The Chart Excites Me! Exploring How Data Visualization Design Influences Affective Arousal

Xingyu Lan, Yanqiu Wu, Qing Chen, and Nan Cao

Abstract—As data visualizations have been increasingly applied in mass communication, designers often seek to grasp viewers immediately and motivate them to read more. Such goals, as suggested by previous research, are closely associated with the activation of emotion, namely affective arousal. Given this motivation, this work takes initial steps toward understanding the arousal-related factors in data visualization design. We collected a corpus of 265 data visualizations and conducted a crowdsourcing study with 184 participants during which the participants were asked to rate the affective arousal elicited by data visualization design (all texts were blurred to exclude the influence of semantics) and provide their reasons. Based on the collected data, first, we identified a set of arousal-related design features by analyzing user comments qualitatively. Then, we mapped these features to computable variables and constructed regression models to infer which features are significant contributors to affective arousal quantitatively. Through this exploratory study, we finally identified four design features (e.g., colorfulness, the number of different visual channels) cross-validated as important features correlated with affective arousal.

Index Terms—Data Visualization, Affective Design, Visual Communication, General Public, User Experience.

1 INTRODUCTION

Data visualization is now widely used in mass communication in forms such as infographics, data-driven articles, and data videos [1], [2], [3]. Due to the traits of mass communication (e.g., information overload, impatient viewers), visualization designers often need to activate viewers emotionally to grasp them immediately and motivate them to read more. In research, this design goal is closely related to a concept called affective arousal, which measures the activation of emotion on a continuous scale [4]. Research from fields such as marketing and communications has provided abundant evidence that affective arousal can moderate people’s willingness to spend time and money on visual media [5], or lead to behaviors such as clicking and sharing [7], thereby making it an important perspective of investigating visual communication [8]. In the visualization community, some practitioners have also stressed the importance of affective arousal. For example, a data visualization that looks exciting is usually more desirable in advertising as it can attract more clicks, likes, and sharing [9].

For nonprofits, designers may want a data visualization to elicit high-arousal affects in order to raise funds and call for social collaboration [10]. In addition, previous work has shown that design elements such as color and imagery can effectively influence arousal levels [6], [11], which from another perspective confirms the possibility of conducting research on the relationship between data visualization design and affective arousal.

Although many researchers have acknowledged that affects are an indispensable part of users’ experience with data [1], [12], [13], previous literature has mostly viewed affects as discrete categories rather than examining them in a continuous space. For example, Kennedy and Hill [14] investigated people’s affective responses to data visualizations by conducting a diary study. The affects reported by the participants were mostly categorical, such as surprise and disgust. Boy et al. [15] focused on examining how data visualization design influences one particular type of affect, empathy. Lan et al. [16] proposed an affective animation design scheme for common charts to convey positive affects such as joy and tenderness in data stories. In their recent work about serious data storytelling [17], the researchers focused on examining how design methods facilitate the communication of negative emotions (e.g., anxiety, helplessness). The work by Bartram et al. [13] is more relevant to affective arousal. They proposed a set of color palettes to help encode eight types of affect that represent typical combinations of valence and arousal (e.g., positive, negative, calm, exciting). However, this study still simplified affects as categories and did not show how affects change in the dimensional space continuously. To sum up, although the above work has contributed to our understanding of how data visualization design influences affects, as yet no systematic work has been carried out to address this problem through the lens of affective arousal.

To fill this gap, this study first explores what data visualization design features may influence the perception of affective arousal. To begin with, we prepared a corpus containing 265 data visualization images based on the MASSVIS dataset [18], which provides single media, and governments. To prevent the bias caused by semantics (because the content of the images can strongly influence affects), we blurred all the texts on these images. Based on this corpus, we conducted a crowdsourcing study involving 184 participants and asked the participants to assess the affective arousal elicited by the designs in the corpus. We then analyzed the experimental results and derived a set of design features that the participants thought related to affective arousal by coding their comments manually. These design features were grouped into three main categories: color, graphics, and information. Next, we mapped these features to computable variables and constructed regression models to identify the most significant features and assess their importance. By comparing the results of the models, we finally identified four design features that were cross-validated as important features.
correlated with affective arousal, including colorfulness, the number of
different visual channels, the X and Y coordinates, and the
grid layout. Finally, based on all the quantitative and qualitative
analyses above, we discuss the implications that arise from our
work, reflect on the limitations of this work, and propose future
research opportunities.

2 RELATED WORK
2.1 Data Visualization for Communication
In recent years, a notable phenomenon in the visualization commu-
nity is that data visualization has been massively applied in mass
communication (i.e., the process of creating, sending, imparting,
and exchanging messages to a large number of audiences) through
media such as infographics, data-driven articles, and data videos [1].
[2]. [3]. [4]. However, on the other hand, the features of contemporary
mass communication have posed new challenges for visualization
design. As found by research in communications et al. [5], the
abundance of information produced by mass media today has
narrowed people’s attention span and made them more and more
impatient. To grasp and engage more viewers, designers have to
consider user experience and modify their design according to how
viewers might respond.

In response to such challenges, a growing number of studies in
the visualization community have adopted a user-centered
perspective and examined visualization design through the lens of
user experience. For example, Saket et al. [6] argued that
more efforts should be put into understanding people’s subjective
responses to visualization design. Cawthon et al. [7] and
Harrison et al. [8] investigated how data visualization influences
aesthetic feelings. Amini et al. [9] and Lan et al. [10] used
indicators such as likability and enjoyment to evaluate data stories.
Borkin et al. [11] evaluated a series of visualization designs by
assessing how memorable they were. However, so far, existing
studies have only addressed limited aspects of user experience.
Many important concepts are left underexplored.

Therefore, in this work, we choose to focus on affect arousal,
a core construct of user experience in mass communication, and
examine how it correlates with data visualization design. We hope
our work can contribute a new perspective to understanding data
communication and user-centered visualization design.

2.2 Affective Arousal
Affective arousal is about the activation of emotion [12] and is
viewed as a key construct of human affects. For example, the
well-known circumplex model [13] views affects as combinations of
valence and arousal. While valence describes whether an affect
is positive or negative, arousal reflects the intensity of the affect,
ranging from calm to excitement. Along with the conceptualization of
affective arousal, many researchers began to conduct studies to
investigate how to elicit affective arousal specifically. For example,
Sundar and Kalyanaraman [14] examined the relationship between
animation and affective arousal using physiological indicators.
Lang et al. [15] and Gorn et al. [16] used self-report methods to
gather ratings from users and assess how color and pacing
influenced perceived arousal.

Meanwhile, as affective arousal is closely related to people’s
reactions, behaviors, and information processing [17], it has been
massively studied in research about visual communication, such
as web advertising and TV broadcasting. For example, Singh and
Hitchon [18] reviewed dozens of studies conducted in the last
century that examined arousal-centered topics, such as how to
arouse viewers most advantageously in a TV show and how to
increase consumers’ desire for a product by eliciting arousal. Given
the fundamental role of affective arousal, this thread of research
continues to prosper until today while dealing with trending topics
such as how to design arousing games, user interfaces, or immersive
environments [19], [20]. For example, Aoki et al. [21] examined how to design chat balloons that represent various levels of arousal in text chats. Cusveller et al. [22] explored how to evoke affective arousal in computer games.

This work follows this research thread and studies affective
arousal specifically in the context of visualization design. We see
this work as an initial step towards exploring what design factors contribute to affective arousal in data visualization.

