# Double Tap for This Post: Understanding the Communication of Data Visualization on Social Media

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Data visualizations are increasingly used by news outlets on social media to communicate insights to a broad audience. However, little is known about how readers interact with and respond to data visualizations in these quick-consumption environments. In this work, we introduce a conceptual model that categorizes visualization reading that leads to the communication effect of likes on Instagram. The model was developed through a grounded theory analysis of the statements explaining the reasoning behind the likes of visualization, which were recorded from a preliminary study. Informed by coding the statements from two dimensions including scopes and design patterns concerning visualization, our model consists of three levels: depicting the "look" of a visualization (e.g., artistic style and color scheme); interpreting the "flesh and bones" of a visualization (e.g., visualization and narrative); and elucidating the "heart and soul" of a visualization (e.g., insights and conclusion). We also conducted an online crowdsourcing user study with 200 participants to demonstrate how our model can be applied to improve the communication of visualization by comparing the three levels.

CCS Concepts: • **Human-centered computing** → **Visualization theory, concepts and paradigms**; **Social content sharing**; • **Social and professional topics** → *User characteristics.*

Additional Key Words and Phrases: Data Visualization, Mass Communication, Design, Social Media

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## 1 Introduction

Given the ability to transmit knowledge from experts to the general public, data visualization has been used by news outlets such as the New York Times and the Guardian as useful tools on their social platforms such as Twitter and Instagram to attract, persuade, or educate readers [29]. Notable examples include the data visualization by Guardian called "*The planet is heating*" [104], which visualizes temperature trends with a minimal chart to promote public awareness of climate change and has received 29k likes on Instagram. With the high volume of data visualization being consumed in such casual, skimmable formats on social media [81], developing a systematic understanding of how visualization is communicated to readers is particularly important.

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The communicative process of information can be described using models of communication. For example, Lasswell's model [57] uses five questions including "who?", "says what?", "in what channel?", "to whom?", and "with what effect?" to help identify the main aspects of communication. In the visualization community, exploring the communication of visualization on social media has received increasing research interest. Researchers sought to explore the characteristics of a specific communication effect, comments [42, 48, 115]. For example, CommentSpace et al. [115], a collaborative visual analysis tool, allows analysts to comment on interactive visualizations and supplement their comments with tags and links. Kauer et al. [48] investigated user comments related to visualizations on Reddit and identified ten reaction types such as observation, critique, and hypothesis. However, the aforementioned work has focused on qualitative signals such as comments rather than broader quantitative engagement through likes. As the barrier to liking is lower compared to commenting or sharing, analyzing patterns in likes allows us to understand reactions from a wider audience who simply skim visualization posts. Also, readers' interaction with data visualization that leads to the intended communication effect remains unknown.

To fill the gap, our work introduces a conceptual model categorizing how readers receive and interpret a visualization post on social media, through which they decide whether to like the content. Understanding such a communicative process can help improve the effectiveness of the message and thus achieve better communication effects [61]. To do this, we first collected a corpus of 252 visualizations from a range of news outlets on Instagram and conducted a series of interviews with 40 participants to understand the reasoning behind the likes of a visualization. Second, we developed a three-level conceptual model through a grounded theory analysis of the statements recorded from the interviews. The model was informed by coding: (i) **scopes** meaning the part of a visualization a reader refers to, combined with (ii) **design patterns** indicating the textual or visual elements of a scope that captivate the reader's attention and raise his or her interest. As a result, our model spans three levels: depicting the "look" of a visualization (e.g., artistic style and color scheme); investigating the "flesh and bones" of a visualization (e.g., data and visuals); and tapping into the "heart and soul" of a visualization (e.g., insights and conclusion). Third, we conducted a crowdsourcing user study with 200 participants to demonstrate the effectiveness of our model. The results of our user study suggested that the three levels in our model can help improve the communication of visualizations on social media regarding communication effects, perceptions, and engagement. The corpus and additional details of our user study can be accessed at our explorer of visualization, https://idvxlab.com/infocommunication.

## 2 Related Work

To motivate our research, we review the literature on the communicative characteristics of visualization, visualization on social media, and design patterns of visualization.

### 2.1 The Communicative Characteristics of Visualization

Communication is often understood as an exchange of messages [56, 75, 86], with the ultimate goal of producing the desired effect in the receiver [80]. Lasswell's model [57] is an early and influential model of communication, which identified five fundamental elements of the communicative process, including sender, message, channel, receiver, and effect. Effective communication can impact the receiver from different perspectives. According to William McGuire [73], source, message, channel, receiver, and destination are all input communication factors that drive the change in altitude, which is a process consisting of five output persuasion steps, including attention, comprehension, yielding, retention, and action [72]. Bryant and Zillmann [19] identified five types of communication effects: behavioral, attitudinal, cognitive, emotional, and physiological.

Visualizations, as a means of communication [2], also embody these essential components and can significantly influence the audience. For example, the presentation of Covid-19 visualizations has been investigated by identifying who, (uses) what data, (to communicate) what messages, in what form, and under what scenarios [119]. Also, the communicative characteristics of visualization have been explored by examining the sender's purpose and stance [2, 63] as well as design patterns applied to the information [35, 41]. Researchers have widely studied the effects of visualization on communication, focusing on perception and cognition [11, 37, 44, 79], emotion [52, 54], and behavior [16, 31, 42, 48]. In terms of perception and cognition toward visualization, research efforts have been devoted to investigating the influence of visualization on reader perception of uncertainty [37] and risk [11], as well as how misinformative visualizations may mislead or even deceive the receiver [66]. Also, visualization can trigger readers' emotional responses such as surprised and shocked [52]. Communication effects of visualization can manifest as interaction [16, 31]. For example, Feng et al. [31] studied if text-based search in interactive visualizations on the web can engage readers and found that this form of interaction can increase user engagement and support information-seeking goals. Inspired by the aforementioned work, our work focuses on readers' interpretation of visualization that leads to the intended communication effect, likes.

### 2.2 Visualization on Social Media and User Engagement

With the growth of social media, visualizations can be communicated to the public more quickly and accessibly. Researchers have studied visualizations on social media across different platforms, such as Twitter [8, 47, 50, 60], Facebook [6, 50, 60, 67], Instagram [21, 111], and Reddit [48]. These studies primarily focus on topics such as political affairs [6], academic subjects [8, 50, 67], and Covid-19 [15, 47, 60, 62, 111]. Their findings suggest that visualizations have visual appeal and make complex information easier to understand [62], thus enhancing user engagement in communication. For example, visualizations have been found to play a significant role in the viral dissemination of information and opinions on social media [60].

User engagement is broadly defined as the attention and types of responses that content elicits from its audience [78]. On social media platforms like Twitter, user engagement can be measured by various metrics, including retweets, responses, followers, likes, links, cards, hashtags, embedded media, usernames, profile photos, and Tweet expansion [47]. Among these metrics, researchers often focus on likes, shares, and comments [6, 8, 47, 67, 111], as these metrics are the most prominent and provide quantifiable insights into user reactions to different social media strategies and choices [6, 70]. For example Amit et al. [6] defined user engagement by these metrics and used them to analyze which features lead to higher user interaction with political infographics. Kunze et al. [50] used the Altmetric Attention Score, a cumulative measure of social media attention to compare the effectiveness of infographics and baseline articles without visualizations. Kauer et al. [48] explored characteristics and motivations of people's verbal or textual expression when viewing, reading, and/or interacting with visualizations on Reddit. Specifically, comments are often used for qualitative analysis [42, 48], while metrics such as likes are commonly used for quantitative analysis and developing models [8, 47]. Compared to prior work, our work focuses on identifying the design patterns of visualization that lead to increased liking on Instagram. We specifically developed a conceptual model that describes how readers interact with visualizations in a way that leads to improved engagement.

### 2.3 Design Patterns of Visualization

Over the past decade, visualization researchers have identified various design patterns for visualization [18, 74, 84, 93]. A set of design patterns is frequently used to provide design guidelines to researchers and practitioners as well as the development of visualization authoring tools. For example, Segel and Heer [84] identified visual narrative tactics (visual structuring, highlighting, and transition guidance) and narrative structure tactics (ordering, interactivity, and messaging) to support data-driven storytelling. Recent research exploring the design patterns of visualization has focused on specific aspects of design, including visual design [22, 58, 68, 94], animation design [24, 88, 117], interaction design [87, 113], affective design [51–54], and narrative structure [5, 43, 55, 118]. For example, Byrne et al. [22] collected 50 award-winning visualizations and analyzed their use of figurative elements and representations of time. After that, they proposed seven design guidelines such as using recognizable images and a more realistic style for context. In terms of animation design, Shi et al. [88] collected 82 data videos and identified design patterns of animated visual narratives such as emphasis, suspense, and comparison. With regard to interaction design, Shi et al. [87] collected 58 interactive data stories that leverage breaking the fourth wall (BTFW) interaction, which directly addresses readers and asks for input related to themselves. They used an input-output framework to analyze BTFW interaction and identified design patterns such as spotlight.

