The Hue-Man Factor: An Empirical Evaluation of Visualization Perception and Accessibility Across Color Vision Profiles

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Fig. 1: Five core accessibility challenges surfaced by color vision deficient (CVD) participants during our qualitative feedback study. For each chart, participants viewed both the original and a simulated version (rendered using Adobe Illustrator [1]). Quotes reflect their experience interpreting the original (left side of each chart pair), while simulated views (right) provide context for how the visualization may have appeared. While simulations approximate some aspects of CVD perception, participants emphasized that visual appearance alone does not capture the full extent of interpretive difficulty.

Abstract—Color is a powerful tool in data visualization, but for individuals with color vision deficiencies (CVD), hue can become a barrier rather than an aid. In this paper, we examine how real-world visualizations are perceived across vision profiles through three complementary studies. Study 1 assessed how normal vision participants rated 46 visualizations shown in original and simulated red/green colorblind versions. Study 2 collected matched responses from participants with diagnosed CVD. Study 3 involved in-depth interviews exploring how users interpret, adapt to, and evaluate inaccessible designs. Across studies, we find that simulations capture directional perceptual shifts but fail to reflect the interpretive breakdowns and emotional work described by real CVD users. Factor analysis reveals two dominant perceptual dimensions: functional utility and affective experience. While normal vision participants prioritize functional clarity, CVD users rely more on structural cues and emotional resonance, particularly when color is unreliable. Qualitative insights show that perceptual breakdowns occur not only in high-interference charts but also when redundant encoding or layout scaffolding is missing. We synthesize these findings and offer empirically grounded design recommendations to guide inclusive visualization practices. Our results argue that accessibility must go beyond color correction, embracing structural clarity, redundancy, and real-user validation to ensure inclusive visual communication.

Index Terms—Information Visualization, Perception & Cognition, Colorblindness, Accessibility

1 Introduction

Color is a powerful design channel in data visualization. It can encode categorical and quantitative information [51], guide attention and emphasize narrative [2, 31, 32], and shape the affective tone of a visual display [44, 68]. Yet, despite its communicative strengths, color can also serve as a barrier to accessibility. Approximately 1 in 12 men and 1 in 200 women globally experience some form of color vision deficiency (CVD) [8], with red-green deficiencies being the most common [82]. When visualizations rely heavily on color, they can hinder comprehension, increase cognitive load, and reduce user trust [9].

While visualization researchers have long offered design heuristics for colorblind accessibility—such as using luminance contrast, redundant encodings, or avoiding red-green pairings [48, 74, 76]—these recommendations are often general and inconsistently applied. Simulation tools, like those embedded in Adobe applications [1], attempt to preview how visualizations might appear to individuals with CVD, but few studies validate whether these simulations accurately reflect lived experience. As a result, accessibility decisions are often reactive rather than proactive, with responsibility falling on the viewer to interpret content not perceptually designed for them.

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Moreover, empirical evidence about what kinds of design choices truly improve accessibility for color-deficient populations remains sparse. Prior work has primarily focused on visual search tasks or palette preferences [2, 6], with limited investigation into how CVD affects broader aspects of visualization perception, such as emotional impact, narrative comprehension, or trust. Equally underexplored are the adaptive strategies CVD users employ when navigating inaccessible visualizations—how they reinterpret, work around, or compensate for missing visual cues. In response, recent scholarship has called for a shift away from post-hoc "correction" towards inclusive visualization practices that foreground the needs of diverse perceptual audiences [45, 81]. This perspective emphasizes that designing for accessibility is not merely a technical challenge, but a question of equity in information access—especially in domains like public health, climate communication, and social justice, where data-driven visuals carry high interpretive stakes [27, 30, 43, 57].

In this paper, we examine how color vision differences shape the viewing experience of real-world data visualizations. We curated a diverse set of 46 real-world visualizations from government, journalism, and scientific sources, coding each for visual structure, color usage, accessibility features, and potential for perceptual interference. Across three complementary experiments, we evaluated how participants with normal color vision and those with CVDs perceive these visualizations. In Study 1, participants (n=97) with normal vision viewed either original or simulated CVD-filtered visualizations (protanopia or deuteranopia), and rated each on six perceptual dimensions. In Study 2, 131 participants (67 with normal vision and 64 with real-world CVD) completed a matched protocol using unaltered visualizations. Finally, in

Study 3, we conducted in-depth interviews with 18 participants (six with normal vision, three from each CVD group: red-blind, green-blind, red-green blind, and blue-yellow blind), investigating how viewers interpret inaccessible designs and articulate their adaptation strategies.

Our goal is to move beyond simulation-based heuristics by grounding accessibility guidelines in the lived experiences of diverse users. Across Studies 1–3, we observed a consistent gap between simulated and real CVD experiences: while simulations captured directional perceptual shifts, they missed the interpretive breakdowns and emotional effort reported by real users—especially when visualizations lacked redundancy, structure, or contrast. Notably, challenges emerged even in low-interference charts when such supports were absent. Fig. 1 summarizes key breakdown patterns described by CVD participants.

At a high level, our findings provide both theoretical and practical insights for making data visualizations more equitable, interpretable, and perceptually inclusive. Specific contributions include the following: (i) a structured annotation framework of color properties across a set of 46 real-world visualizations, including interference potential and accessibility indicators; (ii) a comparative evaluation of simulated versus real colorblind viewing experiences across perceptual, cognitive, and affective dimensions; (iii) a qualitative analysis of how participants with different types of CVD describe, interpret, and adapt to inaccessible designs; and (iv) a set of empirically grounded design strategies to guide inclusive visualization practices.

2 Background

2.1 Perception, Cognition, and Adaptive Strategies in Visualization

Visualization perception emerges from the interplay of low-level visual features (e.g., position, length, hue) and higher-level interpretive cues shaped by layout and task demands [28, 50, 79]. Pre-attentive attributes such as proximity and contrast direct early attention [20, 77], while Gestalt principles aid grouping [35, 71]. Eye-tracking and memory studies suggest that layout, labeling, and salience play a critical role in shaping visual comprehension under cognitive load [36, 37, 54]. Higher-level interpretation also depends on domain familiarity and visual literacy [14, 53]. Semantic annotations, such as text labels, improve interpretability and reduce ambiguity [5, 10, 13]. While many models assume typical visual function, few consider how perception and strategy differ for viewers with CVD [25, 45].

Moreover, while the above literature provides a solid base, few studies explore how perception unfolds for users with CVD. Emerging findings suggest CVD users rely more on titles, shapes, or spatial grouping [59], but such strategies are rarely integrated into design guidelines, and recent scholarship calls for inclusive frameworks that combine perceptual modeling with lived experiences [45, 81]. In this paper, we combine perceptual modeling and qualitative analysis to investigate how CVD and normal vision users interpret visualizations. We evaluate six perception metrics (Table 1) and map them to latent dimensions of affective and functional experience (Sec. 4.1).

2.2 The Role of Color in Visualization

Color is a key visual channel, valued for drawing attention, encoding meaning, and evoking emotion [32, 44, 51], and is used for both categorical (hue) and quantitative (luminance) encodings [19, 46, 61]. However, its effectiveness depends on discriminability and cultural context [60, 79]. While less precise than position or length [19, 37], hue remains common due to salience. Overinterpretation of gradients is frequent in maps and heatmaps [23, 28]. Crameri et al. [22] warn that gradients like rainbow introduce false perceptual boundaries and distort magnitude perception—creating artificial segmentation even in smooth data—especially when color-bars or reference labels are omitted.