2.3 Affective Design in Data Visualization
In recent years, researchers [1], [13] have introduced the idea of
affective design to the community of data visualization and aimed
to understand how design elements influence viewers’ affective feel-
ings towards data visualization. For example, Bartram et al. [13]
identified a set of affective color palettes that can elicit eight
categories of affects, such as calmness and positivity. Boy et al. [15]
investigated one specific category of affects, empathy, and found
that using anthropomorphic pictograms to represent human rights
data does not help trigger empathy. Lan et al. [1] summarized
a set of affect-related design factors in infographics, such as the
usability of the design and the expressiveness of the design. They
also explored the dynamic design elements in data visualization
design [16] and proposed an animation design scheme, Kineticcharts,
for creating charts that express five positive-valenced affects, such
as joy, surprise, and amusement. After this work, they continued to
explore negative-valenced affects in serious data storytelling [17].

However, although the aforementioned work has laid a foun-
dation for investigating how data visualization design influences
affects, it has two main limitations. First, previous work usually
treats affects as discrete categories, and this paradigm has largely
overlooked the continuous aspects of affects. Second, compared
to other concepts such as valence, arousal has been less studied,
thus limiting our understanding of how affects are activated by
visualization design. To bridge this gap, this work investigates
affective arousal specifically. As a continuous measurement, af-
fective arousal helps capture the intensity of people’s affective
experience with visualization, thus contributing new knowledge
around affective visualization design.

3 DATASET AND PILOT STUDY
To identify design factors that contribute to affective arousal in data
visualization design, we prepared a corpus of data visualization
designs and conducted a crowdsourcing study with 184 participants.
The participants were asked to view the data visualizations randomly chosen from the corpus and rate the affective arousal
triggered by these images. Afterward, we analyzed the data
collected from the study to summarize a set of potential arousal-
related design features. The study materials can be accessed at
https://bit.ly/3Ntv5ck

3.1 Dataset
We aimed to use a dataset that contains diverse data visualizations
and reflects the variety of data visualization design in the real world.
A dataset that meets such needs is the Massachusetts (Massive) Visualization Dataset (MASSVIS) [18]. MASSVIS has collected thousands of data visualizations by balancing four types of sources: infographics, galleries, news media, governments, and scientific journals. Due to its representativeness in visualization design and public availability, MASSVIS has been used frequently in previous studies [18], [26], [34], [35]. MASSVIS is constituted of several sub-corpora with different data sizes and labels. For example, single2k is a corpus that contains more than 2000 pieces of single data visualizations labeled with basic meta-information such as sources and titles. Targets410, another sub-corpus, contains 410 representative data visualizations selected by experts from single2k. It contains a more suitable amount of images to be used in a user study while maintaining the design diversity of single2k. Besides, targets410 has been labelled with more design-related tags, such as the visualization type and data-ink ratio. Therefore, targets410 suits our study better.

Besides, according to previous literature [14], the semantics carried by a data visualization will remarkably influence people’s affects. Many people would react affectively to the content or the topic of a data visualization. Besides, embellishments such as an illustration of violence and a photograph of a child can also trigger strong affects. Such affects brought by semantics will be confounded with the affects brought by design and thus hinder our understanding of the exact impact of visualization design. Therefore, to get rid of the influence of semantics, we blurred all the texts and embellishments on the images so that the participants in our studies could focus on perceiving the affects triggered by design only.

3.2 Pilot study
We used the blurred version of targets410 as our stimuli and conducted a pilot study to investigate whether it was appropriate to use this corpus in our study. Based on the findings from the pilot study, we refined the corpus to construct the final stimuli for our crowdsourcing study.

3.2.1 Methodology
We recruited 10 participants (7 females, aging from 21 to 26) for the pilot study by posting an open call on social media platforms. Once entering the online survey, the participants were presented with an introduction to our research, such as the definition of affective arousal and how to use the instrument for evaluating affects, namely Affective Slider (AS, see Fig. 1) [36]. AS is a modern version of Self-Assessment Manikin (SAM) [37], which is the traditional instrument for measuring valence and arousal based on the circumplex model. SAM adopts a 9-point scale (e.g., for affective arousal, 1 denotes not at all aroused, and 9 denotes strongly aroused). AS inherits the core spirit of SAM but stretches the scale to 100 by providing a movable slider whose range is 0.00 to 1.00. Such a scale can produce more continuous and precise data, which is more suitable for use in statistical modeling. Note that although this work focuses on arousal, we asked the participants to rate both arousal and valence during the study in case there was any interaction between these two dimensions. After reading the introduction, the participants viewed 20 data visualizations randomly chosen from our corpus, one at a time. We also shuffled the order of the 20 stimuli to ensure the participants viewed a random sequence of images. After viewing each of the images, the participants rated their arousal and valence using AS. They were also asked to provide reasons for their ratings and rate the likability of the design (“Do you like this data visualization?”) using a 5-point Likert scale (1 denotes strongly dislike, 5 denotes strongly like). The question about likability was included because prior literature has suggested that high arousal may not always be favorable [38]. Therefore, we followed their practice [29], [39] and evaluated whether the arousal elicited by stimuli was liked by the participants to facilitate the interpretation of arousal.

After viewing and rating all 20 images, the participants filled out a form to answer four demographic questions (i.e., gender, age, education level, country) and two summary questions to report arousal-related and valence-related design features respectively (e.g., “Please recall the data visualizations you have viewed and list the design factor(s) that helped increase the arousal level.”). Last, we interviewed the participants with a set of pre-prepared questions concerning the study design, such as “Do you think the study instructed you well? Did you feel confused about anything?”, “Do you think 20 is an appropriate number of images to view? Did you feel tired or impatient during the study?”, “Do you think some images are significantly different from others in terms of eliciting your affects?”. On average, the participants spent about 20 minutes completing this study and 10 minutes on the interview.

3.2.2 Results
We collected both positive and negative feedback from the pilot study. For example, most participants agreed that 20 images is an appropriate amount for them to complete the study without losing patience. Also, the participants confirmed that the study task was clear and the whole process was well-guided. However, on the downside, several participants reported that they did not feel confident in their ratings until they had viewed and rated several images (e.g., “Maybe there should be several examples in the very beginning to help me decide my criterion of rating.”). Accordingly, we refined the introduction page by including three examples. The three examples were selected by a visualization expert to demonstrate the diversity of the stimuli.

We also noticed that there were some problems with our stimuli. First, many participants reported that the scientific visualizations (see Fig. 2) were significantly different from others, since the participants were unfamiliar with such designs and felt these images should only be viewed by professional scientists or expert users (e.g., “This is not a visualization that I will come across in my daily life, and I feel it is apparently different from the other charts I saw.”). Second, we found that embellishments are inherently rich in semantics and their semantics could hardly be erased by the blur effect. For example, a participant commented that “I can guess there is a McDonald hamburger through its shape and color: I love hamburgers!”, and another participant said “there is a gym shoe next to the chart and this aroused me.” These
two embellishments were arousing not because of their design, but because of what they represent (see Fig. 2). In other words, the existence of embellishments is likely to trigger a different mechanism of eliciting affective arousal and confound the effects of design with the effects of semantics. Third, several participants reported their discomfort with images that had a large aspect ratio. For example, one participant said, “There was a lengthy chart, and I had to keep scrolling up and down to view it completely. This made it difficult to focus on my emotion.”

Based on these findings, we removed scientific images, embellished images, and images with an aspect ratio greater than 3:1 [26] from the corpus and kept 202 qualified images. However, a consequent problem was that the removal had changed the distribution of the image categories (i.e., Infographic, Government, News Media), since many images removed because of embellishment belonged to the Infographic category. Thus, the sample sizes of the three categories became unbalanced. To deal with this problem, we searched the single2k corpus to identify more qualified infographic images. Finally, we found 63 qualified images. After including these 63 images in our corpus (which resulted in 265 images in total), the corpus contains 83 Infographic images (31%), 82 News Media images (31%), and 100 Government images (38%). The distribution of the image categories is similar to that of the targets410 corpus, thus ensuring the images are representative of the single visualization designs in the wild. In our crowdsourcing study, we used this refined corpus as our stimuli.

4 CROWDSOURCING STUDY

Then, we conducted our formal study. We chose crowdsourcing to collect user data concerning the affective arousal elicited by data visualization design and explore design-arousal relationships.