Research interest in affective design in visualization has also increased. Lan et al. [54] explored the design factors that trigger emotional communication in serious data stories and observed six design patterns such as sensory challenge and loss of control. Some research efforts have been devoted to narratives in visualization. For example, Lan et al. [55] collected 80 time-oriented stories and identified six narrative order patterns that can be used to describe them, such as trace-back and halfway-back. Compared to the aforementioned design patterns derived from visualization researchers directly analyzing and codifying a corpus of visualizations, our work attempts to identify design patterns through the "reader" lens. That is, we conducted a series of interviews with participants to understand their reasoning behind the likes of visualization using think-aloud protocols and mouse tracking methods. Then, we coded the statements from the interviews following grounded theory to derive design patterns that contribute to the likes of visualization.

## 3 Preliminary Study

To understand the reasoning behind the likes of visualizations on social media, we conducted a series of interviews with 40 participants. Specifically, we attempted to gain insights into the following questions: Q1) how do readers receive and interpret a visualization before deciding to give it a like? and Q2) what characteristics of a visualization appeal to readers for liking it?

### 3.1 Methodology

The study simulated the scenario where participants displayed reactive behaviors of liking or skipping Instagram posts featuring data visualizations. As such decisions are usually made within a dozen seconds, both think-aloud protocols and mouse-tracking methods were used to track their thoughts and behaviors.

***Stimuli.*** To collect a corpus of visualizations with like data, we first identified a social platform that publishes visualizations and includes like buttons. We considered social platforms such as Facebook, Twitter, and Visual.ly, and then selected Instagram due to (i) its features of being a visual social media [83], (ii) its availability of like data, and (iii) its high monthly active users, ranked fifth in social media. After that, we identified a list of well-known news outlets that have official accounts on Instagram. To do that, we searched for news outlets on SimilarWeb [90], which helps rank the most popular websites worldwide by traffic share [4]. The most recent search was conducted in June 2023. Additionally, we selected news outlets that have won Sigma Awards [91], an international competition celebrating the best data journalism from around the world. It resulted in 22 news outlets, as shown in Fig. 1 (a). Then, we searched for visualizations posted by these news outlets on

Instagram. We limited their subjects to environmental-related topics due to their global relevance and the availability of extensive data. These topics are universally significant and persist over long periods, making them highly relevant to public interest. The abundance of data on environmental issues also allows for comprehensive analysis.

Our search was also constrained to visualizations that were posted within the past five years [49] and thus yielded 311 visualizations. To ensure that these visualizations are data-driven [52], we mandated that they (i) present messages and arguments supported by data and (ii) include at least one visualization. In accordance with the two inclusion criteria, we identified 252 out of 311 visualizations to be included in our corpus and their distribution regarding publication year and likes is shown in Fig. 1 (b). Finally, we manually selected a subset of 40 visualizations (15.8%) from the corpus as our stimuli [14]. They provide a diverse sample of the corpus regarding their source, likes, publication year, and visualization type. Specifically, the stimuli are distributed across 12 different news outlets and received likes ranging from 721 to 42,386 ($M$ = 8108.05, $SD$ = 9559.37). Their visualization types [13] include map ($N$ = 15), bar ($N$ = 7), line ($N$ = 6), area ($N$ = 4), circle ($N$ = 2), heat ($N$ = 1), tree ($N$ = 1), pictorial ($N$ = 1), text ($N$ = 1), and multiple ($N$ = 2) visualizations and their sub-topics include climate change ($N$ = 16), pollution ($N$ = 8), sustainability and carbon emissions ($N$ = 7), biodiversity ($N$ = 3), and other related topics ($N$ = 6).

***Participants.*** We recruited participants by publishing an invitation poster on the social platform of our lab. In the poster, we informed that we were looking for participants who are interested in data news or visualizations. 40 participants (20 females) aged between 21 and 30 ($M$ = 25.4, $SD$ = 9.6) were recruited, including college students, researchers, and professionals with diverse backgrounds such as design, journalism, and medicine. The participants are fluent in English and have different cultural backgrounds (e.g., China and the United States). They also reported their

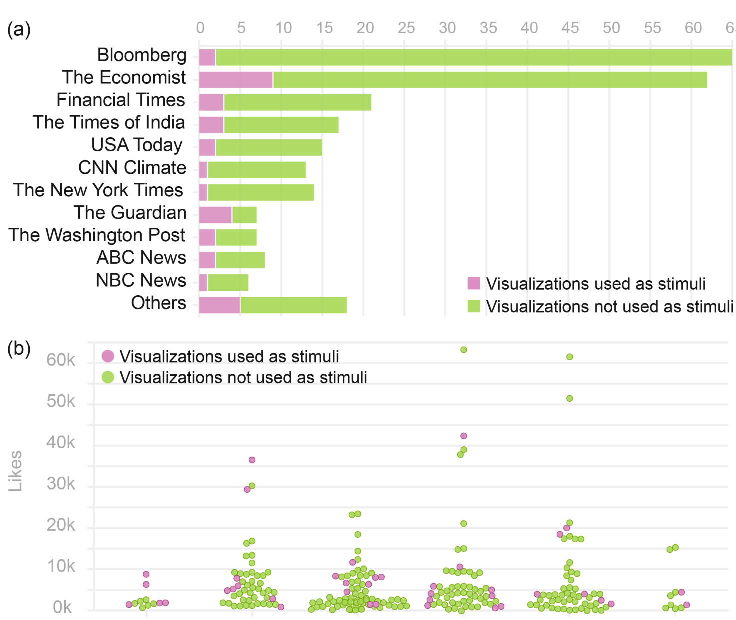


Fig. 1. Frequency of the 252 visualizations in our corpus regarding news outlets (a) and the distribution of likes on Instagram by publication year (b).

knowledge of data visualization, ranging from novice: 2 (5%), beginner: 17 (42.5%), developing: 16 (40%), to competent: 5 (12.5%). Their frequency of reading visualizations on social media includes rarely: 4 (10%), occasionally: 10 (25%), often: 20 (50%), and always: 6 (15%).

***Task and Procedure.*** The preliminary study consisted of three sessions: the **tutorial**, **reading**, and **interview** sessions. Each participant completed these sessions individually. In the tutorial session, we described our research intent, obtained consent for voice and screen recording, and introduced core concepts such as think-aloud protocols and mouse-tracking methods. In the reading session, we first randomly divided the 40 visualizations into four groups, with ten visualizations in each group. Each group of visualizations was presented to 10 participants, with the order of visualizations within each group randomized to avoid bias. Each participant was shown the visualizations one at a time and was asked to either like or skip each visualization based on their preference. When reading a visualization, a participant was encouraged to apply think-aloud protocols to say what he or she is looking at, thinking, doing, and feeling while the verbalizations constituted a statement for this visualization. The participants were also required to use mouse-tracking methods to show what they were looking at using mouse movements. As a result, we recorded 400 statements (2,537 sentences) in total from the 40 participants, with ten statements from each participant. In the interview session, we conducted a semi-structured interview with the participants to learn more about the reasons for their choices (e.g., "*Please describe the visualization with a few adjective words that can explain your choice*") as well as the clarification of their behaviors (e.g., "*I noticed that you had been hovering over this area for a while without saying anything. What were you thinking of then?*"). After the three sessions, the participants were instructed to fill out a demographic survey. The study lasted about 45 minutes for each participant.

### 3.2 Results and Analysis

Through the study, we found that the likes of the 40 stimuli range from 0 to 7 ($M = 2.05$, $SD = 1.57$), which suggests the diversity in the quality of our stimuli. We also collected qualitative data from the 40 participants and analyzed the data to address the two posed questions (Q1-Q2).

*3.2.1 Q1: How Readers Read Visualizations.* We coded our data of the 400 statements following grounded theory, which approaches theory construction from both inductive (through data collection, coding, and refinement) and empirical perspectives ("grounded" in the data) [77]. Specifically, we first utilized open coding to identify emerging dimensions from the data and constructed an initial scheme. Then, we refined the scheme through multiple iterations of close coding.

***Coding.*** The open coding started with an initial qualitative observation of our data by randomly selecting 80 (20%) statements. Two researchers with journalism and design backgrounds, respectively, were involved in this process independently. We built an initial scheme with four dimensions derived from the analysis of our data: (i) the elements of a visualization the participants refer to (e.g., title and chart), (ii) the visual channels of the elements the participants highlight (e.g., color and shape), (iii) the participants' reaction to the elements (e.g., observe and suspect), and (iv) the participants' feelings towards the elements (e.g., annoyed and surprised). These dimensions also align with findings from the literature [20, 69]. Throughout the early iterations, we observed that some of these dimensions appear to be on somewhat orthogonal axes rather than form a partition of the space, or categories depend significantly on the subjective interpretations of the coders. For example, the participants occasionally conveyed feelings through reactions to particular stimuli, e.g., vivid red hues can trigger visual discomfort and shock. Thus, we revised dimensions and categories that led to misleading coding through subsequent iterations of close coding. In each new iteration, a new set of randomly selected 80 (20%) statements was tested, through which similar categories were merged and new categories were added.

