Smile or Scowl? Looking at Infographic Design Through the Affective Lens

Xingyu Lan, Yang Shi, Yueyao Zhang, and Nan Cao

Abstract—Infographics are frequently promoted for their ability to communicate data to audiences affectively. To facilitate the creation of affect-stirring infographics, it is important to characterize and understand people's affective responses to infographics and derive practical design guidelines for designers. To address these research questions, we first conducted two crowdsourcing studies to identify 12 infographic-associated affective responses and collect user feedback explaining what triggered affective responses in infographics. Then, by coding the user feedback, we present a taxonomy of design heuristics that exemplifies the affect-related design factors in infographics. We evaluated the design heuristics with 15 designers. The results showed that our work supports assessing the affective design in infographics and facilitates the ideation and creation of affective infographics.

Index Terms—Infographic Design, Affective Responses, Storytelling, Crowdsourcing.

1 Introduction

INFOGRAPHICS, as visual communication devices that use visualizations, text descriptions, and embellishments to convey data, knowledge, and insights [1], [2], have been increasingly applied to domains such as journalism and marketing to attract, persuade, or educate audiences [3]. When designing infographics, designers often desire to trigger affective responses from viewers, as affect (people's emotion, mood, or feeling) is a critical intelligence of human beings that drives decision-making more intuitively and swiftly than logic does [4]. More specifically, an affect-stirring infographic is felt more interesting, persuasive, and thought-provoking, and can catalyze motivations, learning, and actions [3]. For example, a marketing infographic that looks cheerful and exciting is more likely to boost traffic and sharing [5]. An infographic concerning poverty should communicate empathy and sadness to facilitate the understanding of humanitarian data [6]. *A view on despair* [7], an award-winning infographic that visualizes the number of suicide cases in the Netherlands, was designed intentionally to communicate a feeling of peacefulness and thus call for proper treatment for depression and mental disorders.

Although their role has been highlighted by the design field for more than a decade [8], [9], [10], affective responses have been rarely examined in the visualization community. While prior research has recognized the importance of triggering affective responses in narrative visualization, data personification, and public art [11], [12], [13], [14], little is known about how to design visualization that elicits affective responses. In one case, Bartram et al. [15] suggested that when colored with a different hue, chroma, and lightness, visualizations can trigger affective feelings such as calmness and positivity. Boy et al. [16] found that human-like marks in pictograms may not help trigger empathy for human rights data. However, there is as yet no comprehensive and systematic study on understanding people's affective responses to visualization specifically through infographics. We lack knowledge on *what* affective responses can be triggered by infographics, and *why* they occur, which are important to design affect-laden infographics.

Given such motivations, this work makes an initial attempt to understand the affects elicited by infographics and the design-relevant factors that contribute to such affects. First, we collected a corpus of infographics, based on which two crowdsourcing studies were conducted; one was used to identify 12 affective responses to infographics and the other was used to collect user feedback explaining why the identified affective responses were triggered. By analyzing the user feedback, we built a taxonomy of design heuristics that exemplifies the affect-related design factors in infographics. Finally, to evaluate the usefulness of the design heuristics, we conducted an online workshop with 15 designers. The results indicated that our design heuristics can support assessing affective design in infographics and inspire the creation of infographics that elicit affective responses. Our corpus as well as study materials can be accessed at https://affectiveinfographics.idvxlab.com.

The major contributions of this work include:

- We identified 12 infographic-associated affects and mapped the affects to infographics through two crowdsourcing studies. These findings contribute to understanding what affects can be elicited by infographics.
- We developed a taxonomy of design heuristics that characterizes the affect-related design factors in infographics by analyzing user comments. The design heuristics systematically incorporate affective factors into visualization design for the first time.
- We conducted a workshop with 15 designers. The results of our workshop showed that the design heuristics can support design ideation and evaluation, as well as increase the likelihood of creating affective infographics.

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2 Background and Related Work

In this section, we contextualize our research in terms of relevant fields, including affective design, affective responses to visualization, and design of infographics.

2.1 Affective Design

Affective design combines visual features with communicative intents to achieve an emotional impact on audiences [10], [15]. Due to its significant influence on shaping user engagement, aiding learning, and persuading [17], [18], researchers and practitioners have been applying affective design to fields such as product design [8], user interface design [10], [19], and multimedia [20]. To facilitate affective design, one thread of research focuses on conducting studies with users to characterize their affective responses, understand what leads to such responses, and generate design implications. Since affective experience is context-specific [9], although psychologists have identified a set of primary or basic affective responses [21], [22], researchers have often attempted to understand the spectrum of affective responses arising from specific scenarios. For example, Desmet [9] identified 14 affects (e.g., satisfaction, desire, admiration) frequently elicited by product design (e.g., cellphones and cars). Richins [23] showed that in the shopping scenario, consumers often report affective responses such as discontent, worry, and shame to products. Mikels [24] conducted crowdsourcing studies with images from the International Affective Picture System and found that images usually trigger affective responses such as awe, amusement, and disgust. Another research thread, by contrast, examines how specific design factors lead to affective responses quantitatively through controlled studies or statistical models. For example, Kobayashi [25] analyzed the relationship between color palettes and affective responses through multiple experiments. Machajdik et al. [20] constructed a model that helps explain affective responses to images using features such as texture and the rule of thirds.

This work follows the first research thread by first characterizing the affective responses triggered by infographics using two crowdsourcing studies, and then proposing a taxonomy of affect-related design heuristics to guide the design of infographics. We consider this work as a first step towards incorporating affective factors into infographic design and a basis for developing future creativity-support tools geared towards designing expressive infographics.

2.2 Affective Responses to Visualization

Traditional methods of evaluating visualization mostly focus on how people *use* the visualization, such as their task-completing accuracy and speed [26]. Recently, with the increasing use of visualization in storytelling, business promotion, entertainment, and artistic practice [12], [27], [28], [29], researchers have paid more attention to the subjective experiences of users, namely, how people *feel* about visualization [12], [30], [31]. For example, Kennedy and Hill [30] found that affective responses are a vital component of user engagement with data. Thudt et al. [11] proposed that affective experiences, such as reminiscing about pleasurable moments, play an important role in the growing trend of personal data visualization. Wang et al. [12] acknowledged that affective feelings, as an important dimension of valuing visualizations, are largely overlooked. Bach et al. [13] observed that eliciting affective responses is one of the common purposes of data-driven storytelling; they also identified several narrative patterns (e.g., call to action) that aid in creating affective data stories. Bartram et al. [15] demonstrated that visualizations colored with certain palettes can communicate affectively. Boy et al. [16] found that human-like pictorial visualization may not help elicit empathy when used to represent human rights data.

Although the aforementioned work has highlighted the importance of affective responses, no systematic work has been done to examine what affects are frequently elicited by visualization, why they occur, and to guide visualization design by deriving design implications. This work addresses these questions by first conducting two crowdsourcing studies to understand people's affective responses to infographics, then presenting a taxonomy of design heuristics to aid the creation of affective infographics.