Numerous studies offer guidelines for palette selection [33, 81], emphasizing perceptual uniformity, luminance contrast, and robustness under varied vision conditions [12, 72, 73]. Tools like ColorBrewer [33] offer curated palettes tested for perceptual distinctness and CVD-safety, while Colorgorical [29] uses a quantitative model to balance visual difference, harmony, and aesthetic preference. Recent work highlights how affective tone, culture, and emotion influence color use [7, 67]. Prior work has also examined how color interacts with layout and attention [2], and how meaning is culturally constructed [7, 44]. Schloss et al. [63, 64] show that color preferences vary by culture, season, and individual experience. Color can enhance aesthetics but not always interpretability or memorability [10, 11].

While the above work provides a robust understanding of how people interact with color, few studies have systematically investigated real-world visualizations for color reliance in the context of accessibility risk. We fill this gap through a color annotation framework (Sec. 3.2), applied to diverse visualizations to assess potential CVD interference.

2.3 Color Vision Deficiency and Visualization Accessibility

Color vision arises from the brain's comparison of signals from three types of cone photoreceptors in the retina: L (long-wavelength), M (medium-wavelength), and S (short-wavelength) cones [55]. These cones are not strictly "red," "green," and "blue" sensors (those terms are oversimplifications) but instead respond maximally to different regions of the visible spectrum. Typical color vision (trichromacy) depends on the presence of all three cone types. The ability to distinguish hues arises from contrasts between these cone responses.

Color vision deficiency (CVD) affects over 300 million people globally [8] and occurs when one of these cone types is missing or functionally altered. The most common forms are protanopia (missing L-cones) and deuteranopia (missing M-cones), which impair red-green differentiation because L–M comparisons are disrupted. These forms of dichromacy also lead to confusion between colors like purples and cyans due to "confusion lines" in color space [81]. Less common is tritanopia (missing S-cones), which affects blue-yellow perception [82] and monochromacy. In anomalous trichromacy (e.g., protanomaly or deuteranomaly), all three cone types are present, but one is spectrally shifted, which inhibits color discrimination.

CVD can affect not just hue perception but also saturation and contrast sensitivity [47]. While simulation tools (e.g., for protanopia or deuteranopia) approximate the altered appearance of visualizations, they do not capture the lived experience of CVD—such as the interpretive effort, emotional impact, or compensatory strategies employed during real-world visual tasks. To address this, our study combines simulated and real user data to better understand how people with CVD navigate visualizations. By analyzing both perceptual ratings and qualitative strategies, we seek to uncover how users actively construct meaning under perceptual constraint.

For visualization design, strategies include CVD-aware palette generators [16, 21], hue selection heuristics [76], and redundant encodings [48, 81]. Naturalness-preserving recoloring methods [42] and perceptual models now support optimized palette design [17], while crowd-sourced tools evaluate accessibility in applied contexts [6]. Color correction models have evolved from basic daltonization—simulating+remapping indistinguishable colors— to advanced algorithms that enhance discriminability while preserving perceptual similarity [38, 58]. Still, major challenges remain in balancing fidelity, aesthetics, and adaptation across the diverse types and severities of CVD [78, 84]. Despite this, accessibility remains uneven. For example, many guidelines only target red-green CVD, overlooking low-acuity vision. Simulations (e.g., Adobe Illustrator [1]) approximate appearance but not usability or coping strategies. Physiological models [47] replicate cone-level distortions but miss behavioral adaptations. As recent studies show, simulated results can mask real interpretive challenges [10, 45]. As such, scholarship is increasingly calling for participatory evaluation methods [45, 81] and inclusive designs that require expanding studied conditions and centering user experience.

We help address these needs through a mixed-methods study comparing real and simulated CVD responses (Studies 1–2) and analyzing adaptive strategies via interviews (Study 3). Our findings link accessibility challenges to chart features and user-reported experience, grounding design recommendations in empirical evidence. While color correction approaches are critical to this space, we do not evaluate specific algorithms, as their implementation and efficacy depend on non-trivial trade-offs and are not the primary focus of our contribution.

3 METHODOLOGY

3.1 Research Questions

We investigate three fundamental research questions regarding the impact of CVD on visualization perception. Our analytical approach in Sec. 4 is structured around these questions, maintaining an exploratory stance without asserting specific prediction directions.

RQ1 – Effects of Color Vision Differences on Viewing Experience: How do different color vision conditions (normal vision, simulated color blindness, and actual color blindness) influence the data visualization viewing experience?

Initial theoretical considerations [2, 4] suggest that CVD may reduce both informational comprehension and affective engagement with visual content. However, to develop a robust understanding, we assess variations across six perceptual dimensions: visual appeal, topic familiarity, comprehensibility, design interest, color utility, and emotional response (see Table 1). These dimensions were selected because they align with prior work by Arunkumar et al. [4, 5], from which our stimuli are derived, where these dimensions were used to evaluate the aesthetics [5, 34], affect [44], and effectiveness [49, 56] of real-world visualizations across diverse viewer populations. By analyzing responses from participants with normal color vision, those experiencing simulated color blindness, and individuals with actual CVDs, we can therefore identify patterns in how design elements shape accessibility and the holistic user experience.

Table 1: Perceptual dimensions used to evaluate participants' viewing experiences with data visualizations.

Dimension	Example Survey Statements and Definition
Visual appeal	*"I found this visualization appealing."* How visually attractive or aesthetically pleasing is the visualization? [34]
Topic familiarity	*"I am familiar with the topic of this visualization"* How well do users know the data, topic, and visualization type? [56]
Comprehensibility	*"The visualization was easy to understand."* How easily can users extract and understand information from the visualization? [49]
Design interest	*"The design of the visualization was interesting."* How engaging are the design elements in the visualization? [49]
Color utility	*"The colors used in this visualization are helpful for understanding the data."* How effectively do the color choices enhance visualization understanding? [5]
Emotional response	*"The visualization evoked a strong emotion in me."* How does the visualization elicit different emotions? [44]

RQ2 – The Role of Visualization Design in Mitigating Color Vision Deficiency: Which visualization features help mitigate the perceptual challenges posed by CVD?

We test whether certain visual encoding channels, such as background color, number of color hues, data volume, and mark types (e.g., dots, lines, areas), *moderate* the observed measures of viewing experience. Prior research suggests that visualizations relying heavily on color encoding, especially red-green contrasts, may exhibit perceptual degradation under color blindness conditions [70, 83]. Conversely, designs incorporating redundant channels may enhance interpretability and mitigate accessibility barriers [4, 5, 18]. By analyzing user responses across different visualization designs, we aim to determine which attributes contribute to more inclusive and robust visual communication.

RQ3 – Understanding the Mechanisms Behind Simulated vs. Real Color Blindness Perception: What strategies, expectations, and perceptual priorities distinguish real-world CVD experiences from those that are simulated using normal vision participants?

To better understand the mechanisms underlying our quantitative results, we conduct in-depth interviews with participants from five vision groups. Rather than treating these interviews as a direct validation of simulation tools, we use them to explore how participants with real CVD interpret, adapt to, and evaluate visualizations. Through thematic coding of open-ended responses, we identify how color-related challenges are described, which design features support or hinder interpretation, and how lived experience diverges from simulation-based assumptions. This analysis clarifies not just whether simulations "work" or "fail," but why they might fall short, and reveals how real-world users navigate visualizations when perceptual assumptions break down.

3.2 Stimuli Overview

We began with a dataset of 500 real-world visualizations curated by Arunkumar et al. [4], which span diverse chart types, annotation styles, and design elements, sourced from government reports, infographics, news media, and scientific publications. These visualizations were previously coded using a comprehensive feature taxonomy (across 26 visual feature dimensions) that captures elements such as data-ink ratio, mark types, and presence of human-recognizable objects—based on the frameworks introduced by Borkin et al. [10, 11]. To focus on issues of color vision accessibility, we applied Adobe's color blindness simulation tools (which simulate both forms of red-green-blindness–protanopia and deuteranopia)to all 500 visualizations and manually reviewed them to identify those most likely to cause perceptual interference due to overlapping or adjacent red and green hues [1]. From this process, we selected a targeted subset of 46 visualizations that exhibited potential challenges for humans with red-green CVD (the most common type of CVD [82]). Each visualization was resized then, while maintaining aspect ratios to a maximum dimension of 1000 pixels.