***Final Scheme.*** After five major iterations, we concluded a final coding scheme with two dimensions: **scopes** of a visualization the participants refer to and **design patterns** pertaining to a scope that draw the participants' attention. Based on the coding scheme, the same two researchers who performed the initial coding independently coded the data. We met for three sessions to compare our codes and discuss mismatches until we reached a 100% consensus. From the two dimensions, three different **levels** explaining how our cognition moves the information up to higher levels by a progressive organization began to emerge; first comes Level 1, next is Level 2, and finally comes Level 3. Fig. 2 uses a visual "fingerprint" [69] to show how the three levels are distributed across the sentences in our data: Level 1 (18%), Level 2 (66%), and Level 3 (16%). The distribution suggests that the majority of participants reach Level 2 while a few of them move on to Level 3. We also observed that the participants might hit the like button at any of the three levels. The details of the three levels will be introduced in the following section.

*3.2.2 Q2: How Readers Characterize Visualizations.* From the interviews, we collected a set of 149 distinctive words describing the characteristics of visualization that make it likable to readers. We analyzed these words in two steps. First, we grouped semantically close words according to the English lexicon proposed by prior research [76]. For example, *interesting* and *intriguing* are synonyms, thus can be grouped into the same category. This step yielded 14 categories of 149 words in total. Second, we counted the frequency of each word and added these frequencies for each category. We then identified nine primary categories and used the most frequently mentioned word

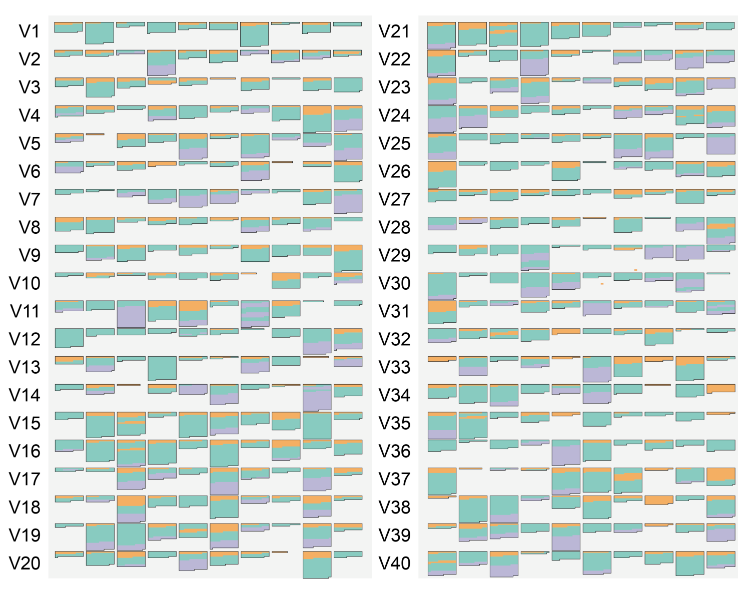


Fig. 2. A visual "fingerprint" [69] of the 400 statements from the preliminary study. Each row corresponds to a visualization. Each column shows a participant-think-aloud statement for that visualization, color coded according to our model, including Level 1: Overall "Look" upon First Glance; Level 2: A Closer Investigation of "Flesh and Bones"; Level 3: Tapping into "Heart and Soul" . 40 visualizations were used as stimuli while each visualization was read by 10 participants.

| Level | Description | Scopes | Categories | Design patterns | # |
|---|---|---|---|---|---|
| 1 | Overall "look" upon first glance | Artistic style<br>Color scheme<br>Layout | C1: Visual complexity | ① A moderate number of information blocks | 7 |
| | | | | ② Structured information blocks | 19 |
| | | | | ③ A moderate number of colors | 14 |
| | | | C2: Figurative representation | ④ Isotype | 20 |
| | | | | ⑤ Embellishment | 24 |
| | | | C3: Color hook | ⑥ Chunks of color | 24 |
| | | | | ⑦ Highly saturated colors | 17 |
| | | | | ⑧ Complementary colors | 24 |
| | | | | ⑨ Gradient colors | 12 |
| 2 | A closer investigation of "flesh and bones" | Data<br>Visuals<br>Narrative | C4: Information accessibility | ⑩ Explained terms | 11 |
| | | | | ⑪ An explicit legend | 15 |
| | | | | ⑫ Timely annotations | 23 |
| | | | C5: Visual anchoring | ⑬ Highlighting | 66 |
| | | | | ⑭ Drawing a line or arrow | 6 |
| | | | | ⑮ Proximity | 8 |
| | | | C6: Color associations | ⑯ Semantically-resonant colors | 17 |
| | | | | ⑰ Echoing with color | 10 |
| 3 | Tapping into "heart and soul" | Subject<br>Insight<br>Conclusion | C7: Narrative voice | ⑱ The first person pronouns | 6 |
| | | | | ⑲ The second person pronouns | 5 |
| | | | C8: Takeaway messages | ⑳ Cohesion | 10 |
| | | | | ㉑ Next steps | 6 |
| | | | | ㉒ Prediction | 9 |

Fig. 3. An overview of our three-level model of visualization communication. Levels are defined by scopes and design patterns. The 22 design patterns are grouped into eight categories (C1-C8). # denotes the frequency of each design pattern mentioned by the 40 participants in our preliminary study.

in each category as its representative word. The final list of the characteristics of visualizations being liked is as follows, *interesting* (21%), *informative* (14%), *clear* (14%), *colorful* (10%), *inspiring* (8%), *easy to understand* (7%), *simple* (5%), *important* (3%), and *useful* (3%).

## 4 A Three-Level Model of Visualization Communication

Our grounded theory process yielded a three-level model to describe how readers engage with a visualization post when liking it on social media. According to our model, readers progressively process information by ascending through different levels; Level 1 commences this progression, followed by Level 2, and ultimately leading up to Level 3. Each level is categorized by a set of scopes that pertains to a specific portion of a visualization that engages readers, along with corresponding design patterns that highlight visual or textual elements of a scope to capture readers' attention and prompt them to give a like, as shown in Fig. 3. Note that not all readers undergo a linear cognitive progression through each of the three levels. Some readers may skip Level 1 and begin at Level 2, while others may return to Level 2 after completing Level 3. We then explain the three levels in detail and relate them back to the statements from the participants and the samples in our corpus.

### 4.1 Level 1: Overall "Look" upon First Glance

The first level involves statements that describe readers' overall impression of a visualization at first glance. It serves as the beginning phase of our model as it emphasizes the "look" of a visualization, where aesthetic appeal plays an important role [39]. Consider the following sentence regarding Fig.4-11 [107].

"*This visualization is absolutely stunning, resembling a watercolor masterpiece. Its design has piqued my curiosity about its subject matter. Even if the content turns out to be mediocre, I am still inclined to hit the "like" button just for the sheer visual pleasure of reading it. It truly is a feast for the eyes*" (P29).