4.0.1 Methodology

We recruited 184 participants from Prolific who speak English as their first language and have correct vision. We rejected the data from ten participants, as they misunderstood the study task (e.g., failed to understand why the texts were blurred and kept complaining about the legibility) or provided data with poor quality (e.g., giving all the images the same ratings without explaining why). The remaining 174 participants included 98 females, 75 males, and one identified as non-binary. Their ages ranged from 18 to 78 (M = 38.47, SD = 13.79), and their educational levels varied (Less than a high school diploma: 0.57%, High school or equivalent: 31.03%, Bachelor or equivalent: 48.28%, Master or equivalent: 16.09%, Doctoral or equivalent: 4.02%). The participants were paid $9 per hour.

The study procedure of the crowdsourcing study was identical to the pilot study. The participants first read an introduction page, then viewed 20 data visualizations (one at a time), rated arousal and valence, wrote down reasons for their ratings, and rated how they liked the designs. After viewing and rating all 20 images, the participants filled out a form to provide their demographic information and wrote down what design features they thought contributed to arousal and valence, respectively. The participants spent 22.34 minutes on average completing this study.

4.1 Analyses and Results

We got 3480 valid ratings for the 265 images, including 1101 for the Infographic category, 1052 for the News Media category, and 1327 for the Government category. Each image received 13.13 ratings on average.

4.1.1 Descriptive Analysis

4.1.1.1 Consistency of Ratings: We examined whether people formed consistent judgments on the arousing level of the images. We used intraclass correlation coefficients (ICC) to calculate the agreement in user ratings, and the result showed that the agreement was moderate (ICC1k = .589, 95% CI = [.512, .658], p < .001), suggesting that users held moderately similar judgments on affective arousal.

4.1.1.2 Means & Distributions Comparison: Overall, the average arousal score of all the images was 0.53 (SD = 0.23, 95% CI = [0.52, 0.54]). The distribution of the arousing levels of the images was close to a normal distribution. However, as shown in Fig. 3, the means and distributions of affective arousal varied in different groups. For example, the mean arousal of the Infographic category was 0.61, higher than that of the News Media category (M = 0.53) and the Government category (M = 0.48).
A Kruskal-Wallis H Test further showed that the difference was significant ($H(2) = 211.866, p < .001$). Dunn’s post-hoc test with a Bonferroni correction showed that the mean arousal of Infographic was significantly higher than that of News Media and Government ($p < .001$), and the mean arousal of News Media was significantly higher than that of Government ($p < .001$).

We also examined the arousal scores set by different age, gender, and education groups. First, a Mann-Whitney U Test ($z = -.886, p = .376$) showed that there was no significant difference between the scores set by females and by males ("Non-binary" was not included because its sample size was too small). Then, we assigned the participants into 5 age groups (<=25, 26-35, 36-45, 46-55, >56) and compared the mean scores of arousal set by these groups. As shown in Fig. 3, the mean arousal scores set by different age groups interestingly decreased with the increasing age. A Kruskal-Wallis H Test combined with a post-hoc test further showed that the difference was significant ($H(4) = 32.072, p < .001$) and mainly caused by the lower mean ($M = 0.48$) of group 5 (age > 56). In other words, in our study, the younger participants were more aroused by the stimuli while the elder participants were generally calmer. A significant difference ($H(3) = 22.838, p < .001$) also existed in the scores given by participants with different education levels ("Less than a high school diploma" not included because its sample size was too small), mainly caused by the higher scores set by participants with a "Doctoral or equivalent" degree ($M = 0.60$). However, this finding should be taken cautiously since the sample size of "Doctoral or equivalent" was not big (7 participants).

We also calculated the mean arousal score for each image. Fig. 4 shows the five images that received the highest scores in affective arousal and the five images that received the lowest scores. In line with the above findings, the top ranked images all belong to the Infographic category (Fig. 4 H1-H5) while the low-ranking images mostly belong to the Government and News Media categories (Fig. 4 L2-L5).

4.1.1.3 Correlation Analysis: Then, we examined the correlations between affective arousal, valence, and likability to see whether an arousing design will be pleasing or favorable. Fig. 5 plots the mutual relationships between these three variables. It can be seen from the figure that they generally showed a positive correlation with each other. Given that likability is an ordinal variable and all the three variables are non-normal, we used Kendall’s Tau (τ) to compute their correlation coefficients and significance levels. The results confirmed that arousal was positively correlated with likability ($τ = .539, p < .001$), so as valence and likability ($τ = .736, p < .001$), whose positive correlation was even stronger. Besides, arousal and valence also showed a moderately positive correlation with each other ($τ = .592, p < .001$). Note that these correlations still held when we conducted the correlational tests within different image categories.

To sum up, in general, high arousal was likely to co-occur with pleasure and high likability. However, there were also cases when arousal did not lead to pleasure or when arousal hindered likability. For example, as shown in Fig. 5, some participants set scores to
"high arousal + displeasure" or "high arousal + low likability". We will discuss such situations in detail in Section 5.2.

4.1.2 Qualitative Analysis
As stated above, at the end of the user study, we asked the participants to write down what design features had helped augment their affective arousal. This resulted in 174 comments that suggest arousal-related design features from the perspective of users.

Then, we conducted an in-depth qualitative analysis on these 174 comments following the bottom-up procedure of thematic analysis [40]. Two of the authors first went through all the user comments and took notes on the messages deemed useful. Then, they coded the comments independently and generated possible themes by grouping the codes. After that, they met to compare codes and discuss mismatches. Through iterative discussions, they generated three themes most commonly mentioned by the participants, including color, graphics, and information. Then, they assigned the low-level codes into these three themes and discussed whether to retain, modify, or merge the codes. For example, when describing colors that had strong visual impact, the participants used different expressions such as strong color, vibrant color, and bold color. Therefore, these similar expressions were merged into one code, namely strong color. It was also noticed that some codes described high-level design strategies rather than specific design features. For example, simplicity can mean simple colors, simple visualization design, or a small amount of data. Unusualness can refer to unusual color, unusual shape, or unusual visual encodings. Therefore, such codes were categorized into another theme called high-level strategies. After iterative discussions, the coders achieved a 100% agreement. At last, they generated 412 codes from the 174 comments in total. The frequencies of all the codes were analyzed and the result visualized, as in Fig. Note that for the clarity of presentation, codes that occurred only once were excluded. Collectively, the codes visualized in Fig. constitute 92.72% of all the codes. Thus, they are highly representative of all the arousal-related design features written down by the participants.

As shown in Fig. color and graphics were the most mentioned themes. Within the theme of color, 49 codes only broadly referred to color as a contributor to affective arousal. Apart from this, bright color (28), colorfulness (25), strong color (14), and contrast (13) were the most frequently-mentioned specific color features. Within the theme of graphics, visualization type (54), layout (17), shape (16), and density (11) were the most frequently-mentioned features. Within the theme of information, 11 codes talked about information amount in a broad sense, while six codes specifically referred to text amount and five codes specifically referred to data amount. Last, with the theme of high-level strategies, unusualness (37), simplicity (17), and easy reading (15) were most mentioned. Besides, clarity (9), aesthetics (9), complexity (5), and boldness (4) were also repeatedly mentioned.

4.1.3 Inferential Analysis
Then, we sought to predict the user ratings for affective arousal using these codes and identify the most significant design features. For each of the codes about color, graphics, and information in Fig. we reviewed previous literature in relevant fields (e.g., computer vision, multimedia) to find the mature and commonly-used methods to map these codes to computable variables. Below we first introduce these features briefly, then report the modeling process.