Next, to support deeper analysis, we developed a complementary color-specific annotation framework, capturing accessibility-relevant attributes: (i) **Color Usage & Interaction**: Encodes background color, hue count, and contrast. (ii) **Color Significance**: Identifies culturally or psychologically meaningful colors (e.g., red = danger). (iii) **Color Interference**: Flags perceptual conflicts, especially under CVD. (iv) **Design Intent**: Notes whether accessibility or palette choice is discussed by the designer. (v) **User Control**: Indicates if users can adjust color settings. (vi) **Legend Dependency**: Captures presence and interpretive necessity of color legends.

Four expert annotators (graduate researchers with 3+ years in data visualization) applied this scheme to the 46 visualizations. Disagreements were resolved through group discussion, leading to full consensus on all codes. Based on the coding results and consensus discussion, each visualization was also assigned a final **color interference level**: high, medium, or low. This stratification yielded a balanced subset of 15 high-interference, 15 medium-interference, and 16 low-interference charts, which formed the stimulus set for our studies (available with annotations in supplemental materials). Here we briefly summarize some of the patterns from this corpus.

3.2.1 Color Usage in Visualization Design

Color as a Visual Channel: Color was a primary encoding in most visualizations, with categorical use (40%) being the most common. Ordinal (22%) and continuous (18%) encodings were typically found in scientific or geographic contexts. Visualizations with high data density often included redundant encodings (e.g., color plus shape or position), while those with high data-ink ratios (32%) lacked such redundancy (potentially posing challenges for viewers with CVD).

Color and Chart Structure: Visualizations heavily reliant on color (24%, marked as high-interference) frequently omitted textual anchors [40] like captions (only 52% included them) and keys (58%). In contrast, low-interference visualizations (28%) more often included text labels (72%), grid lines (42%), and highlights (48%), suggesting that textual redundancy could support accessibility. Axes (76%) and titles (87%) were consistent across all designs.

Assistive vs. Isolated Color Use: Color was often used alongside other encodings: (i) 62% of bar/line charts used color for categorization; (ii) 17% of charts used non-white backgrounds, and only 11% ensured strong contrast; (iii) 15% of charts employed multiple hues, while 14% relied on a single dominant hue; (iv) 21% included 3D elements (thus increasing perceptual complexity). These patterns underscore that many visualizations—whether by design or coincidence— used color in conjunction with other channels (shape, layout, or line style) to support interpretability. Prior work shows that combining visual cues improves perceptual segmentation [62], which could be especially beneficial for viewers with CVDs.

Emotional and Cognitive Associations: Color carried implicit emotional and semantic meaning in 42% of visualizations (as identified through topical relevance of color usage, or text that directly referenced the color's purpose), yet only 9% of designers explicitly acknowledged such intent (e.g.: “the spectrum...subtly matches the diurnal cycle with the dips tending the blue in the night and peaks in the morning/day.” *The Baby Spike, Nadieh Brehmer, 2017*). In general, red, orange, and yellow were commonly linked to urgency, emphasis, or danger, while blue and green were more common in contexts suggesting trust or stability.

Accessibility Awareness and Adaptation: Only 13% of visualizations acknowledged accessibility (e.g.: “the spectrum... shows off both dips and peaks, is color-blind safe” *The Baby Spike, Nadieh Brehmer, 2017*). High-interference charts also often lacked legends (9%), limiting interpretability. Further, only 4/45 visualizations allowed users to modify color palettes with a toggle– highlighting limited support for adaptive color accessibility.

In summary, for the 46 charts in our stimulus set, color is a dominant visual strategy, though it is often used without sufficient structural support or accessibility considerations.

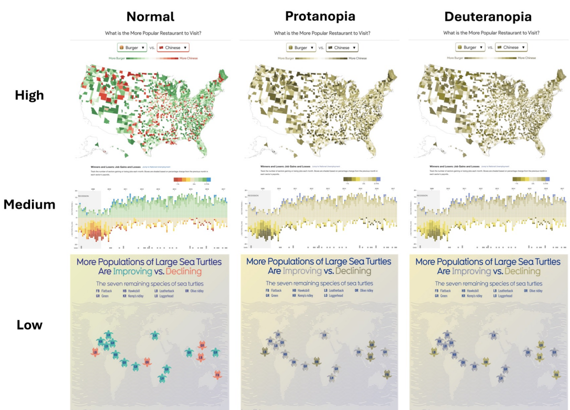

Fig. 2: Examples of study stimuli, organized by **color vision condition** (columns) and **color interference level** (rows). Columns represent three vision conditions: **Normal** (left, original color design), **Protanopia** (middle, simulated red-cone deficiency), and **Deuteranopia** (right, simulated green-cone deficiency). Rows represent increasing color interference: **low** (bottom), **medium** (middle), and **high** (top), based on our expert-coded annotations. The stimuli include: a choropleth map comparing restaurant preferences (high), a timeline of job gains and losses (medium), and a sea turtle population map using colored icons (low).

3.3 Experiment Overview

To investigate how individuals with different types of color vision perceive data visualizations, we conducted a three-part experiment. Each study was designed to address specific facets of the research questions outlined above, particularly focusing on how design choices affect accessibility, interpretability, and emotional engagement across visual and cognitive conditions.

Study 1 examines how colorblindness simulations affect perception among individuals (university students) with normal color vision. This allowed us to test, for example, whether simulated filters can replicate real-world accessibility issues. **Study 2** focuses on individuals (recruited via Prolific) with actual CVDs, offering a real-world counterpart to the simulated vision conditions. This comparison provides insight into the validity and limitations of simulation-based evaluation. **Study 3** uses qualitative interviews to explore how participants (university students) with and without CVD describe and interpret visualizations, enabling a deeper understanding of perceptual mechanisms and lived experiences beyond what structured surveys can capture.

Study 1 – Simulated Color Vision Conditions: We conducted a power analysis using G*Power [26] to determine the required sample size for a one-way ANOVA [75] with three groups, assuming a medium effect size ($f = 0.35$), an alpha level of $\alpha = .05$, and power of 0.80, determining a minimum required sample size of 84 participants (28 per condition). Accordingly, 100 participants were initially recruited from Arizona State University for this study. After excluding 3 participants who failed attention checks or gave incomplete responses, the final sample consisted of 97 participants (23.8 $\pm$ 3.8 y/o, 75 male). All participants self-reported having normal color vision and were currently enrolled in a data visualization course. Participants were given the option to earn extra credit equivalent to 1% of their total grade by completing the survey. To ensure participation was fully autonomous and non-compulsory [69], students could alternatively choose from several extra credit opportunities, including non-research options.

Design and Procedure: We employed a between-subjects experimental design with three conditions of visualizations: (i) Normal Vision (■, $n = 36$), (ii) Simulated Protanopia (■, $n = 31$), (iii) Simulated Deuteranopia (■, $n = 30$). One visualization from the stimulus set was held out for a training trial, meaning 45 visualizations were used for the study.