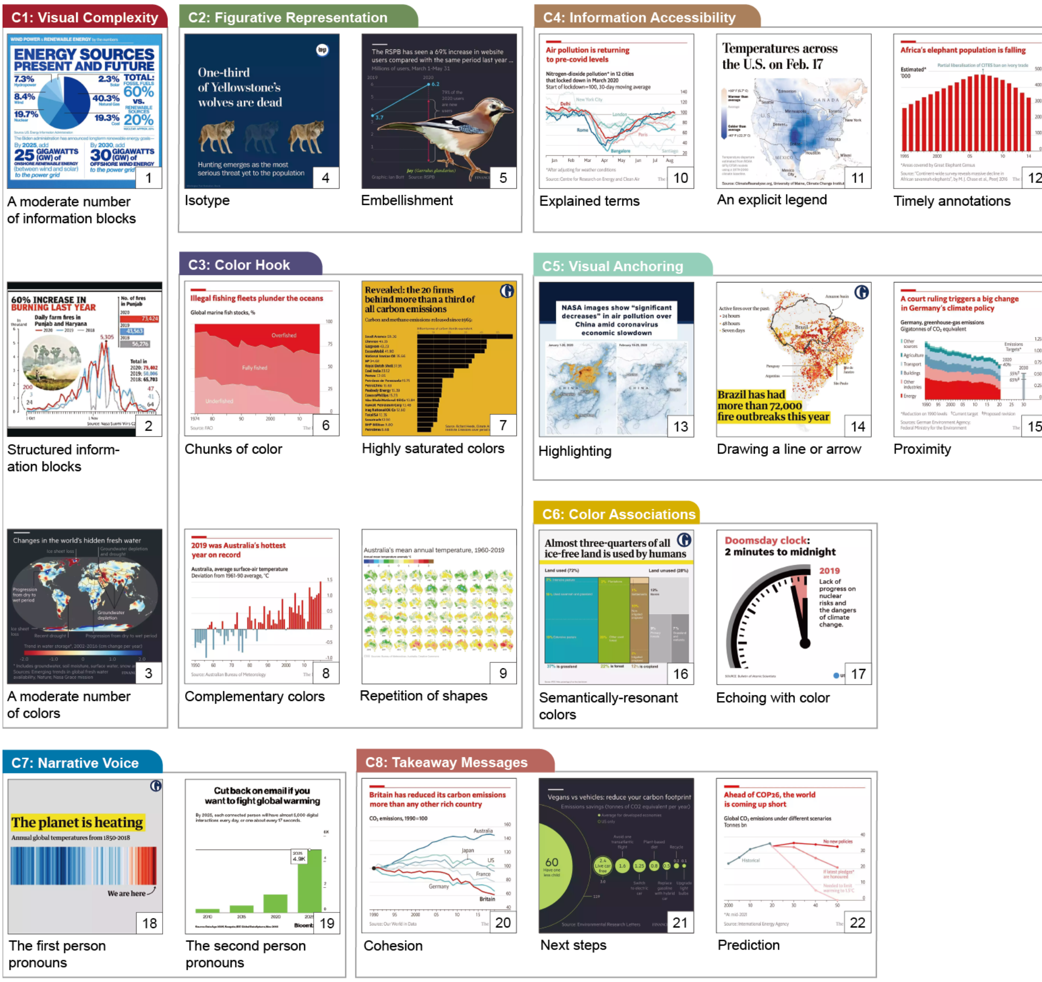


Fig. 4. Eight categories of 22 design patterns in our three-level model. Each design pattern is illustrated with a sample visualization in our corpus. Image sources: [1, 12, 25, 26, 32–34, 95–110].

This sentence suggested that readers respond to the visual appeal of a visualization in a fast, intuitive, and emotional manner. More examples include "*Wow! This color is so dazzling (P36)*" and "*This layout is too crowded, it feels oppressive (P2)*". Such responses often serve as a driver of moving on to the next level, as readers who find the visualization visually appealing are more likely to read the accompanying details [27].

*4.1.1 Scopes.* At this level, the scopes of a visualization tend to be global, where readers usually refer to **artistic style** ("*The artistic style of visualizations from The Economist is quite distinctive, with a clean and modern look that makes it instantly recognizable to me (P5)*", "*It visualizes the data with photos of wolves and features a realistic style (P16)*"), **color scheme** ("*Its colors are vivid and bright (P18)*", "*The contrast between red and blue is eye-catching (P16)*"), and **layout** ("*the visualization is clear and well-organized, with the title prominently displayed at the top and the visual elements* *neatly arranged toward the bottom (P9)*", "*With the plethora of details condensed within the single infographic, it appears to require a significant amount of time to read (P39)*").

*4.1.2 Design Patterns.* Design patterns at this level mainly leverage overall aesthetics to attract readers' attention quickly and increase their curiosity. They can be grouped into the following four categories,

***Visual Complexity (C1)***. This category refers to controlling the level of detail or intricacy contained within a visualization to avoid overwhelming readers at first glance. For example, presenting **a moderate number of information blocks** is an effective design pattern. Here, an information block [65] is a semantic combination of textual and visual elements that is designed to help readers easily distinguish one piece of information from another and facilitate the absorption of new information. According to previous psychological findings, denser information presentation can increase people's perception of complexity [116], which results in low arousal potential [10, 82]. In one case, when P37 first looked at Fig. 4-1 [1], he complained that it was "*crowded with many words and visuals*" and would like to skip it. Also, **structured information blocks** were mentioned, as a well-organized layout can reduce cognitive load and is better understood [36]. For example, Fig. 4-2 [106] was criticized by multiple participants (P34, P35, P40) due to its "*visual clutter caused by crowded and overlapping elements.*" Another design pattern derived from the participants' feedback is using **a moderate number of colors**, as every shade of color should have a meaning and a function [92]. For example, P34 decided to skip Fig. 4-3 [32] at first sight and commented "*it reminds me of advice from stylists, 'do not wear more than three colors in an outfit otherwise you'll look like a clown or a parrot'. The color scheme in the visualization looks messy and I don't feel like reading more about it.*"

***Figurative Representation (C2)***. This category uses concrete objects such as icons and images to illustrate abstract concepts, encouraging readers to inspect a visualization more closely. **Isotype**, an effective design pattern suggested by previous research [38], can also increase engagement among readers. For example, Fig. 4-4 [108] illustrates the fact that one-third of Yellowstone's wolves are dead using three pictographic symbols of wolves with one of them fading out. Such a figurative representation attracted multiple participants' attention (P2, P4, P13, P14) and triggered their curiosity toward the visualization. Another noteworthy design pattern is **embellishment**. Such decorative visual elements have been found to benefit the reception of visualization [7]. For example, Fig. 4-5 [34] decorates the line chart with an illustration of the Eurasian jay. P38 said, "*when looking at it, I assumed that the visualization is about saving wildlife, specifically for birds, and I started getting interested in it.*"

***Color Hook (C3)***. This category uses color size, saturation, and hue to capture readers' attention and evoke their feelings and emotions. The majority of participants mentioned that **chunks of color** can result in a sense of visual intensity. For example, when reading Fig. 4-6 [101], P16 felt "*the large expanse of red immediately catches my attention and shocks me.*" In addition, the participants frequently suggested the use of **highly saturated colors** in a visualization makes it arousing and exciting. For example, Fig. 4-7 [105] visualizing firms behind carbon emissions uses yellow as its background color. P9 noted, "*The eye-catching yellow gives the visualization a sense of energy and urgency. I'm drawn in because it feels bold and intense rather than a boring data chart.*" Another design pattern in this category is **complementary colors**, which refers to combining pairs of 'opposite' colors on the color wheel to create a sense of harmoniousness. For example, Fig. 4-8 [96] uses the combination of red and blue to produce "*a perfect match*" and "*encourages comparing the difference between the two colored components*" (P2). Also, **gradient colors** help create a gradual transition between different hues, shades, and tints, which can add depth, texture, and vibrancy to visualizations. For example, P15 noted that Fig. 4-9 [109] uses "*different shades of pink to create a sense of extension, which looks quite comfortable.*"

### 4.2 Level 2: A Closer Investigation of "Flesh and Bones"

Statements involved in the second level depict readers' attempts to understand the message communicated by a visualization in detail. Level 2 serves as the middle phase of our model, where readers process information concerning the "flesh and bones" of a visualization. Specifically, Level 2 emphasizes more on the content of a visualization in terms of how it tells a data-driven story, such as showing relationships and revealing patterns [28]. Consider the following sentence regarding Fig.4-18 [104].

"*The title explains the main idea of the visualization, 'the planet is heating'. It was also easy to deduce that the transition from blue to red in the chart is a sign of gradually increasing temperatures. the visualization was clearly presented and I could grasp the message in no time. It deserves a 'like'*" (P25).

This sentence indicates that readers respond to the content of a visualization with a slow, analytical, and logical approach. Also, the visualization which is capable of delivering the maximum amount of content in the least amount of space while still being easy to digest [28] can reach a wider reader and also provide necessary food for thought for entering Level 3.

*4.2.1 Scopes.* Scopes with this level refer to local, essential elements that contribute to data-driven storytelling in a visualization, including **data** ("*The data is sourced from UCLA and published by Financial Times, which is generally considered a highly credible source (P15)*", "*It visualizes data from 2011 to 2020, I'll give it a shot considering its timeliness (P23)*"), **visuals** ("*I get that the darker shade represents higher air pollution levels, but I'm curious as to why purple was chosen for color encoding (P19)*", "*The visualization is quite unique. The blue-to-red color gradient clearly indicates temperature levels, with blue being cooler and red being hotter. It's self-explanatory and doesn't require a legend (P7)*"), and **narrative** ("*After reading the title, I was initially confused about the topic. However, the annotations provided clarity by discussing the lack of progress on both the nuclear threat and global warming (P3)*", "*What exactly does 'net zero' mean? I assume it's related to carbon neutrality, but I need more details before I can commit to it (P28)*".

*4.2.2 Design Patterns.* Design patterns at this level use visuals combined with narrative to facilitate the comprehension of data in a visualization. They can be grouped into the following three categories,

***Information Accessibility (C4).*** This category provides details and explanations to signal the transparency and trustworthiness of information presented in a visualization. Visualizations that involve terminologies and abbreviations may set the bar high for readers to understand and interpret. Thus, **explained terms** are necessary. For example, when encountering terms such as AQI (air quality index), the participants (P31, P39, P40) lost enthusiasm for reading and decided to skip that post. On the contrary, Fig. 4-10 [97] uses full names in its data source and legend, which "*present information as clearly as possible and convey a respect for readers*" (P17). In addition, **an explicit legend** can provide readers with a framework for accurately interpreting the data. For example, Fig. 4-11 [107] uses an orange-blue diverging palette in the map, which can be easily mapped to its legend. In the legend, "*it displays the hottest and coldest temperatures in both Fahrenheit and Celsius degrees, making it easy to comprehend at a glance*" (P23). Third, **timely annotations** are frequently used to explain key information or counterintuitive facts, helping answer questions and achieve a sense of enlightenment. For example, Fig. 4-12 [95] adds an annotation to the turning point of the trendline of the bar chart, answering readers' questions when reading the title, why Africa's elephant population is falling.