4.1.3.1 Design Features: The mappings are summarized in Table. Color-based Features. To translate the code chromatic color, we used a nominal variable whose value is yes or no to depict whether a visualization design is achromatic. To translate the code background color in Fig. we coded the images’ background colors manually and found that white and black were the dominant choices. Therefore, this code was translated into a nominal variable whose value can be white, black, or others. For codes that can be measured as continuous variables, such as bright color, strong color, colorfulness, and contrast, we referred to prior literature [41], [42] and extracted corresponding design features, such as calculating the mean and standard deviation of the S (i.e., saturation) and V (i.e., brightness) channels in the HSV color space using OpenCV, computing colorfulness using the algorithm proposed by Hasler et al. [43], and calculating contrast using the RMS contrast algorithm [44]. Note that according to some comments, the participants’ perception of brightness and saturation was also influenced by the dominant color, we also extracted the primary chromatic color of each image using Colorthief [45] and calculated the mean and standard deviation of its saturation and brightness. Last, we translated the code color hue using the algorithm proposed by van de Weijer et al. [46]. This algorithm can identify and calculate the percentages of 11 nameable color hues (i.e., black, blue, brown, green, gray, orange, pink, purple, red, white, yellow) in images.

Graphics-based Features. As two codes in this theme (visualization type, shape) were closely related to how data was visualized into graphical elements, we used five features to depict the visual encodings of the visualizations. First, following the typology in [26], data visualizations were categorized into 12 types (e.g., bar, area, map, circle) and a set of subtypes (e.g., grouped bar chart and stacked bar chart in the category of bar; pie chart and donut
Information-based Features. Information-based features concern the cognitive load of viewing a data visualization and can be further split into two main types: texts and data. First, although all the texts had been blurred, several participants stated that they could still “feel” that there were a lot of texts to be read and this also impacted their arousal. Therefore, we used Tesseract-OCR [49] to identify the texts on the images, manually revised all the texts had been blurred, several participants stated that they could still “feel” that there were a lot of texts to be read and this also impacted their arousal. Therefore, we used Tesseract-OCR [49] to identify the texts on the images, manually revised the real judgments of the participants. Specifically, we tried two common means of

chart in the category of circle). In addition, we used variables to characterize which data marks (e.g., bar, line, geoshape), visual channels (e.g., position, size, shape), and layout (e.g., X and Y coordinates, grid, polar coordinate) had been used according to existing taxonomies [47][48]. For example, H4 in Fig. 4 was characterized as a visualization type called area and a subtype called proportional area chart. The shape of its data marks is circle, and the overall shape of this visualization is also circular because it organizes the marks using a polar coordinate. Two visual channels (color and position) have been used to encode data. For the remaining qualitative codes in this theme, we mapped multiplicity, which defines whether the visualization is stand-alone or somehow grouped with other visualizations, to categories such as single, grouped, and multi-panel [26]. We mapped annotation and 3D to nominal variables (y, no) and computed density by calculating the white space (the percentage of the background color) of each image.

Information-based Features. Information-based features concern the cognitive load of viewing a data visualization and can be further split into two main types: texts and data. First, although all the texts had been blurred, several participants stated that they could still “feel” that there were a lot of texts to be read and this also impacted their arousal. Therefore, we used Tesseract-OCR [49] to identify the texts on the images, manually revised inaccurate identifications, and then counted how many words each image contained and the word density on each image by dividing the word amount by the size of the image. Next, to quantify the amount of data, we counted how many visual channels were used in each image in total, as well as how many distinct visual channels were used. We also counted the number of data marks in each image and how many distinct data marks were used. For example, Fig. 4 H2 only has eight data marks while H4 contains more than 100 data marks, but both of them only used one type of data mark, namely circle. In some images, the data marks were too many to be counted precisely (e.g., thousands of overlapping dots), therefore, we transformed this feature into a nominal variable with three categories (<10, 10-100, >=100). Last, we used an ordinal variable, data-ink ratio ([good, medium, bad]) [26], to characterize the cognitive load brought by information that was neither texts nor data (e.g., axis ticks, gridlines).

4.1.3.2 Modeling affective arousal: Based on the extracted features, we tried five widely used predictive models to explore important moderators of affective arousal. Three are linear models (Multiple Linear Regression, Ridge Regression, Lasso Regression) and two are ensemble models (Random Forest, Decision Tree). These models can help us estimate the relationship between affective arousal and design features while interpreting which features are contributing to the relationship. The dependent variable is the mean arousal scores of the 265 images, and the design features of the 265 images we extracted in Table 1 are independent variables. During the data pre-processing stage, first, we checked and revised empty and mistaken values. Then, for all nominal variables, we used the one-hot encoder in SciPy to transform them into a set of binary variables that use 1 and 0 to indicate the presence or absence of a category [50]. Next, we tried re-scaling the raw arousal scores set by each participant before calculating the mean arousal score received by each image. This step was done because we noticed from both the pilot study and the crowdsourcing study that the participants showed varied rating habits. For example, even with a very similar judgment of a design, some participants tended to set higher scores to arousal (e.g., 0.95) while some thought 0.70 or 0.80 were already high scores. In other words, the participants’ criteria of rating affective arousal were differently-ranged. Therefore, re-scaling the ratings helped mitigate the influence of rating habits and revealed the real judgments of all the participants.

| Theme            | Code                     | Type           | Description of the mappings                                                                 |
|------------------|--------------------------|----------------|---------------------------------------------------------------------------------------------|
| **Color**        | achromatic color         | N              | yes, no                                                                                     |
|                  | background color         | N              | white, black, others                                                                        |
|                  | bright color, strong color | C            | the means and standard deviations of overall brightness and saturation                      |
|                  | colorfulness             | C              | calculated using the algorithm by[43]                                                      |
|                  | contrast                 | C              | calculated using the RMS contrast algorithm[44]                                             |
|                  | color hue                | C              | the percentages of 11 common nameable hues (white, grey, black, red, yellow, orange, blue, green, purple, pink, brown) calculated using the algorithm by[46] |
| **Graphics**     | visualization type, shape| N              | type: bar, line, point, area, circle, distribution, map, diagram, table, text & network, grid & matrix[26] |
|                  |                         | N              | subtype: grouped bar, stacked bar, circular bar, pie, donut, etc.[26]                      |
|                  | data mark shape          | N              | bar mark shape: color, hue, color shade, shape, size, angle, texture, others[47][48]        |
|                  |                         | N              | visual channel: position, color hue, color shade, shape, size, angle, texture, others[47][48] |
|                  |                         | N              | layout: X &Y coordinates, polar coordinate, linear direction, grid, geography, others       |
|                  | multiplicity             | N              | single, grouped, multi-panel, small multiples, combination[26]                             |
|                  | annotation               | N              | yes, no                                                                                     |
|                  | 3D                       | N              | yes, no                                                                                     |
|                  | density                  | C              | the percentage of the background color                                                     |
| **Information**  | text amount              | C              | word amount: how many words have been used in total                                        |
|                  | data amount              | C              | word density: word amount / image size (all images resized to a 500-pixel width)            |
|                  |                         | C              | # of different data marks: how many different types of data marks need to be interpreted   |
|                  |                         | C              | # of data marks: <10, 10-100, >=100                                                         |
|                  |                         | C              | # of visual channels: how many visual channels need to be interpreted                       |
|                  |                         | C              | # of different visual channels: how many different types of visual channels need to be interpreted |
|                  | information amount (others) | O          | data-ink ratio: low, medium, high[26]                                                       |

TABLE 1
The mappings from qualitative codes to variables. For variable types, N denotes nominal, C denotes continuous, and O denotes ordinal.
Multiple Linear Regression

| layout = grid  | .435 | .001 |
|----------------|------|------|
| colorfulness   | .289 | .001 |
| # of different channels | .289 | .001 |
| layout = X & Y coordinates | .141 | .138 |
| subtype = heatmap | .139 | .013 |
| percentage of black | .136 | .003 |
| vistype = circle | .133 | .004 |
| # of data marks >= 100 | .121 | .012 |
| subtype = stacked bar | - .085 | .049 |

Random Forest

| # of different channels | .220 |
|-------------------------|------|
| percentage of green     | .189 |
| layout = X & Y coordinates | .166 |
| mean of saturation      | .103 |
| layout = grid           | .065 |
| colorfulness            | .044 |
| percentage of white     | .042 |
| vistype = table         | .041 |
| mark shape = text       | .017 |
| layout = grid           | .029 |

Decision Tree

| # of different channels | .424 |
|-------------------------|------|
| colorfulness            | .241 |
| percentage of white     | .130 |
| layout = X & Y coordinates | .075 |
| mark shape = text       | .020 |

Fig. 7. Comparing the important features suggested by different models. Note that the Multiple Linear Regression Model indicates importance through statistical significance (p-values) and standardized coefficients, while Random Forest and Decision Tree suggest key features through Gini importance. R² and MSE show the model performance, where R² (the coefficient of determination) represents the proportion of the variance explained, and MSE (mean squared error) measures the difference between the original and predicted values.