CVD simulations were applied using Adobe’s color blindness simulator [1]. Fig.2 illustrates examples of visualizations as they appeared under each vision condition. Participants were randomly assigned to one of the three conditions. To minimize display-related color distortions, participants were instructed to disable all screen color filters (e.g., blue light or night mode settings) before beginning the study. Before running the main study, we conducted a pilot study with three participants to validate the design. Participants completed the study in three phases (see Figure 3):

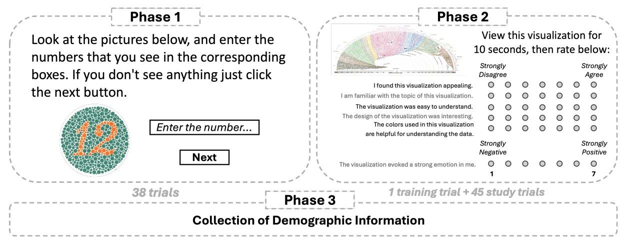

Fig. 3: Study procedure: Phase 1: 38 plate Ishihara test [39] to assess CVDs. Phase 2: 45 trials, collect post-viewing measures across six dimensions. Phase 3: Collect demographic details.

Phase 1: Participants completed a 38-plate Ishihara color vision test [39] as a screening measure to confirm normal vision. **Phase 2**: For each trial, a visualization was displayed for 10 seconds This 10-second exposure time aligns with Newell’s cognitive band of interaction, capturing rapid perceptual and early interpretive judgments within a typical ‘unit task’ window [52]. Then, participants answered six questions (see Table 1) eliciting their perceptual, cognitive, and affective user experience when consuming visualizations on 7-point Likert scales. Each participant completed one training trial, followed by 45 session trials (with visualizations presented in a random order such that an equivalent number of low/medium/high color interference visualizations were seen). **Phase 3**: Participant demographic information was collected (age, gender, visualization familiarity, education level).

Study duration averaged roughly 2.51 $\pm$ 0.65 minutes for Phase 1, 46.67 $\pm$ 11.33 minutes for Phase 2, and 1.45 $\pm$ 0.36 minutes for Phase 3. Participants were also allowed up to two 10-minute breaks during Phase 2 to prevent study fatigue, with an attention check after the 25th question. The average visualization familiarity was 4.02 $\pm$ 1.19 on a 7-point scale (1 = Not at all familiar, 7 = Expert).

This experimental setup allows us to systematically examine how simulated red-green CVDs influence perceptual, cognitive, and affective responses to real-world data visualizations. By comparing the three simulation conditions (see Sec. 4), we can isolate the specific visual design elements that may hinder or support accessibility for individuals with simulated impaired color differentiation.

Study 2 – Real-World Color Vision Differences: A total of 131 adult participants were recruited through Prolific, an online participant recruitment platform. Eligibility was restricted to individuals fluent in English, with at least a high school education, residing in the United Kingdom, United States, Canada, or Australia. Participants also needed an approval rate of 95% or higher and at least 100 previously completed studies on the platform. Group assignment was based on Prolific’s prescreening question on color vision status: those self-reporting CVD were assigned to the colorblind group, and those reporting normal vision to the control group. All responses were self-reported. Power analysis indicated that 128 participants (64 per group) were required to detect a medium effect size ($d = 0.35$), with $\alpha = .05$ and desired power of $1 - \beta = .80$. The final sample included 67 participants with

Table 2: Thematic coding framework for Study 3 interviews. Themes reflect participant experiences with color-based data visualizations and align with key visual features coded in the stimuli.

Theme	Subtheme	Description	Example Quote
Perceptual Challenges	Hue Confusion	Confusion caused by red-green or other difficult color contrasts.	"The red and brown looked the same to me."
	Low Contrast	Poor contrast between foreground and background elements.	"It all kind of blended into the background."
	Legend Dependence	Reliance on the legend to decode visual meaning.	"Without the legend, I wouldn't have known what the colors meant."
Workarounds & Coping	Guessing from Context	Inferring meaning from visual structure rather than color.	"I guessed green was good — that's usually the case."
	Shape Compensation	Using alternative encodings when color was inaccessible.	"I followed the line chart pattern instead of looking at the color."
Emotional & Cognitive Reactions	Frustration / Disengagement	Emotional impact of inaccessible visuals.	"It made me feel excluded — like this wasn't made for someone like me."
	Trust and Clarity	Trust influenced by legibility and perceived intent.	"The simple color scheme made it feel more official."
	Aesthetic Appeal	Whether colors enhanced or distracted from interpretation.	"It looked good, but was hard to read."
Interpretation Strategies	Sequential Reading	Order in which viewers parsed the visualization.	"I always look at the title and legend before anything else."
	Familiar Layouts	Using conventions or expectations to interpret visuals.	"This looked like a financial chart, so I assumed red meant loss."
	Avoiding Color	Skipping color cues due to perceived unreliability.	"I ignored the colors and just looked at the position."
Expectations about Color	Cultural Associations	Color meanings drawn from lived experience or domain norms.	"Green should mean something good, but here it didn't."
	Violated Expectations	Surprise or confusion when color meaning was reversed.	"Red meant increase, which threw me off."

normal color vision (30.8 ± 11.4 y/o, 29 males) and 64 participants (33.0 ± 13.8 y/o, 51 males) with CVD, including 11 with protanopia, 26 with deuteranopia, 15 with mixed protan-deuteran deficiency, and 12 with other types of CVD.

Design and Procedure: We employed a between-subjects design comparing participants with normal color vision (■, $n = 67$) to those with actual CVD (■, $n = 64$). All participants viewed the visualizations in their original, unfiltered color form (no simulated filters were used in this study). Participants in the colorblind group were additionally asked to self-specify their type of CVD. We note that the second normal vision group was intentionally included to verify whether patterns observed among university students in Study 1 would replicate in a broader online population, thereby enabling cross-study comparisons.

Each participant completed the Ishihara test, one training trial, and then evaluated 20 visualizations, randomly drawn from the same 45-visualization set used in Study 1 (such that a balanced sample of low/medium/high color interference visualizations were seen). Participants also completed an attention check after the 10th question. All other procedures, including visualization presentation time, instructions, and Likert-scale questions, followed the same protocol as Study 1. Study duration averaged 2.12 ± 0.17 minutes for Phase 1, 22.31 ± 7.42 minutes for Phase 2, and 1.3 ± 0.21 minutes for Phase 3. The average visualization familiarity was 3.23 ± 1.58 on a 7-point scale. We note that while participants in Study 1 were enrolled in a data visualization course, and those in Study 2 were recruited from the general public, the two groups did not differ significantly in self-reported visualization familiarity ($p > .05$), suggesting comparable baseline experience in interpreting visualizations. This real-world comparison provides a crucial benchmark for validating the assumptions and limitations of Study 1's simulated color vision research. By analyzing responses from individuals with actual CVDs, we can assess the extent to which simulation-based results generalize to real user experiences, and identify any discrepancies that may require improved modeling or design strategies.

Study 3 – Qualitative Interviews on Color Perception: 18 participants were recruited from Arizona State University, for in-depth, semi-structured interviews (26.5 ± 4.8 y/o, all male). Recruitment targeted four distinct vision groups to ensure balanced representation: (i) 3 individuals with normal color vision, (ii) 3 with protanopia (red-blindness), (iii) 3 with deuteranopia (green-blindness), and (iv) 3 with combined red-green deficiency. All participants reported fluency in English, were currently pursuing a computer science degree, and had previous experience interacting with data visualizations in professional or educational contexts. Participants volunteered their time in the study.

Design and Procedure: The interviews focused on eliciting how perceptual mechanisms potentially differed between simulated and actual color vision experiences, and how participants describe these experiences. The study was conducted remotely using video conferencing tools, and each session lasted approximately 63:02±7:08 minutes. Each participant was presented with a curated set of fifteen visualizations, representing a mix (5 each) of high, medium, and low color interference levels (as coded in Sec. 3.2). Visualizations were shown in their original color format without filters, as well as with simulated CVD filters applied. For each visualization, participants completed three sequential tasks: (i) **Free Response**: Participants described what they noticed and interpreted about the visualization without prompting. (ii) **Prompted Evaluation**: Participants answered targeted questions regarding comprehension, emotional impact, perceived clarity, and any visual challenges they encountered. (iii) **Comparative Reflection**: Participants compared visualizations and discussed which ones felt easier or harder to understand, and why.

