied lingering effect of these design methods may also influence their effectiveness in communicating negativity in the long run.

5 DISCUSSION

By investigating serious data stories, this work has shown that emotional experiences beyond positivity can be valuable in data-driven storytelling. Negative emotions, although seemingly less enjoyable or fun than positive emotions, can be beneficial and worthwhile to experience. Especially, fueled by the integration of new design methods such as gamification and multi-modal interaction, it would be increasingly necessary to extend traditional means of evaluating data stories and capture more complex forms of user experience. Also, our work has suggested the importance to include both storytellers and viewers, immediate and lingering experience in the evaluation of data stories. Such a combination of different perspectives will allow us to obtain a richer understanding of the process of data communication. Below we list two main takeaways (**T1** and **T2**) that arise from our work.

Eliciting negative emotions seems to be a double-edged sword (T1). In the context of serious data storytelling, we found that negative emotions contributed to contemplative experiences and long-term recall (T1.1). However, enhancing user engagement, as another benefit proposed by some experts, was not entirely supported by our user study. How to convey negative emotions while interesting and attracting viewers using data visualization design is still an open question. **Besides, the pitfalls of eliciting negative emotions for data stories are still controversial (T1.2).** In our studies, while some experts and participants showed an open attitude to embrace the subjective power of data, some expressed their hesitation. This kind of worry resonates with some classic arguments in the visualization community, such as avoiding manipulating viewers' perceptions of data [22, 28, 32] and understanding the exact impact of emotions on cognitive processes [42]. Regarding this issue, our study has provided some empirical evidence. For example, some participants reported that *user behavior bounded timer/counter* had made them too anxious to continue reading, or that *dense texture* had triggered trypophobia and ruined the viewing experience. In the future, more work should be done to reveal the consequences of triggering negative emotions and how to prevent the side effects of negative emotions.

We found that some design methods proposed by the experts did not deliver negative messages as expected (T2). As suggested by the communication theory [97], this should be caused by various noises between message senders and receivers. **We observed three factors that may influence the effective communication of negative messages during our user study. The first one is the visualization literacy of viewers (T2.1).** In our study, participants who had less knowledge and experience with data visualization seem to be more likely to be distracted by the *novelty effect* [81], that is, paying attention to how novel the design is rather than to the story (e.g., "*the game is so fun that I almost forgot the tragedies told by the game.*"). **The second factor is the thinking styles of viewers (T2.2).** In our study, participants who successfully received the negative messages, especially those who can relate to artistic design methods such as *visual metaphor*, seem to think more emotionally. For example, when viewing S6, a participant said that "*I can feel as if I was walking along a line of buses that are full of dead bodies. I walk for a long time but the buses are just endless. That is so helpless*". However, another participant who defined himself as a rational person said that "*I think using buses to measure the number of deaths is pretty clear.*" **The third factor is emotional intelligence, namely the ability to handle or respond to negative emotions [67] (T2.3).** Several participants in our study mentioned that they were unable to cope with negative emotions very well (e.g., "*I don't like negative emotions because they make me feel uncomfortable and this bad mood can last a whole day*"), which made it difficult for them to enjoy such emotions.

6 LIMITATION

This work has several limitations. First, the design methods we identified are constrained by the corpus collected from the workshop and thus are not exhaustive. We mitigated this limitation by encouraging the experts to contribute diverse stories (resulting in 72 serious data stories in total) and moderating an in-depth focus group until the discussion about design had reached a point of saturation [56]. It should also be noticed that the effectiveness of these design techniques in terms of augmenting negative emotions should be understood within the context of our study (i.e., serious data storytelling) as we examined data stories whose content is inherently negative.

Second, the results derived from our study with viewers were constrained by the limited stimuli presented as well as the relatively small sample size of the participants. Especially, the participants we recruited are relatively highly-educated, which may have influenced the study results. According to previous literature [1], information visualization education is less accessible to people outside of higher education, thus making it harder for them to interpret visualization design. However, there are also arguments that people with similar educational levels but from different domains can also differ in visualization literacy [40]. These education-related factors, together with the factors (e.g., emotional intelligence) we discussed in Section 5, are worthy of further investigation. We hope future studies could involve a larger number of participants with diverse backgrounds and characteristics to investigate these issues.

Third, the quantitative results we derived in this work are mainly correlational. More work should be done to understand the causal interplay among negative emotions, data story design, and user experience. Meanwhile, by incorporating more designers, users, and visualizations into research, future studies could conduct more qualitative research to understand the visual communication process and the role of visualization design more in-depth.

Last, the verbal descriptions of the participants about their emotional experiences may have been incomplete or ambiguous. This limitation was mitigated by giving the participants adequate time to elaborate on their experiences and by asking more in-depth questions in the interviews requiring detailed clarification.

7 CONCLUSION

This work explores negative emotions in serious data stories by conducting studies with both storytellers and viewers. Through the workshop with 9 data story experts, we identified 3 possible benefits of eliciting negative emotions in serious data stories and 19 potential design methods that contribute to negative emotions. Through a user study with 35 participants, we confirmed that negative emotions do not necessarily lead to negative consequences. By contrast, they can be powerful and rewarding. The results showed that negative emotions significantly facilitated contemplative experiences and long-term memory, and increased user engagement from limited aspects. Further, by empirically assessing the 19 design methods proposed by the experts from the perspective of viewers, this work has revealed many shared opinions but also the gap between storytellers and viewers. To conclude, this work contributes to the knowledge around viewers' emotional experience with data stories and highlights user experience beyond hedonism. We hope these findings can extend our understanding of what is a good data story and how to design such stories.

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