After data pre-processing, we used Pearson correlation coefficients to get an initial understanding of the correlations between the independent variables and the dependent variable. Results showed that features such as the number of different visual channels (r = 0.52, p < .001), colorfulness (r = 0.48, p < .001), and standard deviation of saturation (r = 0.46, p < .001) had a significantly positive relationship with affective arousal, while features such as X-Y coordinates layout (r = -0.61, p < .001), table visualization (r = -0.52, p < .001), and percentage of white (r = -0.49, p < .001) had a significantly negative relationship with affective arousal. High correlations also exist between some design features. For example, the percentage of white was highly correlated with mean brightness (r = 0.82, p < .001). These correlations were referred to when performing feature selection to prevent the overfitting problem.

Next, we fed the variables into the five models one by one. To enhance the validity of results, we adopted the idea of machine learning and split the dataset into a training set (70%) and a test set (30%) using Sklearn. When splitting the dataset, we also guaranteed that the distribution of the values of arousal in the test set was similar to that of the training set, which was close to a normal distribution. Then, we fed the training set to the models and evaluated the goodness of fit using the test set.

Linear Models. For the Multiple Linear Regression, we fine-tuned the models by (1) fitting the models using a stepwise approach to drop redundant features; (2) conducting multicollinearity diagnostics using the Variance Inflation Factor (VIF). A VIF above 10 implies serious multicollinearity and a VIF above 5 is usually deemed problematic; (3) Ensuring that there was no autocorrelation problem using the Durbin-Watson test (0 < DW < 2); (4) Ensuring that the residuals were normally distributed by conducting the Anderson-Darling test and plotting a histogram for residuals. For the Lasso Regression and Ridge Regression, we used five-fold cross-validation to identify the optimal values of their key parameter, alpha (i.e., the strength of regularization). As a result, we found that in our case, the optimal alpha values for these two models were 0, which made their results identical to that of the Multiple Linear Regression.

As shown in Fig. 7 the Multiple Linear Regression yielded 11 statistically significant features. Seven features showed a significantly positive correlation with affective arousal, including colorfulness ($\beta = .329, t = 7.536, p < .001$), the number of different visual channels ($\beta = .299, t = 5.828, p < .001$), visualization subtype = heatmap ($\beta = .141, t = 3.013, p = .003$), layout = geo ($\beta = .138, t = 2.588, p = .010$), percentage of black ($\beta = .131, t = 2.957, p = .004$), visualization type = circle ($\beta = .131, t = 2.886, p = .004$), and number of data marks >= 100 ($\beta = .113, t = 2.531, p = .012$). On the other hand, four features showed a significantly negative correlation with affective arousal, including layout = grid ($\beta = -.435, t = -7.279, p < .001$), layout = X and Y coordinates ($\beta = -.153, t = -2.360, p = .019$), channel = texture ($\beta = -.136, t = -3.034, p = .003$), and visualization subtype = stacked bar ($\beta = -.085, t = -2.020, p = .045$). The training set explained 72.6% of the variance in the dependent variable ($R^2 = .726, MSE = .071$), and the test set explained 67.0% ($R^2 = .670, MSE = .099$).

Ensemble Models. For ensemble models, we first identified the optimal hyperparameters (e.g., max depth) for the models by performing five-fold cross-validation within a grid of hyperparameter ranges. We also fine-tuned the hyperparameters by observing the performance of the training set and the test set to avoid overfitting. At last, the Random Forest model had a max depth of 2. After iterating 1000 times, the average $R^2$ of the training set was .644 (MSE = .092), and the average $R^2$ of the test set was .595 (MSE = .122). The Decision Tree model had a max depth of 3. The average $R^2$ of the training set was .668 (MSE = .085), and the $R^2$ of the test set was .616 (MSE = .115). We also computed the Gini importance of the features in these two models and visualized high-ranking features in Fig. 7. The most important features in the Random Forest model included the number of different visual channels (Gini importance = .220), percentage of green (.189), layout = X and Y coordinates (.166), mean of saturation (.103), layout = grid (.065), colorfulness (.048), percentage of white (.042), visualization type = table (.041), mark shape = text (.017), and mean of saturation (.017).
and $\text{mark shape} = \text{circle}$. These 10 features collectively explained 90% of the total importance. The most important features in the Decision Tree model included the number of different visual channels, layout coordinates, colorfulness, percentage of white, mark shape, and layout = grid. These six features collectively explained 99% of the total importance.

**Summary.** By comparing the results in Fig. 7 we found that four design features were collectively supported by all the models as the key moderators of affective arousal, including the number of different visual channels, colorfulness, layout = $X$ and $Y$ coordinates, and layout = grid. The first two features showed positive effects on affective arousal in all models, while the latter two features consistently showed a negative relationship with affective arousal. In other words, in our exploratory study, we found that the participants were more aroused by colorful visualizations with a certain amount of visual complexity. However, conventional layouts that put data in an upright and square space were less arousing. We also noticed that there were features whose importance was not cross-validated by different models. For example, the percentage of green showed high importance in the Random Forest model, but it was not important in other models. Such features are worthy of more investigation in the future.

## 5 Discussion

Below we discuss the design implications that arise from this work, the possible negative consequences of eliciting high arousal, the challenges of automatic visualization design evaluation, as well as limitations and future work.

### 5.1 Design Implications

First, we contribute new knowledge for understanding how data encodings influence affective arousal. An interesting finding of this work is that in data visualization design, graphical elements that are related to data encodings showed significant capability of eliciting affective arousal. For the visualization community, this finding is significant in two main ways. First, we have found new evidence that the appearance of data visualization does affect user experience. In the past, Moere et al. [52] found that when encoded with identical data, different chart types (e.g., treemaps and sunburst diagrams) triggered different subjective feelings and preferences. Borkin et al. [26] found that people remembered certain chart types better than others. In other words, choosing data encodings is not only about how to present data but also about manipulating user experience. Second, this work also supplements the existing knowledge about user-centered visualization design from the perspective of affective arousal. For example, in the study by Borkin et al. [26], the most remembered visualization types were \text{grid} \& \text{matrix} and \text{tree} \& \text{network}. However, in our study, visualizations that use a grid layout (e.g., L1 in Fig. 4) were less arousing than others. This suggests that viewing visualization design from the perspective of affective arousal may be different from viewing it from perspectives such as memorability and aesthetics (although these perspectives are all user-centered). In other words, focusing on different aspects of user experience may also lead to different focuses of design.