This qualitative analysis enabled us to explore how individuals with and without CVD articulate the perceptual consequences of design decisions and whether current simulation methods capture these experiences adequately. It also helped identify design features that participants spontaneously associated with helpfulness or frustration, providing actionable insights for accessible visualization design.

3.4 Data Coding

Study Group Condition: We use the between-subjects participant groups as independent variables in our analyses.

Visualization Features: We utilized the annotation data[1] as moderator variables for analysis. All label values were mapped to either binary (0/1) or ternary (1/2/3) scales when constructing the model.

Observed Measures: In Studies 1,2, for each visualization, participants responded to six statements capturing different dimensions of perception (visual appeal, topic familiarity, comprehensibility, design interest, color utility, and emotional response) as listed in Table 1. All items were rated on a 7-point Likert scale. For the first five items, 1 corresponded to *Strongly Disagree* and 7 to *Strongly Agree*. For *emotional response*, 1 corresponded to *Strongly Negative* and 7 to *Strongly Positive*. These were used as dependent variables in the analysis.

Qualitative Free Response: Interviews were transcribed and analyzed using a reflexive thematic analysis approach. Two independent coders (authors) developed a preliminary codebook using an inductive, bottom-up methodology [4, 11], then iteratively refined it based on emerging patterns and discussion, as shown in Table 2. Disagreements in coding were resolved through discussion until full consensus was achieved. Codes were grouped into five higher-level themes with reference to the contexts of color usage documented by expert annotators in our stimuli overview (Sec. 3.2): (i) *Perceptual Challenges* aligns with our coding of visualizations by interference level, hue contrast, and palette friendliness. (ii) *Workarounds & Coping* corresponds to the absence of redundant encodings such as shape or text labels. (iii) *Emotional & Cognitive Reactions* builds on stimuli-level coding that documented whether color was used to prime emotion, understanding, or familiarity. (iv) *Interpretation Strategies* reflects reliance on layout and legends (mirroring annotation of legend dependency, caption use, and title presence). (v) *Expectations about Color* helps explain mismatches between viewer interpretations and design intent, particularly when no rationale or accessibility consideration was documented. Together, these themes link user experiences back to designer choices, forming a critical bridge between artifact-centered analysis and audience-centered understanding.

4 Results and Discussion

We report results organized around three core research questions described in Sec. 3.1, beginning with perceptual differences across color vision conditions (RQ1), followed by visual design feature effects (RQ2), and concluding with mechanisms explaining differences between simulated and real CVD experiences (RQ3). To analyze group-level effects, we use one-way ANOVAs, and to test moderation we

[1] See Supplemental Materials for a full description of the annotation taxonomy adapted from prior work [4, 11, 15].

employ multiple linear regression models with interaction terms. All statistical tests are evaluated at a significance threshold of $p < 0.05$, unless otherwise stated. We note that although each chart was pre-categorized as low, medium, or high in red-green color interference (see Section 3.2), exploratory analyses showed no significant differences in participant ratings across these interference levels, so we do not include this variable in subsequent statistical models. Summary trends across interference levels are visualized in Fig. 5 and are discussed later in relation to design implications.

4.1 RQ1: How do Color Vision Differences Shape the Perception of Real-World Data Visualizations?

To examine how CVDs influence perception, we conducted two complementary studies. In **Study 1**, participants with normal vision viewed visualizations with either: normal vision (NVS1, i.e., no alteration in the color palette of the visualization), simulated protanopia (SP), or simulated deuteranopia (SD). In **Study 2**, we recruited real-world participants with normal vision (NVS2) and with diagnosed CVD, including protanopia, deuteranopia, combined red-green deficiency, and other forms (including blue-yellow blindness and monochromacy). During our analyses, we noted that participants in the other condition did not significantly deviate in their perceptual patterns from other CVD subtypes, and therefore included them in the analysis as part of the overall CVD group for Study 2.

Color Utility Ratings Reveal Functional Accessibility Gaps: *Color utility* was the most sensitive differentiator. In Study 2, participants with CVD (3.90 ± 0.73) rated color as significantly **less helpful** than NVS2 participants (4.44 ± 1.02; $t = 2.86$, $p = 0.005$, $d = 0.50$), confirming known accessibility challenges [24, 59]. In contrast, simulated groups in Study 1 trended lower (4.61 ± 0.66) than controls (NVS1: 4.70 ± 0.89), but differences were not statistically significant. This suggests simulations *approximate* directionality but may *underestimate* the severity of perceptual limitations.

Aesthetic Impressions Shift Under Simulation, But Not in Real-World CVD: In Study 1, SD unexpectedly led to higher ratings of *appeal* (5.19 ± 0.54; $F = 4.25$, $p = 0.016$), *interest* (5.26 ± 0.54; $F = 4.91$, $p = 0.008$), and *emotional response* (4.75 ± 0.48; $F = 3.95$, $p = 0.021$) compared to the NVS1 condition (4.45 ± 0.63). Post-hoc tests confirmed significantly higher ratings for SD over NVS1, with mean differences of $\Delta\uparrow 0.31$ (*visual appeal*, $p = 0.020$), $\Delta\uparrow 0.35$ (*design interest*, $p = 0.007$), and $\Delta\uparrow 0.30$ (*emotional response*, $p = 0.021$). This may reflect perceptual adaptation when viewing SD: reduced hue salience potentially shifts focus toward structure, layout, or spatial organization [4, 11], thereby enhancing perceived aesthetic salience. Additionally, simulated deuteranopia transformations often introduce more blue and blue/yellow combinations into the visualizations. This modification may induce perceptual shifts due to altered color harmony, making them more pleasing to normal-vision populations [2, 66]. However, this pattern did not appear in Study 2, where no significant differences emerged between CVD and NVS2 groups, likely due to differences in conceptual associations shaped by their perceptual experience, and qualitatively different color preference profiles [2, 65]. This contrast highlights a key discrepancy: while simulated CVD may amplify aesthetic perception, actual CVD users may not experience similar enhancements.

Perceived Comprehensibility Trends Lower for CVD Participants: In Study 2, CVD participants rated charts as slightly *less understandable* (3.92 ± 0.99) than NVS2 participants (4.05 ± 1.18). Simulated CVD groups in Study 1 also rated visuals as less comprehensible (4.78 ± 0.86) than controls, with near-significant differences for both understandability ($p = 0.054$) and color utility ($p = 0.051$). These trends suggest subtle impacts on functional clarity.

Color Vision Shapes Which Aspects of a Visualization Are Noticed: Varimax factor analysis [41] of the six survey questions revealed two consistent latent dimensions across studies (see Fig. 4). Based on item loadings and interpretability, we labeled the factors as: (Factor 1) **Affective Experience** capturing *visual appeal*, *design interest*, and *emotional response*, and (Factor 2) **Functional Utility** capturing *understandability*, *color utility*, and *topic familiarity*. These two factors form the basis for the summary plot in Fig. 5, where we visualize mean ratings and variability across groups and interference levels.