2.3 Design of Infographics

As one of the most popular forms of information visualization, infographics are widely applied to attract, teach, or persuade audiences [3]. In recent years, the design of infographics has received increased academic attention. For example, researchers have found that visual embellishments such as recognizable cartoons and images can enhance engagement and help people memorize or recall visualizations [32], [33]. Byrne et al. [34] conducted a content analysis of 50 award-winning infographics and found that designers frequently use figurative elements in infographics and are skilled at using social conventions in graphical representations. Harrison et al. [35] showed that people form their first impression of an infographic within 500ms, which is mainly due to the infographic's colorfulness and visual complexity. Dunlap et al. [36] analyzed the top 20 "liked" infographics on a website and indicated that effective infographics often have unexpected elements such as the use of humor, metaphor, and storytelling. Tools developed to facilitate the creation of infographics (e.g., DDG [37], InfoNice [2], and Text-to-Viz [38]) also emphasize decoration and expressiveness.

While the aforementioned work has shed light on the design of infographics, the affective quality of infographics remains unexplored. By examining people's affective responses to infographics and then building a taxonomy of design heuristics, our work fills the gap between infographic design and affective design.

3 Exp I: Identifying Affective Responses

To identify the typical affective responses to infographics, we conducted a crowdsourcing study with 245 participants. We manually collected a corpus of infographics and asked participants to label these infographics with words that best described their affective feelings. Then, we analyzed the words to identify commonly expressed affects.

3.1 Methods

Inspired by prior research [23], [24], we used the free-labeling method, which is a self-report approach that allows people to express feelings in their own words, here to characterize the affective responses to infographics. Free-labeling is beneficial for exploring the overall spectrum of affective responses since there are no pre-defined rules that limit people's expressions.

3.1.1 Participants

Our participants were recruited from Amazon Mechanical Turk (MTurk), a crowdsourcing platform that enables collecting data from a large, diverse participant pool. As participants' English vocabulary and writing proficiency might affect the quality of the self-report results, we restricted the task to only workers located in the US and who have previously had at least 95% of their results approved. The participants were aged from 18 to 79 (μ = 37.39, σ = 12.30). We paid each participant \$1.50 for labeling 20 infographics.

3.1.2 Study Material

To collect a corpus of infographics for our experiment, we began by exploring those which have been recognized as *expressive* or *well-designed*. Thus, we collected infographics from the following two online sources: (1) *Kantar Information is Beautiful Award*, one of the biggest competitions for information visualization and is known for its emphasis on design. We manually collected 1026 infographics from its showcase, which were evaluated by domain experts. (2) *Visual.ly*, one of the biggest online visualization communities for infographics sharing. From Visual.ly, we scraped the 500 most-viewed infographics whose page views ranged from 24,000 to 200,000. As a result, 1526 potential infographics were collected for our corpus.

To ensure that the infographics we collected were of high quality, we filtered out infographics if: (1) they were in duplicate, (2) they were of low resolution, (3) they were not English infographics. In accordance with these three criteria, we identified 976 of the 1526 infographics, consisting of 670 (68.65%) from Kantar Information is Beautiful Award and 306 (31.35%) from Visual.ly. We found that some of our infographics were published on news media (e.g., The Washington Post, South China Morning Post) and magazines (e.g., National Geographic, Wired UK), while the rest of them were created by individuals, companies, governments, and non-profits. Given such diverse publishers, the infographics in our corpus cover a wide range of topics such as economics, environment, movies, and sports.

3.1.3 Study Procedure

Experiment I consisted of three sessions. In Session 1, the participants were given an introduction explaining our research intent and the study structure. We also informed them that the infographics may vary in their capability of eliciting affective responses and encouraged the participants to label the infographics with single words that can best describe their affective feelings. Multiple-word labeling was also allowed if the participants experienced mixed affects. In Session 2, we randomly divided the 976 infographics into 49 groups, each with 20 infographics, except that the last group contained 16 infographics. Each participant was presented with up to 20 infographics, one at a time, and was asked to label them with affective word(s). Session 3 asked the participants to fill out a demographic survey on their gender and age. Answers with no reason provided or with reasons that failed to explain labels were regarded as unqualified and excluded. We iterated the process to guarantee that each infographic had received 5 qualified answers. The three sessions lasted about 30 minutes for each participant.

	Primary affect	Affective words	Percentage
Positive	happy	happy, amused, joyful, cheerful, enjoyment, delighted, satisfied, entranced, fulfilled, gratified, elated	16.26%
	surprised	surprised, amazed, astonished	10.52%
	excited	excited, enthusiastic, thrilled	3.43%
	content	content, pleased	3.03%
	awestruck	awestruck	1.95%
	hopeful	hopeful, optimistic, anticipating	1.75%
Negative	sad	sad, depressed, unhappy, despair, hopeless, melancholy, miserable, sorrowful, grief, despondent	9.80%
	concerned	concerned, worried, anxious, upset, nervous, disturbed, uneasy, apprehensive, troubled, dread, distressed	7.75%
	shocked	shocked, fearful, scared, alarmed, frightened, horrified, terrified, appalled, aghast, afraid	6.79%
	overwhelmed	overwhelmed	6.66%
	bored	bored	6.56%
	annoyed	annoyed, irritated, aggravated, agitated, grouchy, mad	5.74%

Fig. 1. 12 infographic-associated affects. For each of the primary affects, we show the relevant affective words in its category and the proportion of the category to the total use of the 123 words.

3.2 Analysis and Results

From the experiment, we collected 4880 labels with 6747 words in total. 27.33% of the labels contained multiple affective words. To identify representative affects associated with infographics, we analyzed these words through three steps, including cleaning, categorization, and summarization.

In the cleaning step, we transformed the words into their adjectival form (if they had one), resulting in 488 distinct words. As not all of the 488 words could be regarded as affective words, we first filtered out those used to describe the infographics (e.g., *colorful*, *beautiful*, *analytic*). We also eliminated words that fall into the following criteria according to [39]: (1) physical or bodily states (e.g., *tired*, *sleepy*, *allergic*), (2) external conditions (e.g., *alone*, *stupid*, *lucky*), and (3) words that are largely cognitive in nature (e.g., *interested*, *confused*, *curious*). As a result, 123 of the 488 words remained after cleaning. In the categorization step, we grouped semantically close words according to the affective lexicon proposed by prior research [40], [41]. For example, *joy*, *cheerfulness*, and *happiness* were found to be of high similarity with each other; *scared* and *frightened* are synonyms and thus can be grouped into the same category. The process of categorization yielded 38 groups of 123 affective words in total. In the summarization step, we first counted the frequency of each affective word and summed these frequencies for each group. We then identified 12 primary groups and used the most frequently mentioned word in each group as its primary affect. Fig. 1 shows the 12 primary affective responses associated with the infographics, including 6 positive affects (*happy*, *surprised*, *excited*, *content*, *awestruck*, and *hopeful*) and 6 negative affects (*sad*, *concerned*, *shocked*, *overwhelmed*, *bored* and *annoyed*). In line with [40], we treated *surprised* generally as a positive affect. These words accounted for 80.24% of the total use of the 123 affective words. Thus, we can say that the 12 affects are the representative affective responses these infographics triggered. The excluded words (e.g., *guilty*, *proud*, and *jealous*) were uncommonly mentioned.