Second, we found colorfulness outweighs other color-based features in terms of moderating affective arousal in the context of data visualization design. Although the affective power of color has long been verified in various domains, in different research contexts, the findings can be different. For example, red was identified as the most arousing color in classic psychological experiments [33], but some researchers also found evidence that green can be more arousing than red [11]. Our work, however, found that colorfulness is more related to arousal than specific color hues in visualization design. According to our study, a reason may be that people’s color perception would be influenced by their attempts to decode data when viewing a data visualization. For example, some participants reported low arousal to designs with a large amount of red because the color had hindered reading (e.g., “it is too bright and dazzling”). Similarly, some participants stated that the use of analogous color hues (e.g., red and orange) had made the graphical elements on the charts indistinguishable, thus lowering arousal. On the other hand, colorfulness can be both viscerally stimulating and useful in presenting data, thus making it the most arousing color-based feature compatible with data visualization design.

Third, data visualizations that belonged to the Infographic category elicited stronger affective arousal than others. Infographics are often seen as a visual form that pays more attention to data communication and appealing to viewers subjectively than traditional visualizations [1]. Previous work [55, 56] has often focused on studying the rich embellishment techniques in infographics such as pictograms, illustrations, and visual metaphors. However, another interesting finding from this work is that even after we removed all embellished designs for our corpus, the images in the Infographic category were still significantly more arousing than others. This finding indicates that the specificity of infographic design may not only lie in embellishment, but also in how it deals with color, graphics, and information. As shown by an empirical study [57], when creating infographics, designers often spend a lot of time choosing encoding approaches and polishing the appearance of the visualization iteratively, because the designers not only hope to present data clearly, but also to create something new and unique. Such needs meet the \textit{unusualness} strategy we mentioned above and may help improve the arousing level of a design.

Fourth, the qualitative and quantitative analyses collectively imply the strategies for manipulating arousal. In the crowdsourcing study, we identified several high-level strategies for eliciting affective arousal by coding user comments qualitatively (Fig. 5). After constructing models to predict arousal, we found that the quantitative results suggested by the models resonate more or less with the qualitative codes. For example, our models showed that affective arousal is significantly higher when a visualization does not use layouts such as Cartesian coordinates, and this resonates well with the most mentioned high-level strategy by the participants, namely \textit{unusualness} (e.g., “The design factors that helped increase the arousal was those that looked interesting and new, something I’ve never seen before.”). Another two strategies mentioned by the participants (\textit{boldness} and \textit{aesthetics}) were partly supported by the significance of colorfulness, as previous research has found colorfulness is linked with the perception of energization and extraversion [58], as well as an indicator of aesthetics [23]. However, there seems to be controversy over \textit{simplicity} and \textit{complexity} (we can see the co-existence of these two strategies in Fig. 5). Our models, however, ended up leaning towards the side of complexity because affective arousal showed a significantly positive relationship with the number of different visual channels. However, by referring to the raw comments written by the participants, we found that \textit{simplicity} and \textit{complexity} may not necessarily contradict each other. For example, when reporting that simple designs had increased their affective arousal, some participants were in
fact emphasizing the understandability of the designs (e.g., “This diagram looks like a really simple way to display data, even to a layperson”). On the other hand, when reporting that complex designs were more arousing, some participants were emphasizing the richness of visuals (e.g., "different graphs and charts - when there was more information on the chart to concentrate on the arousal was higher"). In other words, for designers, it may be beneficial to include an appropriate level of visual complexity while ensuring that the data visualization is understandable.

5.2 The Negative Side of High Arousal
As we have discussed in Section 4.1.1.3, in our exploratory study, high affective arousal did not always lead to high pleasure or high preference. In some cases, the participants did not like or enjoy data visualization designs that elicited high arousal, or they thought high arousal was harmful. By analyzing such comments, we identified two main reasons:

First, high arousal may lead to physical discomfort. In our crowdsourcing study, several participants reported high arousal but thought the corresponding designs were too chaotic and overstimulating (e.g., “It is a very arousing visual in terms of color and design, however looking at it makes your eyes go unwell so does not give great pleasure when looking at the visual.”, "Unpleasant overstimulating colours, chaotic graphic that is difficult to decipher and is unpleasant to look at."). One participant commented that "Too much red is making me feel nervous.” These findings resonate with prior psychological studies that intense affects may bring about side effects [59] or even evolve into tension and anxiety [60].

Therefore, for designers, designing an arousing data visualization is not equal to simply adding up all stimulating design features. On the contrary, it is necessary to find a balance between arousing affects and preventing discomfort.

Second, high arousal may be caused by inappropriate design. In some cases, the participants were affectively aroused because the designs looked confusing or ugly to them. For example, one participant said that a design "looks really cool but I don’t know how easy it would be to interpret data using this”. Similarly, another participant wrote: “A very striking chart that looks like it makes sense only to the person who created it.” We also saw comments that reported high arousal accompanied by negative affects such as anger and irritation (e.g., "I don’t like the orange. It makes me angry.", "The red line is irritating."). Under such circumstances, high arousal is not beneficial.

5.3 Towards Automatic Design Evaluation
Understanding what design features contribute to affective arousal has paved a path toward automatically evaluating the arousing level of data visualizations or automatically generating arousing data visualizations. For example, we can envision a feedback system that can intelligently assess the arousing level of a data visualization design by scoring its design from multiple arousal-related aspects and identifying its strengths and weaknesses, thus guiding designers to improve their work. To achieve such goals, extracting computable features from data visualization designs automatically becomes a pursuit. In this work, although about half of the features were calculated by computer, we noticed that there are three main challenges if we want to fully automate the process of feature extraction.

First, not all the design-related concepts can be easily transformed into computable features. For example, so far, there is no recognized algorithm for evaluating the data-ink ratio of a data visualization automatically. Besides, high-level concepts such as unusualness are difficult to be measured computationally, as they are usually feelings co-shaped by multiple design elements and are moderated by the participants’ own knowledge, values, or preferences. How to take advantage of the valuable signals that arise from such expressions is a tricky problem.

Second, parsing the composition of a data visualization from an image can be difficult. Understanding how a data visualization is composed of data, graphical elements, and texts requires utilizing techniques such as object detection, recognition, and classification. When the input is pixel-based images, the accuracy of the outcomes may not be satisfying. For example, when calculating the whitespace, the algorithm sometimes misunderstood which color is the background color. When detecting texts from the images, the algorithm frequently made mistakes. As a result, we had to adjust these results manually. Therefore, to achieve automatic design evaluation, we still need to incorporate more state-of-the-art techniques from computer vision and develop more models and algorithms customized for data visualization design to improve the accuracy of design feature extraction.

Third, how to assess the quality of a design remains a challenge. Currently, we can use variables to describe the existence of a design feature or to what extent it is used. However, we are not able to judge whether the feature is used "appropriately”. For example, in our study, some participants reported low arousal to visualizations that were badly designed (e.g., “Not much immediate clarity what the visualisation is about hence my interest is low and disinterested.”). In other words, except for "quantifying” the design, the "quality” of a design also counts; except for "describing” the design, "assessing” the design also counts. This has posed another challenge for future research.

5.4 Limitations and Future Work
This work is exploratory in nature so the findings of this work were mainly limited to correlations rather than causal effects and were constrained by the inherent limitations of exploratory studies. First, although we have carefully constructed a corpus that contains diverse data visualization designs, the corpus is still by no means exhaustive. Second, affective arousal is a subjective feeling that is difficult to quantify. To mitigate this problem, we excluded the influence of semantics, sampled diverse participants from a large population pool through crowdsourcing, and normalized each participant’s ratings when constructing the models. However, noise caused by subjectivity may have inevitably entered and lowered the accuracy of prediction. Third, the features we extracted in this work are not exhaustive and are limited in characterizing some high-level subjective concepts such as aesthetics and unusualness. Also, this work is short in revealing the fundamental impact of low-granularity design elements (e.g., angles, roundness) on affective arousal. To address such issues, more controlled experiments should be done to examine the effects of a certain design condition while other variables are rigorously controlled. We also hope a follow-up study can be done in the future to test the generalizability of this study by collecting more samples and systematically manipulating one or more of the identified features.