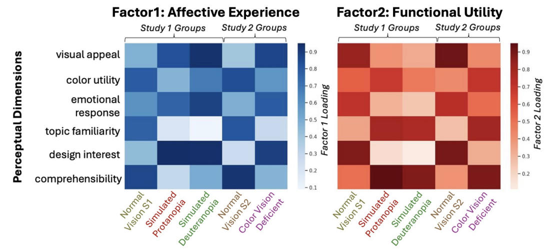

Fig. 4: Heatmaps of factor loadings for all participant groups. The left grid shows loadings on Factor 1 *Affective Experience*. The right grid shows loadings on Factor 2 *Functional Utility*. Rows represent the perceptual dimension ratings collected in the survey, and columns represent the different participant groups across studies 1 and 2. Cell values indicate factor loading strength, with darker shades representing stronger associations.

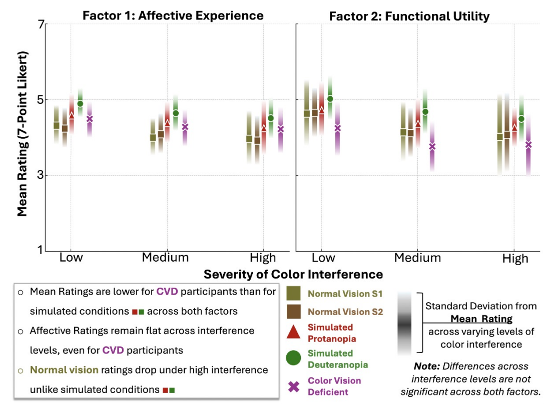

Fig. 5: Plot showing a summary of ratings collected in Studies 1 and 2. We show average Likert ratings collapsed across both factors (*Affective Experience* and *Functional Utility*). The color and shape of the points represents the participant group. Gradient bands represent variability associated with the observed ratings in terms of standard deviations.

NVS1 and NVS2 groups prioritized functional utility, with it accounting for the majority of explained variance (45.6% and 44.6%, respectively). In contrast, all CVD groups (both simulated and real) showed a reversal, with affective experience explaining the most variance (between 42.0% and 54.0% across sub-types), while functional utility was secondary 29.6%. This shift suggests an adaptive strategy: when color is unreliable, users focus more on stylistic or emotional elements to interpret meaning. Notably, the protanopia group had the lowest total explained variance (61.7%), indicating more inconsistent perceptual patterns, possibly due to greater individual variability or poor simulation fidelity. This finding underscores the importance of including real CVD users in design evaluations.

Together, these findings demonstrate that color vision differences reshape not just interpretation, but the entire perceptual focus. Real CVD users experience sharper functional limitations and reweight their attention toward emotional and aesthetic cues. Simulations capture some directional trends but may obscure the intensity or nuance of these experiences. In the next section, we examine which visual design features help, or hinder, accessibility across these groups.

4.2 RQ2: How Do Visualization Design Features Influence Perception Across Color Vision Conditions?

While CVD alters how viewers perceive hue-encoded information, it remains unclear which visualization design features help mitigate these challenges. To address this, we analyze the influence of the 26 visual encoding features (from the categorization and annotation framework coded with four expert annotators as stated in Sec. 3.2) on participant responses in Study 1 and Study 2. Using multiple linear regression, we assessed how each feature predicted the two latent factors (Affective Experience and Functional Utility) revealed during RQ1's analysis.

To streamline our discussion of results, we have grouped these 26 features into five high-level categories based on groupings in prior visualization taxonomies [4, 5, 10, 11], as shown in Table 3. In the subsections below, we report which features (indepdendent variables) within each category *significantly* ($p < 0.05$) impact Affective Experience and Functional Utility (dependent variables) for each group from Study 1 and Study 2. Similar to our discussion for RQ1, we report the regression results over Study 2's aggregated CVD group to simplify interpretation.

As this analysis includes 26 predictors tested across multiple groups and outcomes, we adopt an exploratory stance. No formal correction for multiple comparisons was applied. Instead, we emphasize consistency of effects across studies and groups, and we report standardized effect sizes (Cohen's d, f^2) to aid interpretation. Many of the strongest findings exceed thresholds for medium to large effects, suggesting practical significance even in the presence of statistical noise. We encourage follow-up studies to confirm these patterns in targeted contexts.

Table 3: Conceptual clustering of visual features to contextualize impact on participant perception. * indicates that the features are subjectively coded to agreement by four expert annotators (Section 3.2).

Category	Visual Features
Color-related	background color (white/light/dark), number of color hues, hue matching between background and marks* (yes/no), legend presence (yes/no), necessity of legend to interpret colors* (yes/no)
Mark-related	size* (small/medium/large), mark type (dots/lines/areas/icons)
Density & complexity	data ink ratio* (low/medium/high), data volume* (low/medium/high), visual density* (low/medium/high), data aggregation level, multiplicity* (single/small-multiple)
Structural elements & annotations	presence of axes, title, caption, text labels, arrows, gridlines, other annotations, pictorial units, and human-recognizable objects (yes/no)
Designer-primed color intent	deliberate color use to evoke emotion or clarity* (yes/no)

Color-Related Features: *Background color* significantly influenced Affective Experience across multiple CVD conditions. The strongest effects were observed in the SP group ($\beta = 0.383$, $f^2 = 0.172$, $p = 0.009$), followed by SD ($\beta = 0.331$, $f^2 = 0.123$, $p = 0.025$), and real CVD participants ($\beta = 0.323$, $f^2 = 0.116$, $p = 0.029$). All effects were medium to large (Cohen's $d > 0.75$). This strong, consistent aesthetic effect did not extend to Functional Utility, suggesting that contrast supports engagement more than clarity. This is exemplified in Fig. 6(a): high-contrast background–foreground combinations enhance figure-ground separation, which may support higher affective engagement for CVD users, for whom background contrast [3, 5] may serve as a primary source of visual structure.

Legend necessity negatively impacted both perception factors across nearly all groups. For Affective Experience, significant negative effects were found in SP, NVS1, NVS2, and CVD ($\beta = -0.35$ to -0.41, $f^2 = 0.14$–0.20, $p < 0.05$). For Functional Utility, all groups across the studies showed significant effects: SD ($\beta = -0.333$, $p = 0.024$), SP ($\beta = -0.428$, $p = 0.003$), NVS1 ($\beta = -0.419$, $p = 0.004$), CVD ($\beta = -0.468$, $p = 0.001$), and NVS2 ($\beta = -0.403$, $p = 0.006$), all with Cohen's $d > 0.85$. These results suggest that when legends are required to decode color, perceptual burden increases, especially for actual CVD users. While effects were robust across the studies, we note that feature co-occurence with complex or categorical mark-related features could play a significant role in driving the impact of legends as opposed to mere presence or absence. Fig. 6(b) illustrates this challenge: color-coded categories require repeated legend consultation, which could potentially impair flow and comprehension, as they impose extra cognitive effort.

Mark-Related Features: *Line-based marks* were associated with large, consistent negative effects on both factors. For Affective Experience, all groups across the studies showed significant reductions, with the largest effects in NVS1 ($\beta = -0.507$, $f^2 = 0.347$), SP ($\beta = -0.457$, $f^2 = 0.265$), and NVS2 ($\beta = -0.514$, $f^2 = 0.359$). Similarly, for Functional Utility, all groups showed significant declines (steepest for CVD: $\beta = -0.449$, $p = 0.002$). These findings indicate that line charts, especially dense or overlapping ones, can potentially hinder both affect and clarity. Although the results were highly consistent, these effects may also conflate issues of visual density and color discrimination factors and necessitate isolated exploration. As shown in Fig. 6(c), cluttered trajectories could potentially overwhelm tracking and interpretation (see also [10]) for both normal and CVD users, more so when line color is a primary differentiator.