4 Exp II: Infographic-Response Mappings

Based on the infographic-associated affective words derived from Experiment I, we conducted a second experiment with another 490 participants to construct infographic-response mappings and collect user feedback explaining what triggered affective responses in infographics.

4.1 Methods

In Experiment II, we asked the participants to label the 976 infographics in our corpus with the 12 identified affective words and rate the level of awareness. This method was efficient in gathering uniformly-scaled data while revealing the awareness level of affects [24]. The requirements for recruiting participants and the study material in this experiment were identical to those of Experiment I.

4.1.1 Participants

We recruited 490 participants from MTurk whose ages ranged from 19 to 72 (μ = 38.37, σ = 11.44). We paid each participant \$3.0 for scoring 20 infographics and leaving explanations. An extra \$0.50 bonus was paid if a participant wrote explanations very carefully.

4.1.2 Study Procedure

Experiment II consisted of three sessions, of which Session 1 and Session 3 were similar to the corresponding sessions of Experiment I. In Session 2, we randomly divided the 976 infographics into 49 groups. Each participant was randomly presented with one group of infographics. Fig. 2 shows a screenshot of our user task on MTurk. Each participant was asked to rate up to 20 infographics regarding the 12 affective words using a 5-point Likert scale. Here, 1 denoted "not at all aware" while 5 denoted "extremely aware" [42]. After rating, participants were asked to provide reasons explaining their options. For those participants who did not provide reasons, or the reasons did not explain the ratings, their answers were regarded as unqualified and were thus excluded. We iterated the process to guarantee that each infographic had received 10 qualified answers. We allotted each participant 2 hours to complete the task. The three sessions lasted about 0.5-1 hours for each participant.

4.2 Analysis and Results

As each of the 976 infographics was labeled by 10 different participants in Experiment II, we collected an array of 10 ratings for the 12 affective responses for each infographic, resulting in 117,120 ratings in total.

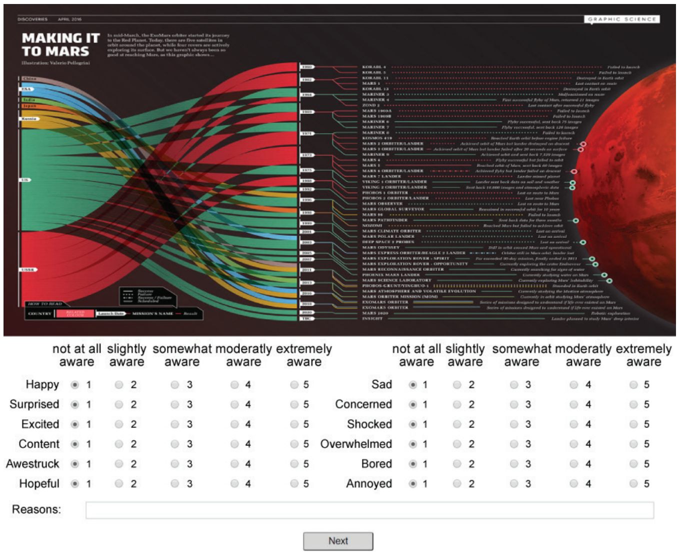

Fig. 2. Screenshot of our user task on Amazon Mechanical Turk.

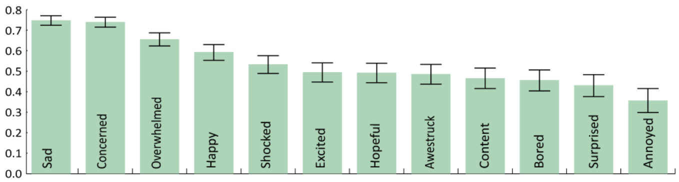

Fig. 3. The results of the ICC analysis. Error bars show the 95% confidence interval (CIs) of the means.

4.2.1 Consistency

First, we calculated the mean standard deviations of the ratings for individual infographics with regard to the 12 affects. The rank of the mean standard deviations in ascending order is: *sad* (0.56), *hopeful* (0.75), *shocked* (0.77), *concerned* (0.80), *excited* (0.86), *annoyed* (0.87), *awestruck* (0.91), *bored* (0.94), *overwhelmed* (1.01), *happy* (1.03), *content* (1.06), and *surprised* (1.24). Then, we used Intraclass Correlation Coefficients (ICC), which is a common statistical method to quantify scoring conformity, to analyze the consistency of ratings [43]. As shown in Fig 3, in general, there is a good agreement in ratings on the affective responses (ICC(2,k) = .540). Of the 12 identified affective responses, *sad* earned the highest ICC (ICC(2,k) = .748; 95% CI is .724 to .771; $F(975, 8775) = 3.974$, $p < .001$), while *concerned* (ICC(2,k) = .740; 95% CI is .715 to .763; $F(975, 8775) = 3.843$, $p < .001$), *overwhelmed* (ICC(2,k) = .656; 95% CI is .623 to .687; $F(975, 8775) = 2.908$, $p < .001$), and *happy* (ICC(2,k) = .593; 95% CI is .553 to .630; $F(975, 8775) = 2.454$, $p < .001$) also had high ICCs. *Annoyed* (ICC(2,k) = .375; 95% CI is .315 to .432; $F(975, 8775) = 1.600$, $p < .001$) and *surprised* (ICC(2,k) = .431; 95% CI is .376 to .483; $F(975, 8775) = 1.757$, $p < .001$), however, showed relatively low ICC. Overall, since the participants formed relatively consistent judgments on their affective responses when viewing infographics, we can say that an affective quality is somehow intrinsic to infographics.

4.2.2 Distribution

We analyzed the distribution of affects using Correspondence Analysis (CA). CA is a multivariate graphical tech-