We see several directions for future research. First, more alternative methods can be utilized to deepen our understanding of the design-affect relationship in data visualization. For example, by excluding any semantics, this work did not examine the interaction
between content and visualization design. Future work could fill this gap by first measuring the arousal caused by content and then analyzing how much arousal is augmented or lessened by design. In addition, future work could examine how the incorporation of embodiment moderates the conveyance of semantics and the elicitation of affects. Second, as our study has suggested that affective arousal may be related to the complexity of data visualization, future work could further investigate how people’s visualization literacy influences their perceived complexity and arousal. Third, more work can be done to investigate another important dimension of affects, namely valence, such as how valence-related design features are different from arousal-related features and how they interact with each other. Last, we hope there will be more research into how we should take advantage of the benefits brought by affective arousal and how we should avoid its negative side effects. This asks for the incorporation of more empirical knowledge, such as understanding the practice of designers, to help outline clearer guidelines for what should and should not be done.

6 CONCLUSION

This work explores the relationship between visualization design and affective arousal. First, we collected a corpus of 265 data visualizations and conducted a crowdsourcing study with 184 participants to gather ratings on the affective arousal elicited by their design as well as qualitative feedback. Based on the study data, we first manually coded the arousal-related design features reported by the participants, then mapped these features to computable variables and constructed regression models to identify the most significant features. By comparing the results of the models, we finally identified four design features (e.g., colorfulness, the number of different visual channels) that were cross-validated as important features correlated with affective arousal. We hope this work will inspire more future research on affective visualization design and user experience with data visualization.

REFERENCES

[1] X. Lan, Y. Shi, Y. Zhang, and N. Cao, “Smile or scowl looking at infographic design through the affective lens,” IEEE Transactions on Visualization and Computer Graphics, vol. 27, no. 6, pp. 2796–2807, 2021.
[2] E. Segel and J. Heer. “Narrative visualization: Telling stories with data;” IEEE Transactions on Visualization and Computer Graphics, vol. 16, no. 6, pp. 1139–1148, 2010.
[3] Y. Shi, X. Lan, J. Li, Z. Li, and N. Cao, “Communicating with motion: A design space for animated visual narratives in data videos,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2021, pp. 1–13.
[4] J. A. Russell, “A circumplex model of affect.” Journal of personality and social psychology, vol. 39, no. 6, pp. 1161–1187, 1980.
[5] E. Sherman, A. Mathur, and R. B. Smith, “Store environment and consumer purchase behavior: mediating role of consumer emotions,” Psychology & Marketing, vol. 14, no. 4, pp. 361–378, 1997.
[6] V. D. Kaltcheva and B. A. Weitz, “When should a retailer create an exciting store environment?” Journal of Marketing, vol. 70, no. 1, pp. 107–118, 2006.
[7] J. Berger, “Arousal increases social transmission of information,” Psychological Science, vol. 22, no. 7, pp. 891–893, 2011.
[8] J. Storbeck and G. L. Clore, “Affective arousal as information: How affective arousal influences judgments, learning, and memory,” Social and Personality Psychology Compass, vol. 2, no. 5, pp. 1824–1843, 2008.
[9] Lin, “Minimal yet powerful: Improving the text on your infographics,” https://dearcontent.com/minimal-yet-powerful-improving-the-text-on-your-infographics/ 2019.
[10] N. Chibana, “The ultimate guide to infographics for nonprofits,” https://visme.co/blog/the-ultimate-guide-to-infographics-for-nonprofits/ 2015.
[11] P. Valdez and A. Mehrabian, “Effects of color on emotions.” Journal of Experimental Psychology: General, vol. 123, no. 4, p. 394, 1994.
[12] Y. Wang, A. Segal, R. Klizaty, D. F. Keefe, P. Isenberg, J. Hurtienne, E. Hornecker, T. Dwyer, and S. Barrass, “An emotional response to the value of visualization,” IEEE Computer Graphics and Applications, vol. 39, no. 5, pp. 8–17, 2019.
[13] L. Bartram, A. Patra, and M. Stone, “Affective color in visualization,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2017, pp. 1364–1374.
[14] H. Kennedy and R. L. Hill, “The feeling of numbers: Emotions in everyday engagements with data and their visualisation,” Sociology, vol. 52, no. 4, pp. 830–848, 2018.
[15] J. Boy, A. V. Pandey, J. Emerson, M. Satterthwaite, O. Nov, and E. Bertini, “Showing people behind data: Does anthropomorphizing visualizations elicit more empathy for human rights data?” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2017, pp. 5462–5474.
[16] X. Lan, Y. Shi, Y. Wu, X. Jiao, and N. Cao, “Kineticcharts: Augmenting affective expressiveness of charts in data stories with animation design.” IEEE Transactions on Visualization and Computer Graphics, vol. 28, no. 1, pp. 933–943, 2021.
[17] X. Lan, Y. Wu, Y. Shi, Q. Chen, and N. Cao, “Negative emotions, positive outcomes? exploring the communication of negativity in serious data stories,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2022, pp. 1–14.
[18] M. A. Borkin, Z. Bylinskii, N. W. Kim, C. M. Bainbridge, C. S. Yeh, D. Borkin, H. Pfister, and A. Oliva, “Beyond memorability: Visualization recognition and recall,” IEEE Transactions on Visualization and Computer Graphics, vol. 22, no. 1, pp. 519–528, 2015.
[19] D. Shi, X. Xu, F. Sun, Y. Shi, and N. Cao, “Calliope: Automatic visual data story generation from a spreadsheet,” IEEE Transactions on Visualization and Computer Graphics, vol. 27, no. 2, pp. 453–463, 2020.
[20] P. Lorenz-Spreen, B. M. Mønsted, P. Høvel, and S. Lehmann, “Accelerating dynamics of collective attention,” Nature communications, vol. 10, no. 1, pp. 1–9, 2019.
[21] B. Saker, A. Endert, and J. Stasko, “Beyond usability and performance: A review of user experience-focused evaluations in visualization,” in Proceedings of the Workshop on Beyond Time and Errors on Novel Evaluation Methods for Visualization,” ACM, 2016, pp. 133–142.
[22] N. Cawthon and A. V. Moere, “The effect of aesthetics on the usability of data visualization,” in International Conference Information Visualization. IEEE, 2007, pp. 637–648.
[23] L. Harrison, K. Reinecke, and R. Chang, “Infographic aesthetics: Designing for the first impression,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2015, pp. 1187–1190.
[24] F. Amini, N. H. Riche, B. Lee, J. Leboe-McGowan, and P. Irani, “Hooked on data videos: assessing the effect of animation and pictographs on viewer engagement,” in Proceedings of the 2018 International Conference on Advanced Visual Interfaces, 2018, pp. 1–9.
[25] X. Lan, X. Xu, and N. Cao, “Understanding narrative linearity for telling expressive time-oriented stories,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2021, pp. 1–13.
[26] M. A. Borkin, A. A. Vo, Z. Bylinskii, P. Isola, S. Sunkavalli, A. Oliva, and H. Pfister, “What makes a visualization memorable?” IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2306–2315, 2013.
[27] S. S. Sundar and S. Kalyanaraman, “Arousal, memory, and impression-formation effects of animation speed in web advertising.” Journal of Advertising, vol. 33, no. 1, pp. 7–17, 2004.
[28] A. Lang, P. Bolis, R. F. Pollock, and K. Kawahara, “The effects of production pacing and arousing content on the information processing of television messages,” Journal of Broadcasting & Electronic Media, vol. 43, no. 4, pp. 451–475, 1999.
[29] G. J. Gorn, A. Chattopadhyay, T. Yi, and D. W. Dahl, “Effects of color as an executional cue in advertising: They’re in the shade,” Management Science, vol. 43, no. 10, pp. 1387–1400, 1997.
[30] S. N. Singh and J. C. Hitchon, “The intensifying effects of exciting television programs on the reception of subsequent commercials,” Psychology & Marketing, vol. 6, no. 1, pp. 1–31, 1989.
[31] I. Mavridou, E. Seiss, T. Kostoulas, C. Nduka, and E. Balaguer-Ballester, “Towards an effective arousal detection system for virtual reality,” in Proceedings of the Workshop on Human-Habitat for Health (H3): Human-Habitat Multidimensional Interaction For Promoting Health and Well-Being in the Internet of Things Era, 2018, pp. 1–6.
[32] J. Cusveller, C. Gerritsen, and J. d. Man, “Evolving and measuring arousal in game settings,” in International Conference on Serious Games. Springer, 2014, pp. 165–174.
[33] T. Aoki, R. Chujo, K. Matsui, S. Choi, and A. Hattasaari, “Emoballoon - conveying emotional arousal in text chats with speech balloons,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2022, pp. 1–16.