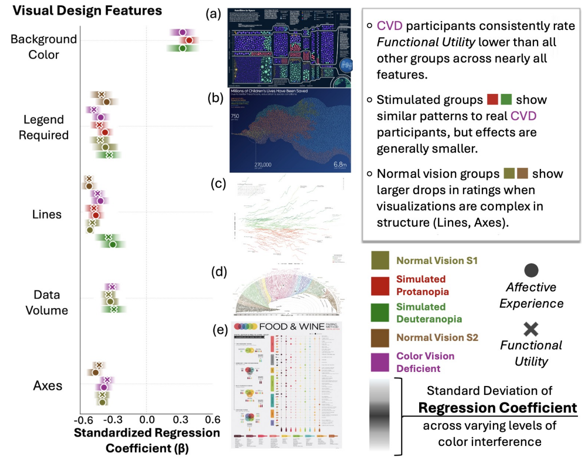

Fig. 6: Plot showing standardized regression coefficients (β) for visual features with statistically significant moderation effects on *Affective Experience* ($\bullet$) and *Functional Utility* ($\times$). Each color represents a participant group: normal vision s1, simulated protanopia, simulated deuteranopia, normal vision s2, and actual CVD participants. All plotted points correspond to statistically significant effects ($p < 0.05$). Example visualizations illustrating the corresponding features are shown on the right: (a) High color saturation on dark background (Background Color); (b) Color-only category encoding with reliance on legend (Legend Required); (c) Dense multi-line plot with overlapping trajectories (Lines); (d) Extremely dense tree structure with many data items (Data Volume); (e) Annotated grid-based visualization with extensive use of icons and text (Axes).

Density & Complexity: *Data volume* negatively affected perception for Functional Utility. Significant effects were found for NVS1 ($\beta = -0.343$, $f^2 = 0.133$, $p = 0.020$), SD ($\beta = -0.298$, $f^2 = 0.097$, $p = 0.045$), and CVD ($\beta = -0.301$, $f^2 = 0.100$, $p = 0.042$). Further, Affective Experience was reduced for NVS1 ($\beta = -0.323$, $p = 0.028$). These results suggest that visual density can overwhelm both CVD and normal vision users. As illustrated in Fig. 6(d), charts with dense data encoding and little hierarchy or segmentation potentially require greater cognitive effort (e.g., see [5, 10]), reducing their overall impact. This result was group-dependent and potentially influenced by specific layouts; moderate effect sizes call for replication with controlled complexity levels.

Structural Elements & Annotations: *Axes* also had a consistent negative effect on perception, despite their common use as orientation tools [5, 11]. For Affective Experience, axes reduced ratings for NVS1, CVD, and NVS2 ($\beta = -0.388$ to -0.452, $f^2 = 0.16$–0.26). For Functional Utility, the same groups showed significant declines– NVS1 ($\beta = -0.397$, $f^2 = 0.187$, $p = 0.006$), CVD ($\beta = -0.353$, $f^2 = 0.142$, $p = 0.016$), and NVS2 ($\beta = -0.427$, $f^2 = 0.223$, $p = 0.003$). This suggests that while axes offer precision, they may also increase perceived complexity, especially in already crowded visuals. In Fig. 6(e), rigid gridlines and heavy axis structures may potentially contribute to visual overload for CVD and non-CVD users alike, especially for users less familiar with the data context. Despite statistical significance, this effect may reflect participants' general aversion to over-structured layouts rather than axes per se.

Designer-Primed Colors: In some cases (<20% of stimuli), designers intentionally select color palettes pertaining to the visualization topic to evoke emotion or further understanding. However, this feature had no significant effect on either perception factor in any group across both studies ($p > 0.3$ in all cases). One possible explanation is that these features, which were annotated based on inferred semantic intent, may not have been perceptually salient enough to independently influence user ratings. Alternatively, their impact may be highly context-dependent and more subtle than can be captured by binary (yes/presence vs. no/absence) coding.

Cross-Study Comparison of Simulated vs. Real CVD Effects:

Study 1 involved normal vision participants viewing either original or simulated red/green colorblind versions of visualizations. Study 2 compared normal vision viewers to participants with actual CVD viewing unaltered charts. Despite these differences, both studies revealed consistent feature effects across perception factors. *Background color*, *legend necessity*, *line marks*, and *data volume* significantly moderated perception in both studies, though effect sizes were generally stronger in Study 2 (especially for Functional Utility). Affective Experience patterns also held across studies: *background contrast* improved aesthetic responses, particularly for simulated CVD conditions ■■, though real CVD participants often tempered these reactions when usability remained low. Additionally, designer-primed color selections had no significant effect in either study, indicating that semantic or emotional intent alone does not translate into measurable impact—particularly when perceptual decoding is impaired.

Taken together, these results suggest that while simulated filters can approximate the direction of perceptual challenges, they may underestimate their intensity. Simulated participants were more likely to rate charts as aesthetically pleasing despite usability issues, while real CVD users demonstrated sharper declines in functional perception when key visual features failed to support redundancy or clarity. In the next section, we draw on qualitative interviews to explore and better understand the lived strategies, expectations, and workarounds employed by individuals with and without CVD.

4.3 RQ3: How do participants with different types of color vision deficiency interpret, adapt to, and evaluate visualizations?

In Study 3, we conducted qualitative interviews with 18 participants across five vision types: six with normal vision, and three each with protanopia, deuteranopia, combined red-green deficiency, and blue-yellow CVD. Using the thematic framework in Table 2, we analyzed how participants interpreted visualizations, navigated color-based challenges, and expressed expectations around design. These accounts provide lived-context insights that complement the mechanisms surfaced via RQ1 and RQ2. Although interference level (low: ■, medium: ■, high: ■) did not show significant effects in Study 1 and 2's quantitative results for RQ1 and RQ2, it emerged as a salient differentiator in participants' qualitative descriptions, especially in shaping how early they noticed problems and how effortful interpretation became. We present the 15 visualizations tested across interference levels in Fig. 7, and summarize high-level trends for charts in Fig. 1.

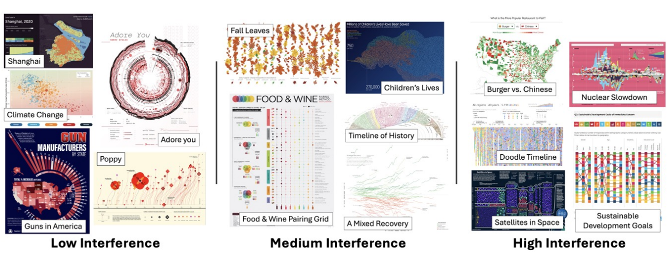

Fig. 7: No color alteration version of visualizations across color-interference levels presented in Study 3 to collect qualitative feedback.

Interpretation Strategies: Structured Viewing & Avoiding Color. CVD participants reported structured, cautious viewing habits, with 5 participants discussing how they start with the title or legend (example comment: "I always look at the title and legend before anything else."). For example, when viewing the Sustainable Development Goals ■ image, participants used the consistent column structure and node alignment as entry points before attempting to interpret color ("I followed the thread with the lines, but not the colors—it was too much."). Similarly, on the Food & Wine Pairing Grid ■, layout structure helped participants interpret relationships: "You kind of guess what they're going for by seeing the pattern, not the color." Eight participants discussed inferring meaning through domain familiarity. For example, for the A Mixed Recovery ■ chart, a red-blind participant stated, "This looked like a financial chart, so I assumed that brownish thing that should be red meant loss." Other participants (6 total) avoided color entirely: "I ignored the colors and just looked at the position," stated about the Nuclear Slowdown streamgraph ■. A consistent pattern here is that these behaviors reflect reliance on structural anchors when hue was unreliable. In contrast, normal vision participants tended to lean on color as a first-order cue, especially in charts like Burger vs. Chinese ■: "The red just popped! It was obvious what meant what."