***Visual Anchoring (C5).*** This category guides readers to quickly identify areas of interest within a visualization by suggesting a clear information flow. The first design pattern is **highlighting**, which uses bright colors, big sizes, or conspicuous positions to direct readers' attention to a focal point at first. For example, P37 read the title of Fig. 4-13 [25] first due to its bold fonts, then noticed the yellow area due to its bright color. Combining these two pieces of information, she quickly understood the core idea conveyed by the visualization. Second, **drawing a line or arrow** from one element to another can emphasize the relationship between the two elements and guide readers' eyes along that path. For example, Fig. 4-14 [103] uses a black arrow and contour line to emphasize where is Amazon basin in Brazil, which is "*easy to follow*" (P37) and "*reader-friendly*" (P34). The last design pattern is **proximity**, which places related elements such as chart and legend, axis and unit, close to each other to form a group, enabling readers to quickly identify the required information. For example, the legend of Fig. 4-15 [100] is placed on the left side of the stacked area chart, and the legend item markers can be easily associated with the corresponding area series through color, from top to bottom. P34 noted, "*although this chart shows multiple data dimensions, it's clear and easy to understand.*"

***Color Associations (C6).*** This category uses color to associate specific elements in a visualization, supporting interpreting concepts or ideas. **Semantically-resonant colors** is a design pattern frequently mentioned by the participants, which refers to color choices that are evocative of a given concept. For example, Fig. 4-16 [102] uses the gray rectangles in the treemap to show land that is unused by humans while the colored rectangles encode three-quarters of all land used by humans. The colored rectangles also employ colors of common associations. "*I can quickly get the idea as the treemap uses green to show the used forest and brown to show the used cropland*" (P3). Besides, many participants mentioned the importance of **echoing with color**, that is, using identical colors to associate textual and visual information. Typical examples include Fig. 4-17 [110], which indicates a reading path using color, "*I read from the title to the visualization, and then to the annotation, all of them use the same color*" (P27).

### 4.3 Level 3: Tapping into "Heart and Soul"

Statements included in the third level explain how readers identify with the core values of a visualization and reflect on its underlying themes. Level 3 appears at the end phase of our model, where readers tap into the "heart and soul" of a visualization by resonating or empathizing with its central insight or main idea. Reaching Level 3 indicates successful completion of the preceding level by receiving the message conveyed by a visualization, accompanied by more profound reflection and a connection with personal experiences. Consider the following sentence regarding Fig. 4-13 [25].

"*In my opinion, the conclusion of this visualization is in line with what I've observed firsthand, and I'm convinced that the decrease in industrial activities during the lockdown is the main reason for the improved air quality in Beijing. What this means is that Covid-19 has inadvertently contributed to environmental management, which is a pretty compelling argument*" (P31).

This sentence implied that reactions to the core message of a visualization are characterized by more integrated and internalized responses. Also, the visualization being regarded to elicit resonance and build trust in data findings can have positive effects on engagement, memorability, or even motivation on action [59].

*4.3.1 Scopes.* Scopes with this level refer to thematic and more in-depth thinking toward a visualization, such as **subject** ("*With so many wolves being reduced, protecting wildlife has become an* *urgent matter (P25)*", "*It feels like I can't do much in the face of global warming, but at least I don't contribute to it by driving an electric car and using an environmentally-friendly air conditioner (P14)*"), **insight** ("*This visualization depicts the general trend of air pollution worsening over time, with the exception of 2019, and I wonder why is that (P23)*", "*I learned from the area chart that greenhouse gas emissions from various sources are declining (P16)*"), and **conclusion** ("*I can't believe that a quarter of the ice-free land is unused by humans. Considering how deserts and mountains have been successfully inhabited, it's only a matter of time before this land is used, right? (P6)*").

*4.3.2 Design Patterns.* Design patterns at this level mainly use narrative to augment the core values of a visualization in an engaging and relatable manner. They can be grouped into the following two categories,

***Narrative Voice (C7).*** This category describes the format through which a visualization is communicated, an intimate narrative voice can help establish a deeper connection between readers and the story delivered by a visualization. Using **the first person pronouns** is a helpful method to allow readers to feel closer to the story and relate to it more easily. For example, P27 mentioned that in Fig. 4-18 [104], the annotation of the temperature trend, "we are here", "*immediately caught my attention and evoked empathy for the situation: this summer has been unusually hot, it hasn't rained for a long time.*" Using **the second person pronouns** can also be effective to involve readers in the story. It breaks the forth wall of visualizations by acknowledging the existence of readers and speaking to them directly [87]. When reading Fig. 4-19 [12] which directly addresses readers in its title, "cut back email if you want to fight global warming", P2 felt "*more engaged and connected as it feels as if I'm part of the story*".

***Takeaway Messages (C8).*** This category emphasizes the main idea or key message of a visualization to promote self-reflection and a call to action. First, **cohesion** links the headline of a visualization to its visually prominent features, creating the effect of bringing data-driven storytelling full circle. For example, Fig. 4-20 [99] conveys the main idea of "Britain has reduced its carbon emissions more than any other rich country" in its title, while in the line chart, the decreasing trendline representing Britain, its color, and the bold font of the annotation all echo the title. "*It holds things together and presents the conclusion very clear*" (P29). Also, many visualizations were observed to list **next steps** by providing solutions to the discussed issues. For example, Fig. 4-21 [33] shows advice for reducing carbon footprint using a bubble chart, with bubble size illustrating emission savings. P13 related the advice to herself, "*having one less child can reduce a significant amount of $CO_2$ emissions. It seems that as a DINK (Double Income No Kids), I'm doing the Earth a favor.*" The third frequently mentioned design pattern is using **prediction** to provide a glimpse of future data trends. For example, Fig. 4-22 [98] uses a forecast visualization to show global $CO_2$ emissions under different scenarios by 2050. P17 noted, "*I'll give it a heart, as it visualizes both the present and the future, I can learn more from it.*"

## 5 User Study

To evaluate the effectiveness of our model on the communication of visualization, we conducted an online crowdsourcing within-subjects design user study.

### 5.1 Methodology

The study simulated the scenario where participants exhibit a reactionary behavior, like or skip, when exploring a visualization post on Instagram, similar to that of our preliminary study.

***Stimuli.*** To prepare the stimuli for our user study, we first selected a set of eight visualizations published by five different news outlets (e.g., the Economist, USA Today) from our corpus with less

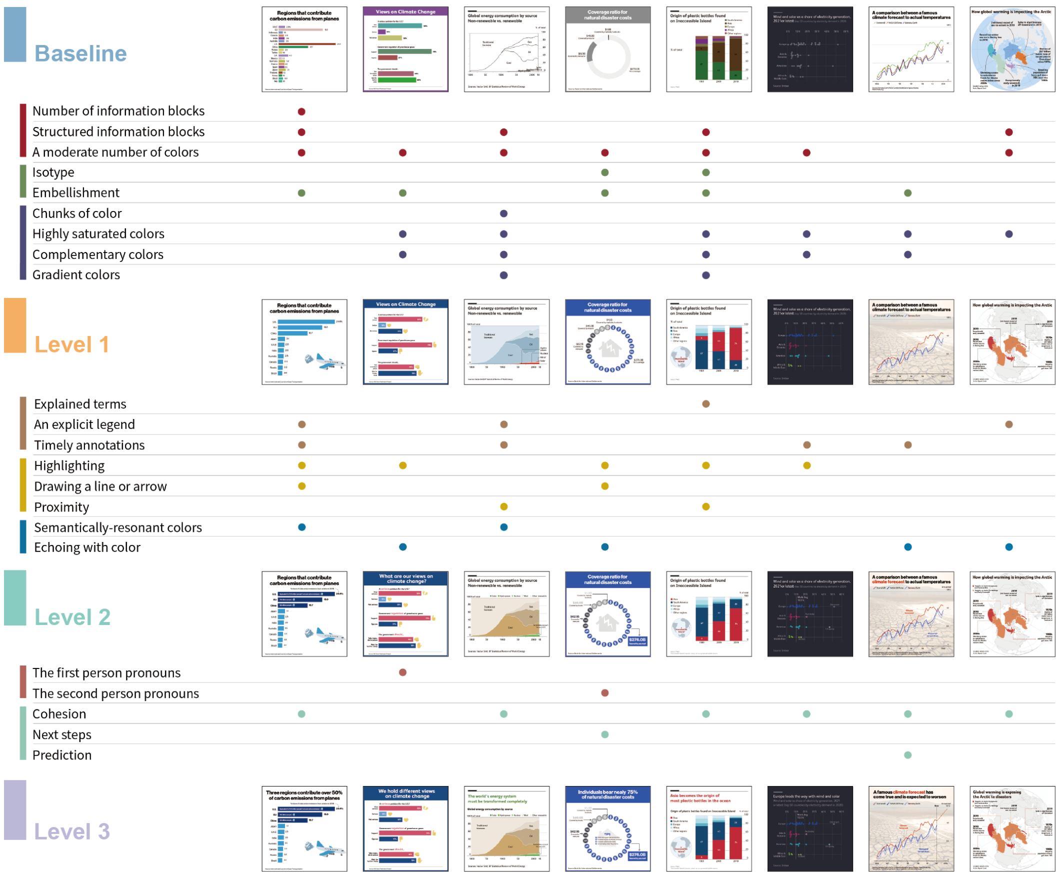


Fig. 5. We created four different counterparts (V0-V3) based on each of the eight visualizations selected from our corpus. The figure rows show all changes for each visualization across the four counterparts.