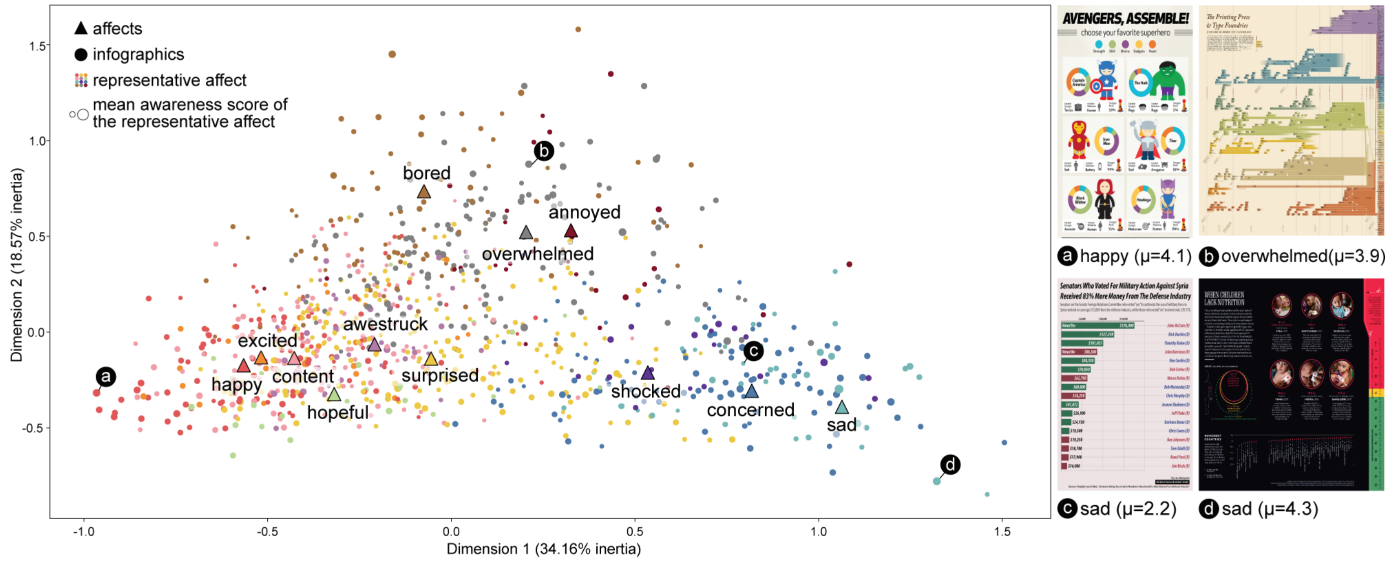

Fig. 4. We conducted a crowdsourcing study in Section 4 to label 976 infographics with 12 affects. We visualized the labeled dataset using Correspondance Analysis (CA). Each infographic is represented as a dot. The 12 affects are illustrated as triangles. The proximity between dots and triangles shows their relationship. For example, (a) locates close to *happy*, suggesting that it is more likely to elicit happiness than (b). A dot is colored by its representative affect and sized by the mean awareness score of its representative affect. For example, both (c) and (d) trigger sadness while (d) elicits a stronger sense of it.

nique used to analyze and explore categorical data such as the categorization of affects. In the field of affective design, some researchers have used CA to visualize users' affective responses to design stimuli [44]. To perform CA, we first transformed user ratings to categorical data. For each of the user ratings, we analyzed whether the user experienced any of the 12 affects. Since in our study, "1" denotes "not at all aware" while "2, 3, 4, 5" denotes "slightly, somewhat, moderately, extremely aware", respectively (which means the user experienced the affect more or less), we included an affect as experienced if it earned a score above 1. For example, if a user set score 3 to *happy*, score 4 to *exciting*, and score 1 to the rest of the affects, we thought that he/she experienced two categories of affects (i.e., *happy* and *exciting*) when viewing the infographic. Then, we performed the same data transformation on all the user ratings and counted how often each of the infographics was thought to express the 12 categories of affects. As a result, we got a cross table (or matrix) which has 976 rows (i.e., 976 infographics) and 12 columns (i.e., the 12 affects), showing the frequencies of how each of the infographics expresses the 12 affects. This cross table was then used as the input of the CA analysis.

The results of CA show that the total inertia equals 0.64 (chi-square = 15968, df = 10725, p <0.0001), suggesting there is a statistically significant association between the infographics and affective responses. Fig. 4 visualizes the two-dimensional map of our analysis. The 12 affective responses are represented as triangles, with colors illustrating their category. The 976 infographics are represented as dots. We used the color of each dot to encode the category of its representative affect. We identified the representative affect of each infographic by checking which affective response had the highest score. We found that 559 of 976 infographics had positive representative affects (*happy*: 126, *surprised*: 210, *excited*: 30, *content*: 118, *awestruck*: 46, and *hopeful*: 29) while 417 had negative representative affects (*sad*: 38, *concerned*: 103, *shocked*: 21, *overwhelmed*: 133, *bored*: 94, and *annoyed*: 28). For each infographic, we also calculated the average awareness score of its representative affect, which is illustrated by the size of the dot. For example, the dot showing Fig. 4 (d) is larger than that of Fig. 4 (c), suggesting that more participants reported high awareness of sadness towards Fig. 4 (d). In the CA space, the proximity between two dots shows their similarity. The further a dot or a triangle is from the origin (x, y = 0), the more discriminating its expressed affective response is. For example, dot (a) receives a high score in *happy* while it does not trigger other affective responses saliently. Similarly, dot (d) triggered a dominant affective feeling of *sad*.

Three findings can be derived from the CA space: First, we found that positive and negative affects locate on the opposite sides in Fig. 4, suggesting that people are unlikely to experience positive and negative feelings at the same time when viewing infographics. Second, affective responses are often blended. For example, the infographics that elicited *happy*, *excited*, and *content* are located close to each other, suggesting that the three positive affects are often experienced together. Also, *surprised* spreads over a larger area around the origin, which means that it is often experienced in company with other affective responses and is less discriminating. In other words, although *surprised* is one of the most mentioned affective responses by users, it can be difficult to design an infographic that triggers *surprised*, specifically. Third, *bored*, *overwhelmed*, and *annoyed* form a separate island in the CA space. As we discuss in detail in Section 5, these three affects were mainly triggered by design with low usability (e.g., complex encodings). Thus, some affective responses can occur beyond the expectancy of designers and hinder user engagement. We also collected a large amount of user feedback whereby the participants described what triggered their affective responses in the infographics. We analyze this qualitative data to derive our taxonomy of design heuristics in Section 5.

5 Developing Design Heuristics

This section presents a taxonomy of affect-related design heuristics in infographics. We first describe the methodology used to derive the taxonomy. Then, we introduce the design heuristics and our observations.

5.1 Methodology

We collected more than 9,000 pieces of user comments explaining what triggered affective responses in the infographics from Experiment II. Two of the authors were in charge of analyzing and coding these comments. During the coding process, we found that multiple factors can lead to affective responses. First, the content of infographics can be affective; about a half of the user comments we collected talked about how the topics, themes, or data had triggered affects (e.g., "*I am saddened that coral reefs are dying*"). Design, as another affect-related factor, was also extensively mentioned, either independently (e.g., "*The color of this image is pleasing to eyes*") or accompanied with content (e.g., "*A nice graphic that communicates the autumn data easily. I really like the color scheme, very autumnal*"). Besides, personal preferences (e.g., "*I am not interested in politics*") or states (e.g., "*I live in poverty and will be homeless soon, so this infographic scares me*") also influenced how people felt about the infographics. Since this section aims to focus on what *designers* can do to present given content, we then filtered out user comments that talked about content, personal preferences or states and only analyzed design-related comments.