[34] M. Brexmer, B. Lee, B. Bach, N. H. Riche, and T. Munzner, “Timelines revisited: A design space and considerations for expressive storytelling,” IEEE Transactions on Visualization and Computer Graphics, vol. 23, no. 9, pp. 2151–2164, 2016.

[35] D. H. Kim, V. Setlur, and M. Agrawala, “Towards understanding how readers integrate charts and captions: A case study with line charts,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2021, pp. 1–11.

[36] A. Betella and P. F. Verschure, “The affective slider: A digital self-assessment scale for the measurement of human emotions,” PLOS ONE, vol. 11, no. 2, p. e0148037, 2016.

[37] M. M. Bradley and P. J. Lang, “Measuring emotion: the self-assessment manikin and the semantic differential,” Journal of Behavior Therapy and Experimental Psychiatry, vol. 25, no. 1, pp. 49–59, 1994.

[38] D. E. Berlyne, Conflict, arousal, and curiosity. McGraw-Hill Book Company, 1960.

[39] M.-C. Lichtlé, “The effect of an advertisement’s colour on emotions evoked by attitude towards the ad: The moderating role of the optimal stimulation level,” International Journal of Advertising, vol. 26, no. 1, pp. 37–62, 2007.

[40] V. Braun and V. Clarke, “Using thematic analysis in psychology,” Qualitative Research in Psychology, vol. 3, no. 2, pp. 77–101, 2006.

[41] J. Machajdik and A. Hanbury, “Affective image classification using features inspired by psychology and art theory,” in Proceedings of the ACM International Conference on Multimedia. ACM, 2010, pp. 83–92.

[42] K. E. Reinecke, T. Yeh, L. Miratrix, R. Mardikio, Y. Zhao, J. Liu, and K. Z. Gajos, “Predicting users’ first impressions of website aesthetics with a quantification of perceived visual complexity and colorfulness,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2013, pp. 2049–2058.

[43] D. Hasler and S. E. Suesstrunk, “Measuring colorfulness in natural images,” in Human Vision and Electronic Imaging VIII, vol. 5007. SPIE, 2003, pp. 87–95.

[44] E. Pelí, “Contrast in complex images,” Journal of the Optical Society of America A, vol. 7, no. 10, pp. 2032–2040, 1990.

[45] L. Dhakar, “Color thief,” https://lokeshdhakar.com/projects/color-thief/.

[46] J. Van De Weijer, C. Schmid, and J. Verbeek, “Learning color names from real-world images,” in IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2007, pp. 1–8.

[47] A. Satyanarayanan, D. Moritz, K. Wongsuphasawat, and J. Heer, “Vega-lite: A grammar of interactive graphics,” IEEE Transactions on Visualization and Computer Graphics, vol. 23, no. 1, pp. 341–350, 2016.

[48] T. Munzner, Visualization analysis and design. Boca Raton, FL, US: CRC press, 2014.

[49] R. Smith, “An overview of the tesseract ocr engine,” in International Conference on Document Analysis and Recognition, vol. 2. IEEE, 2007, pp. 629–633.

[50] S. García, J. Luengo, and F. Herrera, Data preprocessing in data mining. London, UK: Springer, 2015, vol. 72.

[51] G. James, D. Witten, T. Hastie, and R. Tibshirani, An introduction to statistical learning. Springer, 2013, vol. 112.

[52] A. V. Moere, M. Tomitsch, C. Wimmer, B. Christoph, and T. Grechenig, “Evaluating the effect of style in information visualization.” IEEE Transactions on Visualization and Computer Graphics, vol. 18, no. 12, pp. 2739–2748, 2012.

[53] K. W. Jacobs and F. E. Hustmyer Jr, “Effects of four psychological primary colors on sr, heart rate and respiration rate,” Perceptual and motor skills, vol. 38, no. 3, pp. 763–766, 1974.

[54] J. Lankow, J. Ritchie, and R. Crooks, Infographics: The power of visual storytelling. Hoboken, NJ, US: John Wiley & Sons, 2012.

[55] Y. Wang, H. Zhang, H. Huang, X. Chen, Q. Yin, Z. Hou, D. Zhang, Q. Luo, and H. Qu, “Infonince: Easy creation of information graphics,” in Proceedings of the CHI Conference on Human Factors in Computing Systems. ACM, 2018, pp. 1–12.

[56] L. Byrne, D. Angus, and J. Wiles, “Acquired codes of meaning in data visualization and infographics: beyond perceptual primitives,” IEEE Transactions on Visualization and Computer Graphics, vol. 22, no. 1, pp. 509–518, 2015.

[57] A. Bigelow, S. Drucker, D. Fisher, and M. Meyer, “Reflections on how designers design with data,” in Proceedings of the International Working Conference on Advanced Visual Interfaces. ACM, 2014, pp. 17–24.

[58] A. D. Pazda and C. A. Thorstenson, “Color intensity increases perceived extraversion and openness for zero-acquaintance judgments,” Personality and Individual Differences, vol. 147, pp. 118–127, 2019.

[59] M. R. Hyman and R. Tansey, “The ethics of psychoactive ads,” Journal of Business Ethics, vol. 9, no. 2, pp. 105–114, 1990.

[60] R. B. Malmo, “Anxiety and behavioral arousal.” Psychological Review, vol. 64, no. 5, p. 276, 1957.

Xingyu Lan received her Ph.D degree in design from Tongji University, China, in 2022. She is going to work as an assistant professor at the College of Journalism, Fudan University, China. She conducts interdisciplinary research across fields such as data visualization, data journalism, digital communication, and design. Her research interests include data-driven storytelling, visualization design, human-computer interaction, and visualization for the masses.

Xingyu Lan received her Ph.D degree in design from Tongji University, China, in 2022. She is currently a research assistant with Intelligent Big Data Visualization Lab (iDV’ Lab), the College of Design and Innovation, Tongji University, Shanghai, China. Her research interests include data visualization design, intelligent user interfaces, and human-computer interaction.

Qing Chen received her B.Eng degree from the Department of Computer Science, Zhejiang University and her Ph.D. degree from the Department of Computer Science and Engineering, Hong Kong University of Science and Technology (HKUST). After receiving her PhD degree, she worked as a postdoc at Inria and Eziole Polytchnique. She is currently an assistant professor at Tongji University. Her research interests include information visualization, visual analytics, human-computer interaction, online education, visual storytelling, intelligent healthcare and design.

Nan Cao received his Ph.D degree in Computer Science and Engineering from the Hong Kong University of Science and Technology (HKUST), Hong Kong, China in 2012. He is currently a professor at Tongji University and the Associate Dean of the Tongji College of Design and Innovation. He also directs the Tongji Intelligent Big Data Visualization Lab (iDV’ Lab) and conducts interdisciplinary research across multiple fields, including data visualization, human-computer interaction, machine learning, and data mining.

Before his Ph.D studies at HKUST, he was a staff researcher at IBM China Research Lab, Beijing, China. He was a research staff member at the IBM T.J. Watson Research Center, New York, NY, USA before joining the Tongji faculty in 2016.