than 15k likes ($M$ = 4895.13, $SD$ = 5181.04). We then invited two experts, a data journalist and a visualization designer with more than five-year professional experience, as a group to create four different counterparts (V0-V3) based on each of the eight visualizations. To do this, the details of our model were first explained to the experts via a step-by-step walkthrough. For V0, the experts adapted the eight visualizations as the baselines by excluding features that were listed as the design patterns in our model (e.g., removing annotations, replacing highly saturated colors with darker colors) and following minimalist design rules [3, 7]. Note that while not all real-world visualizations exclude all of these "liked" features, we excluded a large number of them for each baseline to maximize the chances of these features affecting participant performance in counterparts V1-V3. V1, a counterpart of V0, was created by following the design patterns at Level 1. Similarly, V2 was created based on V1 using the design patterns at Level 2 while V3 was created based on V2 inspired by the design patterns at Level 3. As a result, 32 visualizations (8 visualizations × 4 counterparts) were created and constituted the stimuli of our user study. The stimuli were divided into four groups, with only one counterpart (V0, V1, V2, or V3) of the eight visualizations included in each group. The specific changes made between V0, V1, V2, and V3 for each visualization are shown in Figure 5. The details of the stimuli are outlined in our explorer, https://idvxlab.com/infocommunication.

***Hypotheses.*** As suggested by previous studies in mass communication [6, 28], the communication of visualization is usually measured by social media signals such as likes. Also, our preliminary study identified a set of characteristics pertaining to visualizations being liked, which were used as another aspect of measurements. Thus, we form hypotheses as follows,

**H1** V1, V2, and V3 receive significantly more likes than V0 (**H1a**). Among V1, V2, and V3, V3 performs significantly better than V1 and V2 (**H1b**).

**H2** V1, V2, and V3 are perceived to be significantly more *interesting*, *clear*, *inspiring*, *simple*, *colorful*, *easy to understand*, *important*, and *useful* than V0 (**H2a**). Among V1, V2, and V3, V3 performs significantly better than V1 and V2 (**H2b**).

***Participants.*** To estimate the appropriate sample size of our study, we performed a power analysis in Independent Samples t Test. The results indicated that at least 64 participants should be recruited for each counterpart condition to achieve a 0.8 statistical power with an $\alpha = 0.05$. Thus, we recruited 200 participants (90 females) aged between 18 and 66 ($M = 31.6$, $SD = 10.1$) from Prolific. The participants are fluent in English and have different cultural backgrounds (e.g., the United States and Italy). Their education levels (some high school or trade school: 2.8%, high school diploma: 31.1%, Bachelor's degree: 48.3%, Master's degree or above: 17.8%), expertise in visualization (novice: 25.6%, advanced beginner: 28.3%, competent: 30.6%, proficient: 15.6%), and the frequency of reading visualization posts on social media (never: 2.8%, rarely: 10.6%, occasionally: 47.2%, often: 34.4%, always: 5%) also vary. Each of the participants was paid $8 for completing the study.

***Task and Procedure.*** The user study consisted of three sessions: the **tutorial**, **reading**, and **recall** sessions. In the tutorial session, we introduced the goal of our study and core concepts (e.g., visualization post, Instagram). In the reading session, we first divided the 200 participants into four groups, and each participant was presented with one of the four stimuli groups. We ensured that each stimuli group was read by 50 participants. The order of the stimuli in each stimuli group was randomized to avoid confounding effects. After the participants finished reading a visualization post, they were required to make a choice between like and skip. Then, they were asked to rate it on the eight measurements described in **H2** using a 5-point Likert scale. They were also encouraged to provide reasons explaining their options. One week after the reading session, we sent emails to the participants to inquire about their willingness to participate in the following recall session online. The goal of the recall session was to explore the long-term effects of liking a visualization, assessing how initial engagement influenced participants' lasting impressions and memory. We invited 20 of the participants who responded positively first to participate in this session. In the recall session, we first asked the participants to redraw as much as they could remember about the stimuli they had read using Figma. For each of the stimuli, we also asked questions such as "Do you remember the subject matter of the visualization?" and "What insights or conclusions can be derived from the visualization?". The reading and recall sessions lasted about 45 and 30 minutes, respectively.

### 5.2 Results and Analysis

After the user study, we collected the quantitative data from the 200 questionnaires to conduct statistical analysis and transcribed the qualitative data from the questionnaires and the recall session to gain in-depth user feedback.

***Communication Effects.*** First, we counted how many stimuli were liked in each condition. Fig. 6 shows that 42.8% of the stimuli in V0 were liked, and the like ratio of stimuli in V1, V2, and V3 were 53.5%, 58.5%, and 63.0%, respectively. Then, a chi-square test was conducted to analyze the significance of their mutual differences. The results showed that the like ratio of V0 was significantly

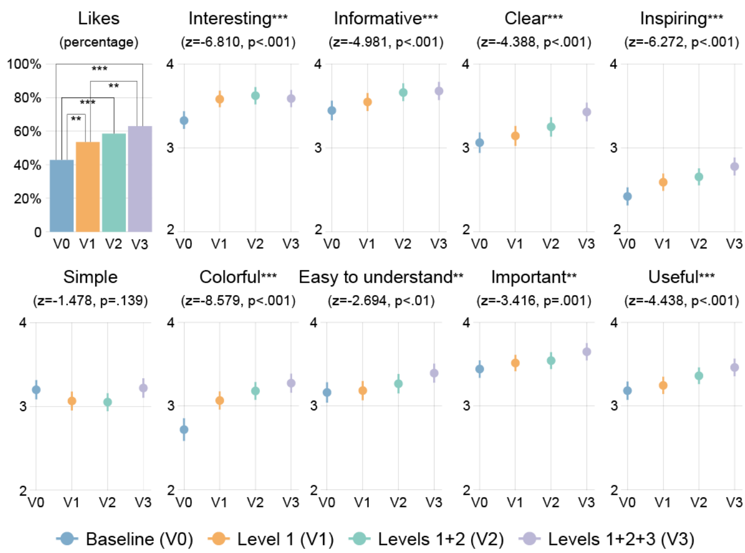


Fig. 6. Quantitative results of like ratio and measurements of visualizations between the baseline (**V0**) and the three levels (**V1-V3**). Specifically, all measurements are measured by user ratings on a 5-point Likert scale while the y-axis range is adjusted to 2-4 to improve the readability of the data points. Error bars show the 95% Confidence Interval (CI) of the means. Likes as well as all measurements except for *simple* showed significant differences. Statistically significant results are reported as $*$: $p < .05$, $**$: $p < .01$, $***$: $p < .001$).

lower than that of V1 ($\chi^2 = 9.258$, $p = .002$), V2 ($\chi^2 = 19.848$, $p < .001$), and V3 ($\chi^2 = 32.914$, $p <$ .001) (**H1a** accepted). There is also significant difference between V1 and V3 ($\chi^2 = 7.422$, $p = .006$) (**H1b** partially accepted). However, the differences between V1 and V2 ($\chi^2 = 2.029$, $p = .154$), V2 and V3 ($\chi^2 = 1.699$, $p = .192$) were not significant.

***Reader Perception.*** To perform statistical analysis on the ratings of the visualizations, Wilcoxon Signed-Rank tests was used to compare V0 with V1-V3 as a group. We found that V1, V2, and V3 showed significantly higher scores than V0 across eight out of nine measurements (Fig. 6), including *interesting* ($z$ = -6.810, $p < .001$, $r = 0.144$), *informative* ($z$ = -4.981, $p < .001$, $r = 0.112$), *clear* ($z$ = -4.388, $p < .001$, $r = 0.105$), *inspiring* ($z$ = -6.272, $p < .001$, $r = 0.135$), *colorful* ($z$ = -8.579, $p < .001$, $r$ = 0.233), *easy to understand* ($z$ = -2.694, $p < .01$, $r = 0.086$), *important* ($z$ = -3.416, $p = .001$, $r = 0.158$), and *useful* ($z$ = -4.438, $p < .001$, $r = 0.130$). With respect to *simple*, the four conditions showed no significant difference ($z$ = -0.478, $p = .139$, $r = 0.115$) (**H2a** partially accepted). Then, Kruskal-Wallis H tests were used for the mutual comparison among V1-V3. Among these conditions, V3 performed significantly better regarding *clear* ($p < .05$) and *useful* ($p < .05$) than V1 (**H2b** partially accepted).