Given that the data amount was large, we used random sampling in the coding process. The two coders first coded a subset of 100 design-related comments independently. As a set of initial codes emerged from this procedure, we met to compare and refine the codes, during which identical or similar codes were merged, while controversial ones were rephrased or discarded. For example, codes such as *information displayed in an odd fashion* and *very informative* convey ambiguous meanings and were thus dropped. We also used affinity diagramming to structure the codes hierarchically. For example, we found that *small font size* and *spelling or grammar errors* are about readability issues so that the two codes were assigned as branches of readability. Once we had achieved agreement on the codes, we extracted another 100 design-related comments from the data pool randomly, coded them with the established codes, and kept refining the codes through iterative discussions. We terminated the process when we had repeated the above procedure five times and found no more new codes emerged. Last, the frequency and saliency of the codes were also considered. For example, *use color-blind-friendly colors* was only mentioned once, so we did not include it as an important affect-related design factor. Also, while some users appreciated the beauty of the *circular layout*, others reported annoyance to tilted elements (e.g., "*The circle chart is annoying to read as the font is not all facing one way. As such, I have to keep turning my head to read the words.*") Given that this code was very controversial, we excluded it from the final codes. Finally, we derived 22 codes, grouped into two categories and seven sub-categories. We then transformed the codes into *design heuristics* [45], a series of design guidelines that help designers ideate or assess their work systematically and efficiently. In line with previous research [46], we phrased the low-level design heuristics into positively-told sentences to help designers map the heuristics easily to specific infographics.

5.2 Design Heuristics

We divided the heuristics that relate to affective responses in infographics into two categories: *Usability*, and *Expressiveness*. The structured heuristics are listed in Fig 5.

5.2.1 Usability

Usability, the degree to which something can be used, is about the functionality and understandability of infographics. When viewing a design, people will judge whether they can master the design. If the design helps them accomplish goals with minor effort, people react positively; otherwise, negative responses arise [8]. To augment the usability of infographics, four factors should be considered.

Accessibility Accessibility concerns how difficult it is to interpret and absorb the information in infographics. We found that many people responded positively to simple visualizations such as bar charts, pie charts, and maps (e.g., "*Happy to see the map. Very familiar and concise way of presenting data*"). Some users mentioned their satisfaction with how the infographics helped condense a large quantity of information (e.g., "*I feel content with this infographic because it provides abundant information for me*"). Another design factor is the layout. For example, infographic (d) in Fig 6 visualizes the timeline of Twitter as a bird's flight to guide reading progress, making users feel content with the information flow. However, on the other hand, high visual complexity may lead to affects such as boredom and annoyance. For example, infographic (j) in Fig 6 uses unconventional data encodings, making data interpretation difficult: "*A lot of unfamiliar symbols and marks make me feel bored*". Infographics (k) and (l) received comments such as "*It looks like a big tangled mess and it is annoying; I do not know where to begin and do not want to bother making sense of it.*" Thus, to achieve appropriate accessibility, we propose that three design heuristics should be considered: First, whether the infographic uses comprehensible data encodings (H1-1-1). Second, whether the infographic provides an appropriate amount of information (H1-1-2). Third, whether the infographic provides a clear reading path (H1-1-3).

Readability Readability is the quality of being legible or decipherable. When the font size is comfortable to read, people respond with positive affects (e.g., "*I like the big font, easy for my eyes.*") Also, adequate foreground-background contrast can ease reading efforts: (e.g., "*This infographic pleases me because there is enough contrast between the texts and the background so I can see everything clearly.*"). However, unreadable infographics can trigger negative affects immediately. Infographic (j) in Fig 6 received user comments such as: "*There is no enough contrast between the tiny texts and the background. It hurts my eyes which makes me irritable.*" Spelling or grammar errors can also lead to negative feelings (e.g., "*I*

			2 Happy	Surprised	Excited	Content	Awestruck	hopeful	Sad	Concerned	Shocked	1 Bored	Overwhelmed	Annoyed
H1 Usability	H1-1 Accessibility	**H1-1-1** The infographic uses comprehensible data encodings	3		1	8	1					-2	-8	-3
		H1-1-2 The infographic provides an appropriate amount of information	1			2	1	1				-11	-31	-4
		H1-1-3 The infographic provides a clear reading path	8	1	1	6						-3	-5	-4
	H1-2 Readability	**H1-2-1** The infographic uses readable font size	1									-4	-7	-6
		H1-2-2 The infographic's graphics and texts stand out from the background	1			2						-1		
		H1-2-3 The infographic has no spelling or grammar errors										-1		-2
	H1-3 Messaging	**H1-3-1** The infographic provides clear labels and legends for data visualization	2									-1	-1	-1
		H1-3-2 The infographic provides contextual information for data visualization										-5	-2	-1
		H1-3-3 The infographic provides a detailed explanation for data visualization	5		1	4			-1			-2	-3	
	H1-4 Credibility	**H1-4-1** The infographic presents information in an impartial way												-2
		H1-4-2 The infographic uses data that is valid and clearly collated	1											-2
H2 Expressivess	H2-1 Embodiment	**H2-1-1** The infographic incorporates topic-relevant imagery into visualization	4	1		2	2		1	2	3	-1		
		H2-1-2 The infographic uses topic-relevant imagery as embellishment	7	1	1	3		1	1	3	1		-1	
		H2-1-3 The infographic uses bright/dark color for positive/negative tone	2					1	1	1				
		H2-1-4 The infographic uses warm/cold color for positive/negative tone	2						1	1				
		H2-1-5 The infographic is of high/low colorfulness for positive/negative tone	6		3	2		1				-4	-2	
		H2-1-6 The infographic uses semantically-resonate colors	2	1		1			1		2			-1
	H2-2 Narrative	**H2-2-1** The infographic emphasizes key data facts	2	11	1	1	2	1	7	4	3		1	1
		H2-2-2 The infographic addresses the audience directly	1	1								-1		-1
		H2-2-3 The infographic uses powerful wording	2			1				1	1			1
	H2-3 Uniqueness	**H2-3-1** The infographic uses novel data visualization	7			1	4					-2		
		H2-3-2 The infographic has a salient style or personality	1		1	1								

Fig. 5. Design heuristics derived from our analysis of user feedback. Rows indicate the observed design heuristics, categorized into two main dimensions: *Usability* and *Expressiveness*. Affective responses are represented as columns. Each cell is colored according to the frequency of this heuristic being mentioned by users. If the heuristic was mentioned for being adhered to, it earned a positive score (green). If the heuristic was mentioned for being violated, it earned a negative score (orange). For example, eight users said that they felt overwhelmed because the infographics did not use comprehensible data encodings. Regions 1 to 3 are discussed in Section 5.3.