***Improving the Effectiveness of the Message.*** We observed that when the participants found a visualization easy to understand, they were more inclined to like it. For Level 1, **figurative representation** helps attract the participants and makes them grasp the subject matter of a visualization quickly (e.g., "*the coin symbol is effective in immediately conveying the theme of the visualization related to money*" (P7), "*the use of emojis to depict public attitudes towards climate issues is an innovative approach. It facilitated a prompt comprehension of their stance*" (P16)). **Complementary colors** was also frequently mentioned as effective in facilitating data comparison (e.g., "*utilizing of contrasting colors for distinct data sets has proven effective in making information visually distinct and discernible, thereby enabling me to differentiate between various pieces of information*" (P175)).

For Level 2, the participants reported that **structured information blocks** and the **highlighting** of key information can accelerate their reading speed and efficiency (e.g., "*placing the title at the top, presenting it in a large and bold font, and coding key information in red within the chart are effective design techniques that greatly facilitate my reading process*" (P3)). Some of the participants mentioned their appraisal of **timely annotations** (e.g., "*the use of a dashed line to connect the data of four regions, representing the global average in this visualization, effectively enhances contrast and accentuates the rich content hierarchy, leaving no opportunity for expression wasted*" (P16)). Besides, **semantically-resonant colors** was appraised by the participants (e.g., "*drab colors are effective - soil feel. The browns mean a connection with the earth. Green renewables is a good highlight*" (P125)). For Level 3, the participants thought that **cohesion** had quickly helped them gain takeaway messages (e.g., "*alignment between the title and key components of a visualization facilitates my decision to engage with it, based on my familiarity with the topic and the major points conveyed. If the visualization does not capture my interest, I tend to skip it*" (P4)).

***Increasing the Credibility of the Message.*** We found that the recognition of the credibility and trustworthiness of visualizations was another reason for likes, which is in line with previous findings [30]. Some of the design patterns in our model were related to such characteristics. For Level 1, **structured information blocks** provide a perceptually fluent visualization, enhancing the credibility of the information (e.g., "*lots of data but laid out in a clear and interesting way which encourages detailed reading*" (P110), "*I find it well laid out, and well readable, accurately provides the requested information. I can read it and find what I need*" (P164)). When **structured information blocks** was combined with **a moderate number of colors**, one participant commented, "*the display exudes professionalism with an elegant color palette, well-balanced image and text. It is the best one so far*" (P71).

For Level 2, **timely annotations** is able to reduce the perceived bias and increase the educational value of visualizations (e.g., "*the level of detail and professionalism in the writing was exceptional. I gained a thorough education on a topic that I had previously overlooked, which was a pleasant surprise*" (P158)). **An explicit legend** improves users' perception of data accuracy (e.g., "*the chart legends follow a sensible pattern, providing me with a great deal of specific information, which avoids misunderstanding. It is clear that the chart was professionally designed*" (P143)). **Explained terms** can improve the comprehensibility and credibility of a visualization. The explanation of "Inaccessible Island" in the visualization addressed P160's skepticism about the data source, "*so Inaccessible Island actually exists. I thought it was just a pseudonym or something the author made up.*"

For Level 3, **cohesion** adds to the trustworthiness of the information presented (e.g., "*the use of a conclusive result is effective in communicating the importance and the correctness of the data presented. It suggests that the data is complete and conclusive*"(P175)).

***Augmenting the Expressiveness of the Message.*** Our observations indicated that participants were more inclined to click 'like' on a visualization post when they felt inspired and actively engaged in forming a connection with the visualization. Certain design patterns in our model contribute to this feature. For Level 1, **embellishment** that echoes the theme can increase the perceived familiarity (e.g., "*I use emojis frequently, so when I saw it in the content, it immediately caught my attention. It perfectly aligns with the expressive tendencies of our generation*" (P16), "*using emojis makes the content feel more contemporary and relatable. It is an engaging feature that I have come to expect when interacting on social media*" (P62)). For Level 3, incorporating **the first person pronouns** enhances the perception of personal involvement in the information. After reading the title "our views on climate change," P87 started comparing his own answers with the data in the visualization. He became puzzled and wondered, "*why do most people think environmental problems are serious but are not inclined to take action immediately?*" Using **the second person**

**pronouns** generates a conversational atmosphere (e.g., "*the phrase 'beared by yourself' immediately transported me into the scenario*" (P13), "*it is very social media-friendly, as people are attracted to this type of post. It prompts you to question where you stand within each percentage and encourages you to read the entire post to learn more*" (P142)).

***Triggering Affective Responses.*** We observed that when the participants explored colorful, interesting, or inspiring visualizations, they were more likely to experience certain emotions or feelings and preferred to like it. For Level 1, many of the participants were emotionally aroused due to **figurative representation** and **gradient colors**. For example, when viewing a visualization with pictorial embellishment, one of the participants said, "*these emojis look playful*" (P4), and another thought, "*the data appears to possess a certain warmth that prevents it from feeling impersonal*" (P6). Regarding **gradient colors**, we received feedback such as "*the variations in color intensity create an effect that resembles watercolor paintings, resulting in a visually pleasing and soothing aesthetic*" (P7).

For Level 2, the use of **semantically-resonant colors** encourages the participants to infer the symbolic meaning of coloring and resonate with the emotions conveyed therein (e.g., "*the red and orange makes me think about global warming and invokes feelings of urgency*" (P27)). **Drawing a line or arrow** serves as " *unexpected surprises that not only guide the viewer's attention but also disrupt their expectation of a conventional layout for the visualization, creating a sense of excitement and playfulness*" (P4). Also, nearly a quarter of the participants reported that they clicked the skip button because they did not experience strong emotions. As P4 stated, "*using desaturated colors can be likened to a calm narrative, while highly contrasting colors can be compared to sensational headlines that abruptly seize readers' attention*". For visualizations that the participants clicked the skip button, "boring" was mentioned as many as 341 times, mainly due to "*lack of color*", "*too 'earthy' and too similar colors*", which suggests the importance of design patterns such as **a moderate number of colors** and **complementary colors**. For Level 3, the participants noted that using **the first or second person pronouns** can "*create a sense of intimacy or highlight impact on individuals*" (P17).

***Enhancing Information Recall.*** In general, the participants' memory of the visualizations faded remarkably after one week. We coded the 160 redrawing visualizations (20 participants $\times$ 8 visualizations) collected from the recall session and found that 137 out of 160 visualizations were able to be more or less recalled by the participants. Usually, the participants could only recall high-level messages, such as the insights provided by the visualizations (recall ratio = 56%) and their own conclusions drawn from the visualizations (55%). As for the design of the visualizations, visualization types (96%), icons (86%), colors (72%), axis (66%), titles (44%), and annotations (31%) could be recalled by certain proportions of the participants. Only a few of the participants could recall numerical values. This indicates that design patterns such as **embellishment**, **complementary colors**, **highly saturated colors**, **chunks of color**, and **timely annotations** can leave a deep impression on the participants. We also found that more information from the visualizations being liked could be recalled than that from the visualizations being skipped, including insights (like: 67%, skip: 47%), conclusions (like: 62%, skip: 49%), titles (like: 50%, skip: 39%), and annotations (like: 37%, skip: 27%).

Regarding the four conditions (V0-V3), we found that the visualizations in V1-V3 elicited a stronger impact on the participants than those in V0. Specifically, the participants could recall 82% ($N$ = 36) of the visualizations in V0, while recall ratios for V1, V2, and V3 were 84% ($N$ = 37), 86% ($N$ = 31), and 92% ($N$ = 33), respectively. Regarding elements that were remembered, V1-V3 all performed better than V0. For example, V3 clearly outperformed V0 in terms of the proportion of recall on title (V3: 58%, V0: 36%), annotation (V3: 39%, V0: 22%), insight (V3: 64%, V0: 42%), and conclusion (V3: 64%, V0: 39%). Interestingly, we found that ill-designed visualizations also left an impression on the participants, such as the haphazard color scheme and overlapping elements. The reason may be that "*bad design prompts me to consider alternatives*" (P4).

## 6 Discussion

In this section, we discuss design implications regarding our model as well as the limitations of our current work.

### 6.1 Possibilities for Models of Visualization Communication

Our three-level model provides an initial descriptive framework that engages social media readers with visualization. However, a single visualization is unlikely to incorporate all of the design patterns identified in our three-level model. This provides an opportunity to refine the model into more specific design guidelines that prioritize certain scopes and patterns depending on the communication goals. For example, if the goal is quickly capturing attention, emphasizing novel artistic styles may be most impactful. For conveying key insights, the textual narrative and conclusion may deserve primary focus. The relative importance of different patterns likely depends on the desired effect and social platform constraints.

Our findings reveal tendencies for social media environments where skimmability is critical. Guidelines tailored for this domain could highlight balancing elaborate graphics with visual clarity and brevity for easy consumption. For example, for visualization types that are less common to the public, such as scatter plot and treemap, the participants complained about their "*complexity*" and "*obscurity*". One reason explaining this finding is the lack of visualization literacy of readers [17]. Thus, accessible material such as cheat sheets [114] that support a wider audience in understanding visualization techniques should be explored in the future. Another reason is the great amount of data and information conveyed by such charts. Thus, we recommend that designers maintain the simplicity of visualizations by carefully selecting the data to visualize, such as providing timely annotations at only critical data points in scatter plot instead of describing all data dimensions. Also, designers should better guide readers to engage with an appropriate amount of information at each step of their reading experience. By doing so, readers can peel off the layers of a visualization and "*draw the conclusion from step-by-step analysis*" (P7).

### 6.2 Engaging Readers for Visualization on Social Media

Engaging readers beyond passive consumption is crucial for impactful visualization communication on social media. For example, in our preliminary study, P25 exclaimed, "*I am confused about why elephant numbers have decreased post-ivory trade ban. I feel saddened and want to raise awareness about their significance through commenting and reposting to garner wider attention.*" This suggests that he not only spent a few seconds on a single post, but actively engaged with the visualization by reading, commenting, and sharing. Compared to merely liking, commenting and sharing demonstrate a higher level of engagement. Thus, effective visualization posts should aim to inspire critical thinking, strengthen emotional connections, improve attention span, and prompt further actions beyond likes. Our suggestions include enhancing the data-driven storytelling of visualizations. For example, providing contextual information in the user comments of a visualization post, such as statistical data and expert commentary, can help readers better understand its background and motivation, thereby increasing the credibility and depth of the narrative. Second, starting with a small and accessible aspect of a broader topic can be beneficial. For serious topics such as marine pollution, visualizing data that is more closely related to daily life, such as the number of plastic bottles, rather than displaying the total amount of garbage over the years, can be more helpful. By bringing data findings closer to people's daily experiences, it can be easier for them to empathize with the message. Third, enhancing the interactivity of visualizations is crucial. For example, incorporating quizzes and polls asks for readers' input and allows their data to become a part of visualizations, enabling a deeper self-story connection [87].

### 6.3 Visualization Design for Social Media

The high volume of visualization being consumed on social media puts forward new requirements and future research directions for visualization design. When creating visualizations for casual, skimmable reading formats, two approaches can be used to improve the efficiency of information communication. One is to augment the comprehensibility of visualization by making the essential information highly identifiable. For example, **highlighting**, which was more frequently mentioned in the preliminary study and user study, is able to increase the speed at which people find the key information. Another approach is to improve user retention and time spent exploring visualization posts. For example, **isotype** and **embellishment** with figurative graphics can boost the engagement of readers and encourage them to transfer from "skimmable" reading to "in-depth" reading. As P37 says, "*This bird looks beautiful. I think I would like to know what is happening to the little bird.*"

In addition, news outlets can capitalize on readers' perception of color and corresponding affective responses to enhance brand association [45]. For example, the Economist incorporates red from its logo into its visualizations. The red usually symbolizes authority, energy, and urgency, which could fit with the magazine's focus on current events and analysis. Also, the red has a lasting impression on the participants, leading them to form an intuitive association of "*seeing bright red and thinking of the Economist*" (P23). Thus, we encourage news outlets to consider applying the primary color from their brand identity to their visualizations, ensuring consistency across all their designs. It is also worth considering whether visualization design optimized for communication on social media may compromise the rigor and accuracy of the visualization. For example, while colors can attract user attention and evoke affective responses, they might also carry designers' preferences or even biases, which potentially compromise the objectivity of the news. For example, using highly saturated colors or complementary colors may sometimes be "*overemphasizing certain points and conveying unnecessary negative emotions*" (P12). Such concerns align with long-standing arguments in data journalism about avoiding manipulation of readers' perceptions of data [23].

### 6.4 Design Patterns of Visualization for Communication

The different communicative goals of visualizations naturally lead to a variety of design patterns. Our analysis of visualizations from various news outlets on Instagram not only echos existing knowledge but also expands and occasionally challenges previous understandings in this field. First, we found that the established design patterns align with existing findings. For example, design patterns such as **highlighting** ($n$=66) and **highly saturated colors** ($n$=17), which were frequently observed in our studies and are known for capturing attention at first glance, are also well-documented in prior research [64, 112]. This consistency underscores the generalizability and effectiveness of these visual strategies across different contexts and platforms.

Second, our research extends the current literature by uncovering additional design patterns. Previous studies on color usage in visualizations [40, 89] primarily focused on color-coding schemes and complementary colors. However, our findings highlight that the volume and variety of colors, such as **chunks of color** and **a moderate number of colors**, play a crucial role in enhancing the overall impact of visualizations. Also, we identified design patterns that, while less frequently mentioned in our preliminary study, offer promising new avenues for research. Design patterns such as **narrative voice** and **take-away message**, which are not commonly emphasized in infographics design, emerged as significant in the context of social media communication. These elements help users to better understand and retain the information presented, suggesting that a more narrative-driven approach can be highly effective in digital media environments.

Third, some of our conclusions may challenge current findings regarding visualization design. Traditionally, clarity and simplicity have been paramount, adhering to the principle of maximizing the data-ink ratio by minimizing decorative elements [79]. However, our work suggests that in the realm of mass communication, especially when engaging audiences with lower visualization literacy, the inclusion of "data junk"—decorative or non-essential elements [7, 9]—can enhance understanding. This counterintuitive finding prompts a reevaluation of minimalist design philosophies and encourages a more nuanced approach that considers the diverse needs of audiences.

### 6.5 The Multifaceted Role of Likes on Social Media

As one of the most common and easily quantifiable metrics on social media, the "like" encompasses diverse meanings and functions, reflecting a complex interplay of user behaviors and motivations. In our study, likes primarily serve as an indicator of communication effectiveness, signaling that information has been effectively disseminated and understood by the audience. However, it is essential to recognize that likes can be influenced by factors beyond the intrinsic quality of the content. For example, a well-executed and clear visualization might not receive likes if it conveys distressing information about environmental degradation, while a visualization with a positive message might garner likes despite being unclear or aesthetically lacking.

Beyond serving as a quantitative metric, likes can signify a range of user responses. They can act as social proof, demonstrating that others find the information credible and valuable. This collective validation enhances the perceived trustworthiness of the content, as studies have shown that social media ads with higher like counts are viewed as more trustworthy, leading to more favorable attitudes towards the brand [85]. This underscores the power of social validation in shaping user perceptions and interactions. Likes also reflect collective user interest, providing a snapshot of what resonates with the audience. User preferences, expressed through likes, offer a valuable gauge of interest, serving as an effective means of sharing and promoting content on social media [46]. However, it is important to acknowledge that a "like" does not fully equate to a user's value judgment or endorsement of the content. Many users employ likes as a bookmarking tool, a way to guide recommendation algorithms, or as a "soft share" mechanism to push liked content to friends. Research also indicates that a "like" from a friend can even prompt users to engage with content they were previously uninterested in [71].

### 6.6 Limitations and Future Work

There are several limitations of our work. First, the model was developed by analyzing a corpus of 252 visualizations pertaining to environmental-related topics while topics such as poverty and education share similar features such as long-standing and of broad public interest. Thus, future research can include visualizations of diverse topics in the corpus to increase the generalizability of our model. Second, although our user study included 200 participants, the audience for visualizations on social media is highly diverse. Factors such as living environment, cultural background, and economic status can significantly influence their decision to hit the like button. To address this diversity, our future work will explore the demographics of users relative to their preferences. For example, we will investigate whether individuals with higher visual literacy find visual complexity less problematic compared to the general population, who might prefer simpler visualizations. Third, regarding communication channels, while we have simulated the scenario of reading visualizations on Instagram, certain factors have not yet been taken into accounts such as the specific timing of visualization dissemination and the duration of their exposure. Thus, future work can explore the effect of publishing stimuli at different timing, prolonging exposure duration, and tracing the like data of visualizations. Finally, the decision of hitting a like button usually happens within a dozen seconds while think-aloud protocols used in our preliminary study may not fully capture every thought and detail when the participants read visualizations. The design patterns identified may also be related to the participants' moods, expression skills, and visualization literacy. Future work can explore more techniques such as electroencephalography and eye-tracking to help supplement the development of our model with more materials.

## 7 Conclusion

This paper introduces a three-level model categorizing how readers interact with and respond to data visualizations on social media. The three levels include overall "look" upon first glance, a closer investigation of "fresh and bones", and tapping into the "heart and soul" of visualization. Each level can be described along two dimensions: scopes and design patterns. The results of the user study suggested that our model can positively affect communication effects and reader perception of visualization posts. The model advances knowledge of crafting compelling data narratives tailored for digital channels, where visualizations can capture fleeting user focus within endless content streams. This work represents an initial step toward bridging theories of mass communication and information visualization. We also hope our findings can inspire further exploration of visualization communication principles, leveraging models of communication to systematically design engaging visualization.

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