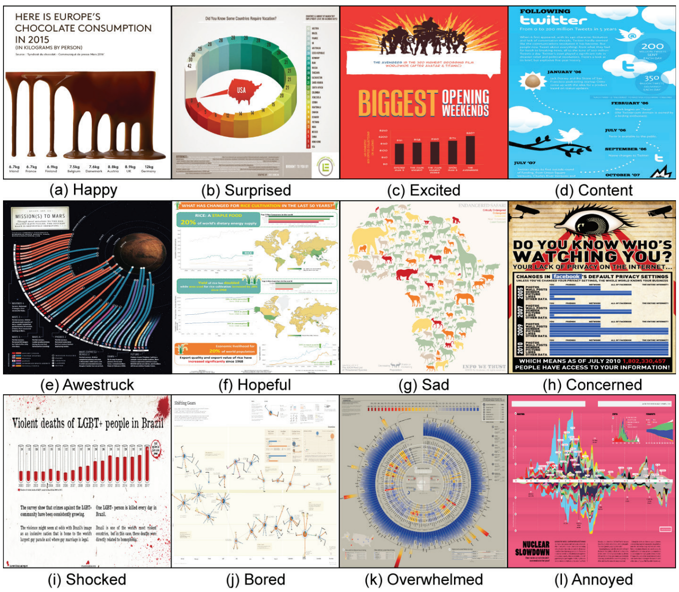

Fig. 6. Exemplar infographics and the primary affects they triggered.

feel annoyed because SO MANY typos and misspellings are distracting from the message.") Therefore, to improve readability, three design heuristics should be considered: First, whether the infographic uses legible font sizes (H1-2-1). Second, whether the infographic's graphics and texts stand out from the background (H1-2-2). Last, whether the infographic has no spelling or grammar errors (H1-2-3).

Messaging Messaging provides essential instructions, guidance, or contexts for the data visualizations. For example, affects can be triggered when visualizations are clearly labeled (e.g., "*I was pleased that all the points and the scales were well labeled.*"). Users also appreciated the existence of contextual information for the data visualization (e.g., "*content because it provides me with appropriate context to read the graph*") and detailed data explanations (e.g., "*I like this infographic because it provides me with a lot of details which help me absorb the data better.*") By contrast, insufficient messaging can hinder sense-making and lead to negative affects (e.g., "*I have no idea what this is about or what it means. I need more explanation.*"). Therefore, we claim that to facilitate messaging, three design heuristics require attention: First, whether the infographic provides clear labels and legends for data visualization (H1-3-1). Second, whether the infographic provides contextual information for data visualization (H1-3-2). Third, whether the infographic provides a detailed explanation for data visualization (H1-3-3).

Credibility Credibility refers to how trustworthy an infographic is. For example, professionally listed references can trigger positive affects (e.g., "*I liked all the data sources are listed below the infographic, it seems professional.*"). On the contrary, a user may feel annoyed when the data source is unclear or not reliable (e.g., "*There is no source. Anyone can make up any numbers.*"). Several people also mentioned that they felt annoyed because the data or visuals are biased (e.g., "*Annoyed because I think this infographic is really deceptive. I thought that the visuals didn't do it justice in a way to not overly scare someone.*") Thus, to guarantee credibility, two design heuristics should be considered: First, whether the infographic uses data from sources that are valid and clearly collated (H1-4-1). Second, whether the infographic presents information in an impartial way (H1-4-2).

5.2.2 Expressiveness

Expressiveness denotes the design traits that make infographics vivid, eloquent, and storylike. It is an important contributor to affective responses since human beings react affectively to storytelling factors, such as the story's vibe, scenes, and main ideas [18]. To improve expressiveness, three design heuristics should be considered.

Embodiment Embodiment refers to visual representations that create tangible or situated feelings. It works to remind the audience of their life experience, evoke senses, and make abstract data experienceable. One way of augmenting embodiment in infographics is through imagery (e.g., pictures, icons, and illustrations). For example, infographic (a) in Fig 6 uses the image of chocolate to substitute the bar chart, making the statistics about chocolate seem touchable and eatable: "*I am happy to see that the chart was drawn in chocolate*". Infographic (g) uses icons to visualize endangered animals in Africa: "*The animal shapes make me feel sad to think about how many of them are endangered or vulnerable*". Imagery can also be used as embellishment; for example, infographic (h) illustrates online surveillance with an Orwellian eye. Another way to shape embodiment is through color. When the color brightness or temperature is in line with the storytelling tone, the design becomes more embodied (e.g., "*This infographic gives off a serious and concerning tone, thanks to the dark color*", "*Blue is cold, so as the story.*") Some users also demonstrated the affective impact of colorfulness (e.g., "*The various colors of the infographic make it feel quite inviting and cheering*"). Or, designers can attach a meaning to color. For example, infographic (i) uses red, the semantically-resonate color [47] of blood, to strengthen the message of violence against LGBT+ people: "*I mostly felt shocked because there is a lot of blood depicted on this page and also a lot of red. This has a horror vibe.*" Therefore, we propose that six design heuristics about embodiment should be considered in an infographic: First, whether the infographic incorporates topic-relevant imagery into visualization (H2-1-1). Second, whether the infographic uses topic-relevant imagery as embellishment (H2-1-2). Third, whether the infographic uses bright/dark color for positive/negative tone (H2-1-3). Fourth, whether the infographic uses warm/cold color for positive/negative tone (H2-1-4). Next, whether the infographic is of high/low colorfulness to express positive/negative tone (H2-1-5) Last, whether the infographic uses semantically-resonate colors (H2-1-6).

Narrative Narrative communicates data to the audience through content structuring, wording, and phrasing. In infographics, a narrative works to emphasize certain facts or ideas and start a dialogue with the audience. For example, infographic (b) in Fig 6 tells a story about the required vacation days across countries. It intentionally emphasizes the number for the US, thus appealing strongly to its target audience: "*I am really surprised that every country listed in the infographic has more vacation days than the United States.*" Similarly, infographic (f) uses big bold fonts to highlight the increase of the yield of rice, making viewers feel optimistic about the future. Besides, linguistic tactics are also used to empower narratives. For example, infographic (h) has a strong tone of communication by talking directly to its audience: "*I was reading the title and was shocked by it immediately before I even read the content.*" Short phrases, such as a slogan and a call to action, are also viable means to appealing to the audience directly. In addition, designers may use powerful words to communicate affectively (e.g., "*I feel concerned because the wording in this infographic suggests that water pollution is such a serious problem.*") Thus, we propose that three design heuristics should be considered to build emotive narratives: First, whether the infographic emphasizes key data facts (H2-2-1). Second, whether the infographic addresses the audience directly (H2-2-2). Third, whether the infographic uses powerful wording (H2-2-3).

Uniqueness Uniqueness is the quality that makes a design exceptional and is often the manifestation of creativity. People react affectively to uniqueness because human beings are sensitive to unexpected and unconventional things [48]. For example, infographic (e) was viewed by many users as a novel way of presenting data: "*Really clever way to demonstrate missions to Mars. The shapes make me in awe of how humans are constantly trying to explore new worlds.*" Also, people respond affectively to infographics that have a salient style or persona. For example, infographic (c) "*reminds me of an old-style comic book cover. It is interesting to look at and visually pleasing.*" Thus, uniqueness asks for two design heuristics to be considered: First, whether the infographic uses novel visualization (H2-3-1). Second, whether the infographic has a salient style or personality (H2-3-2).

5.3 Design Heuristics Observations

The heat map in Fig. 5 indicates the empirically observed distribution of the design heuristics among the 12 identified affects. The heuristics are presented as rows and affective responses as columns. Each cell is colored by the frequency of a heuristic mentioned by users. If the heuristic was adhered to, it earned a positive score (green). If the heuristic was violated, it earned a negative score (orange). By observing the distribution of colored cells, we derived three findings, marked from regions 1 to 3 in Fig. 5:

First, affective responses including *bored*, *overwhelmed*, and *annoyed* are mainly caused by poor usability (H1), especially low accessibility (H1-1), small font size (H1-2-1), and inadequate messaging about data (H1-3-1, H1-3-2), as suggested by region 1. We also found that, occasionally, these three affective responses may be triggered by flaws in expressiveness, especially the wrong use of colorfulness (H2-1-5). This helps explain that the separate island formed by *bored*, *overwhelmed*, and *annoyed* in the CA space (see Fig 4) is caused by bad design. Second, as shown by region 2, positive affects such as *happy* and *content* may occur when infographics present a comprehensible data visualization (H1-1-1), a clear layout (H1-1-3), and detailed explanations

(H1-3-3) to the audience. In other words, when people find that they can master the design and absorb the information smoothly, they will react positively. Third, once the usability issues are satisfied, improving the expressiveness of design (H2) can evoke more affective responses, suggested by region 3. Therefore, both usability and expressiveness can influence people's affective responses to infographics, and usability usually acts as the basis of a good design, guiding it towards triggering wanted affects while expressiveness will further augment the affective vividness of the infographic. In other words, to trigger desired affective responses, designers should prioritize usability-related factors before augmenting expressiveness-related factors.

Among various design factors, relevant imagery (H2-1-1, H2-1-2), color (H2-1-3, H2-1-4, H2-1-5), and emphasis (H2-2-1) were mentioned most often. Another interesting fact is that while color and imagery are frequently associated with *happy*, *excited*, *content*, and *awestruck*, data highlighting is more relevant to affects such as *surprised*, *hopeful*, *sad*, *concerned*, and *shocked*. This suggests that the inherent mechanisms of triggering different affective responses may vary. For happy, *excited*, *content*, and *awestruck*, the perception of embodiment is important, while for *surprised*, *hopeful*, *sad*, *concerned*, and *shocked*, narratives and persuasiveness count more. In addition, *happy* and *awestruck* seem to be particularly related to novelty (H2-3-1). Given these empirical observations, we frame the design heuristics as a tool to support design ideation and evaluation, helping designers present content better. For example, when a designer is given a story from an editor and asked to design an affective infographic, he/she can refer to the design heuristics for inspirations or turn to the design heuristics after finishing the first draft to seek for improvements.

6 Workshop

We conducted an online workshop with 15 designers where the participants used the design heuristics to redesign the infographics to augment intended affect(s). To guide the analysis of the workshop results, we posed three research questions regarding our taxonomy of design heuristics: RQ1) how it was used by the participants, RQ2) whether it is useful, and RQ3) whether it is easy to use.

6.1 Methods

The workshop was conducted online using Zoom. The participants first evaluated three infographics through the affective lens with our design heuristics, then redesigned one of the infographics and provided feedback.

6.1.1 Participants

Our participants were recruited via social media platforms. Our recruitment material demonstrated that we were looking for designers who have experience in creating infographics. We recruited 15 designers (11 females) aged between 21 and 31 (μ = 24.56, σ = 2.20), including 8 college students majoring in data visualization, graphic design, and interactive design, and 7 professional designers from news agencies, business intelligence companies, design consultancies, and governments. All participants indicated that they have experience with creating infographics and their design skills varied (excellent: 13.33%, very good: 33.33%, good: 40.00%, fair: 13.33%, poor: 0.00%).

6.1.2 Study Procedure

The study consisted of three sessions. In Session 1, we began with a 40-minute introduction explaining the intent of our research, core concepts (i.e., infographics, affective design, design heuristics), and a step-by-step walkthrough of the design heuristics. Then, the participants carried out a 20-minute warm-up exercise. The participants were presented with an infographic sample and were asked to evaluate it by rating whether they agree that the infographic adheres to each of the design heuristics using a 5-point Likert scale (1 denotes strongly disagree, 5 denotes strongly agree). Then, the participants were asked to summarize their evaluations and discuss how they decided to redesign the infographic to make it affect-inducing. We used this warm-up exercise to familiarize the participants with the design heuristics. Session 2 asked the participants to redesign infographics with the goal of augmenting intended affect(s) (except for *bored*, *overwhelmed*, and *annoyed*). The participants were given three infographics (marked from O1 to O3 in Fig 7). Each participant selected one infographic, then evaluated the infographic using the design heuristics as they did in the warm-up exercise, and wrote down their redesign plans. The three infographics were respectively created by The World Health Organization, World YWCA, and Black Female Development Circle, and were not part of the corpus we used to create the heuristics. The participants were given three days to complete the task offline. In Session 3, we collected infographics from the participants and asked them to fill out a brief questionnaire to evaluate the design heuristics in terms of usefulness and ease of use. We also conducted a 30-minute online semi-structured interview with each participant to collect more feedback.

6.2 Results

We collected 15 redesigned infographics that express specific affects, including eight for O1, four for O2, and three for O3 in Fig 7. Fig. 7 also shows some examples of the redesigned infographics (R1-R6).

RQ1) Usage: By coding the 15 infographics collected from the participants, we found that 12 of the 22 design heuristics were used in the redesign task. Imagery as embellishment (H2-1-2) was the most popular heuristic with the highest usage frequency (10). For example, R1 in Fig. 7 used the imagery of a knife and blood to strengthen the feeling of shock. R2 used a dark cloud to imply concern about suicide and an umbrella to convey an optimistic attitude to prevent it. R4 changed the background of the original infographic to a horrible photograph to convey shock. Besides, layout (H1-1-3: 9), color brightness (H2-1-3: 5), color warmth (H2-1-4: 4), and emphasis (H2-2-1: 4) were also used often. For example, R1, R4, R5, and R6 adjusted the layout of the original infographics to create clearer reading paths and communicate the affects more smoothly. R4 and R6 highlighted key numbers and sentences to intensify seriousness or positiveness. R4 used dark colors to create a negative vibe while R6 chose a bright color to convey happiness. To

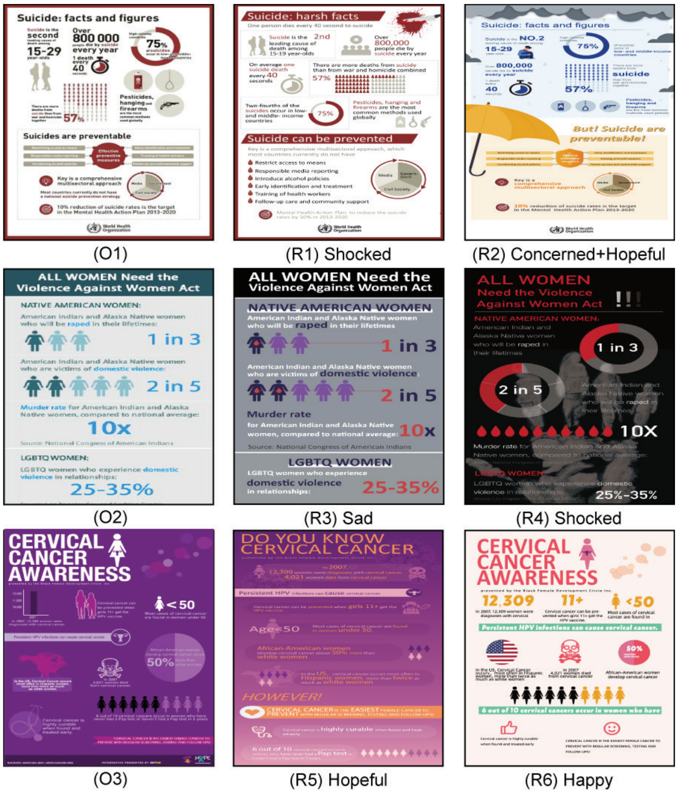

Fig. 7. Examples of the redesigned infographics collected from the workshop (marked from R1 to R6 in company with their affective design goals) compared with the original works (O1-O3).

convey the hopefulness of curing disease, R5 lets the color change from dark to bright to end the story with a positive tone. Other design heuristics used in the workshop include addressing the audience (H2-2-2: 2), semantically-resonate color (H2-1-6: 2), powerful wording (H2-2-3: 1), font size (H1-2-1: 1), contrast (H1-2-2: 1), imagery as visualization (H2-1-1: 1), and colorfulness (H2-1-5: 1). For example, R4 used blood-like icons to make the visualization more embodied. R5 modified the title to talk directly to the audience.

RQ2) Usefulness: Overall, the participants indicated that our taxonomy of design heuristics was useful. The average rating of usefulness was 5.73 on a 7-point Likert scale 1 7. We found that there are two main benefits that the design heuristics can bring compared to the designers' previous infographic-design experience. First, the design heuristics provide a systematic framework to facilitate design ideation and spark creativity: *"I have been using some of those methods in my previous design but didn't realize they could be organized in such a systematic way"* (P3), *"It provides more design options than I could think of. I adopted the methods about embodiment in my design as it's such a creative way to bring data to life"* (P9), *"The heuristics about narratives have inspired me most. (Without them) I may focus on visuals too much and forget how powerful texts can be"* (P14), *"The taxonomy shows design directions without limiting my thoughts. I'll definitely use it in my future ideation process."* (P2). Second, the design heuristics could facilitate design evaluation: *"The design heuristics helped me quickly decide the pros and cons of the original infographic"* (P5), *"I checked the design heuristics one by one to make sure that my design has achieved good usability and expressiveness"* (P1). Two participants noted that they would like to see more low-level techniques (e.g., color palette solutions) apart from heuristic guidelines.

RQ3) Ease of Use: Most participants (14 of 15) agreed that our taxonomy of design heuristics is easy to use. The average rating of ease of use was 6.07 on a 7-point Likert scale 1 7: *"The design techniques are well-organized... I used it as a handbook of designing affective infographics"* (P15). *"I like the heatmap in your design space where frequently-used techniques are colored darker. It's easy for me to make a choice at a glance"* (P2). One participant, however, thought the design heuristics were not easy to learn at first: *"I think understanding some of the design terms is not easy for beginners; maybe providing a detailed explanation for each heuristic might help."* We also analyzed the reliability of our design heuristics using the participants' evaluation records. Results indicated that our taxonomy of design heuristics was clear and of high reliability (average Cronbach α = .850).

7 Discussion

This section discusses the implications derived from our work, our limitations, and future work.

7.1 Measuring Affective Responses to Visualization

This work makes an initial attempt to understand the affects elicited by infographics and the design-relevant factors that contribute to such affects. However, we found that measuring affective responses is still challenging in many aspects. For example, we noticed that users often experience blended affects, especially positive ones such as *happy*, *excited*, and *content*, which echos previous findings [24]. Second, we found that users may experience more affects as the story unveils itself. For example, one participant described her affective experiences towards infographic (g) in Fig 6: *"these animal icons are so cute that makes me smile, but I feel much sadder when I realize they are endangered"*, suggesting that affective responses can be measured as a dynamic sequence. Thus, to capture affective responses more precisely, building more standardized measurements is desired.

Although being difficult to measure, affective responses have offered a lens to see why people like or dislike a visualization and whether they want to consume it or take actions (e.g., *"I'm totally cheered up by this infographic; I'm not a math person, but it makes me want to learn more about the data"*, *"The infographic makes me realize how air pollution is damaging our earth. I feel I need to do something"*). Given that visualization is increasingly applied in storytelling, marketing, and education [3], [27], we see measuring affective responses to visualization as an important and promising research direction.

7.2 Designing Affective Infographics

The taxonomy of design heuristics we derived has shed light on various affect-related design factors in infographics. Given that the psychological mechanism of triggering affective responses is universal across storytelling mediums [48], the design heuristics we derive for infographics are likely to be translated into other storytelling genres, such as data videos [49] and data comics [50]. We also noticed some challenges for designing affective infographics. First, the design heuristics suggest that *visual communication* is a vital skill. For example, how to use imagery and color to create vibes, how to achieve a good telling flow, and how to use narratives to convey feelings. Mastering these techniques requires designers to have a good understanding of the data while being familiar with storytelling. Second, some design factors are more controversial than others in terms of eliciting affective responses. For example, although people appreciated infographics for encapsulating adequate information in limited space, they reacted negatively to crowded layout. Also, while people reacted positively to novel data visualization, they turned to feel bad when failing to make sense of a too-novel design. This happened to many award-winning infographics which use unusual encodings, symbols, or metaphors in visualization, but result in making viewers bored and overwhelmed. Given such challenges, we propose that more work should be done to look into the uncertainties of affective design in infographics as well as the interrelationship between different design factors.

7.3 Limitations and Future Work

There are several limitations in our work. First, our crowdsourcing studies limited the participants to only US workers who speak English, so the results can only be applied to the US context. Second, although this work first conducts a systematic examination of people's affective responses to infographics, the resulting taxonomy of design heuristics is constrained by our manually-curated corpus and analysis methodology. For example, although we tried to only distill design-related user comments, a 100% separation of infographics' design and content is not possible. Also, the empirical methods we used are insufficient to reveal the one-to-one causal relationships between design and affects. More controlled experiments should be done to determine such relationships. In the future, we also need a more standardized methodology for measuring affective responses to visualization, more visual literacy to conceptualize the evolving features of affective design, and more knowledge about the consequences of triggering affective responses.

8 Conclusion

By conducting two crowdsourcing studies and analyzing user comments, this work identified 12 common infographic-associated affects and derived a taxonomy of design heuristics that exemplify affect-related design factors in infographics. This work takes the first step towards understanding visualization design through the affective lens. We claim that designing for affective experience is an important complement to traditional principles of visualization design as it is user experience-centered and crucially related to user engagement. We think incorporating affective factors into visualization design will open up rich avenues for future studies. We hope our work will inspire more research on affective visualization as well as user experience-centered visualization design.

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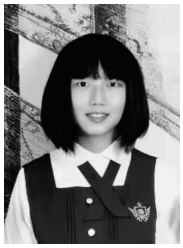

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