Perceptual Challenges: Hue Confusion & Legend Dependency. All CVD participants reported difficulty with color discrimination. Viewing the Climate Vulnerability Map ■, one participant said: "The legend hue and the background just blended. I couldn't tell where one thing ended and another started." A similar reaction occurred with Children's Lives Saved ■: "I know the blue is supposed to mean something, but on this dark background, I can't see it." Six (out of 12) CVD participants expressed similar "everything blended into the background" types of statements, especially in low-luminance visuals like the Timeline of History ■: "All the lines looked brown. I could barely tell what direction anything was going." Four flagged specific hue confusions, such as, "[t]he red and brown looked the same to me," while viewing Nuclear Slowdown ■, or "Teal and yellow are too close. It's like reading something half-erased" (noted about Fall Leaves ■). Legends were particularly challenging. All 12 CVD participants struggled with hue-only legends: "The legend looked like a smooth rainbow, but it didn't tell me what any of the shades were," said one about Climate Vulnerability ■. In contrast, normal vision participants often called these same legends "clear" or "self-explanatory."

Workarounds & Coping: Layout, Context, and Redundancy. CVD participants tended to use alternative cues; e.g., 10 inferred meaning from layouts, especially for Food & Wine Grid ■ and Sustainable Development Goals ■ ("I guessed that shade was green because it was grouped with other good things."). Redundancy was considered helpful across multiple charts; e.g., in Guns in America ■, bars accompanied the colored map: "I couldn't tell the red states clearly, but the bars told me what was more." Similarly, in Satellites in Space ■, several CVD participants praised symbol use: "Even though the dots were all blueish to me, the shapes gave me something to go on." Though arrows and icons had weaker effects in the quant study, they surfaced in eight interviews as useful: "The icon helped me figure out the category," said one participant referencing the Food & Wine Grid ■. Another said of Fall Leaves ■: "At first it looked like a mess, but then I noticed the shape of the leaves and that helped." Normal vision participants appreciated redundancy too: "The shapes and colors worked together. It just felt well-designed," noted one person on Satellites in Space ■.

Emotional & Cognitive Reactions: Trust, Frustration, and Selective Focus. CVD participants described several frustrations: "It made me feel like this wasn't made for someone like me," said one, referencing Timeline of History ■. Others emphasized usability over beauty: "It wasn't that it looked good. It was that it didn't fight me," while viewing Food & Wine Grid ■. These support RQ1's finding that for CVD users, Aesthetic Experience is often a proxy for usability. Normal vision participants, by contrast, described the same charts with affective language: "This one popped," said one about Children's Lives ■; "The contrast worked really well," noted another for Burger vs. Chinese ■. Dense or cluttered visuals led to "visual filtering." A blue-yellow blind participant described Children's Lives ■ as "a wall of fog." Another said of the Doodle Timeline ■: "I just zoomed in on one area and gave up on the rest." These charts were all of varying interference levels, suggesting that even seemingly safe designs can cause visual overload if mark types (like dots and lines) lack clarity.

Expectations About Color: Cultural Norms & Simulation Limits. Color expectations were deeply tied to perceived meaning. Viewing Guns in America ■, a participant said: "Redder should mean more I get it, but here I couldn't even tell if that was red." On Children's Lives ■, another noted: "I know the blue is supposed to mean something hopeful, but it was just blurry." One participant looking at the Poppy Chart ■ remarked: "I didn't know that was supposed to be a poppy until I saw war mentioned." This underscores how symbolic interpretations, like poppies representing remembrance, may be inaccessible without color cues or cultural context. Some normal vision participants referenced cultural conventions: "Red meant increase, which threw me off." CVD participants, however, described detachment: "If you're saying red and green are supposed to tell me something, I'm not the person who's going to catch it." These interpretations often emerged in high-interference charts like Burger vs. Chinese ■ or Nuclear Slowdown ■.

Additionally, nine CVD participants disagreed with simulation accuracy. One said: "Filters show washed-out colors, but not how confusing it is." Another added: "It's not what you see, it's what you miss." This aligns with RQ1, RQ2 findings: simulations approximate appearance, not perceptual breakdown, and reinforces the importance of involving real CVD users in design evaluation. Further, though charts labeled as high-interference were more frequently associated with challenges, participants also reported confusion in low and medium interference cases when redundant cues were absent or layouts were overly dense. Interference alone did not predict breakdowns– fragility emerged when color carried meaning without adequate scaffolding.

5 Discussion and Design Recommendations

Our findings show that for viewers with CVD, visualization accessibility is shaped not just by what can be seen, but by how meaning is constructed under perceptual constraints. While Study 1 showed that simulated filters can influence ratings, Studies 2 and 3 revealed that simulations alone do not capture the real-world strategies, effort, or interpretive gaps experienced by CVD users.

Designers often assume that colorblind-safe palettes are sufficient [16, 21]. Yet our findings emphasized that usability depends on a combination of contrast, structure, and redundancy. When color was unreliable, viewers reported relying on shape, layout, legends, and labels to interpret meaning, especially in dense or unfamiliar charts (RQ3). Our RQ1 and RQ2 findings emphasized how CVD users need **layered access** to meaning, where color is just one of several coordinated channels. Normal vision participants, by contrast, placed more weight on aesthetics/layout clarity, often overlooking whether color could stand on its own. This gap highlights the importance of designing not just for visual appearance, but for perceptual resilience [13, 28, 54]. Put another way, effective design should provide multiple channels for understanding.

Below, we elaborate a set of guidelines with supporting evidence from prior work and our study findings. We note that while individual perceptions for specific visualizations may exhibit variability, our recommendations are intended as general guidelines rather than prescriptive rules for every single chart.

(D1) Scaffold Meaning Beyond Hue. Avoid using color as the sole encoding channel. Charts lacking secondary structure, such as shape, outlines, or labeled groupings, caused confusion even among participants with mild interference. Our Study 3 interviews emphasized the importance of line weights, bounding regions, and labeled anchors in helping CVD users resolve ambiguities. Embedding structural elements ensures viewers can reconstruct meaning without relying exclusively on hue [10, 76], especially in dense or unfamiliar charts.

(D2) Design for Both Functional Utility and Affective Experience. Factor analysis revealed two key perceptual dimensions: Functional Utility (comprehensibility, clarity) and Affective Experience (visual interest, emotional tone). Participants with CVD frequently reweighted toward affect when functional cues were degraded, such as in low-contrast or legend-heavy visuals. However, designers should not treat these priorities as either/or. Layout, contrast, and grouping can enhance both factors simultaneously, ensuring that charts are both usable and engaging [5, 7].

(D3) Design Legends for Interpretability. Legends requiring repeated consultation increased perceived effort and decreased ratings across both studies, especially for CVD participants. In Study 2, legend necessity was among the strongest negative predictors of Functional Utility. Embedding keys into the chart (e.g., direct labeling of marks or use of labeled textures) and using semantically meaningful color–label pairings can reduce this burden [54]. This not only supports CVD users but improves flow for all viewers.

(D4) Maintain Strong Background Contrast. CVD users described many charts as "blending into the background" in Study 3. Further, background–foreground contrast played a significant role in both Affective Experience and Functional Utility in Study 2, particularly among participants with real CVD. Consistent with accessibility best practices [3], using white or light backgrounds with high contrast foreground elements (text, lines, icons) improves both graphical perception and visual tone.

(D5) Test with Real Users, Not Just Simulations. Simulated filters (Study 1) approximated directional effects but failed to capture the intensity and nature of perceptual challenges. Real CVD participants (Study 2) showed sharper declines in perceived utility when designs lacked redundancy. Study 3 revealed rich compensatory strategies, such as mentally substituting meanings or using associative color memories—phenomena not visible through simulation. Inclusive design requires input from real users to understand interpretive breakdowns and adaptations [28, 80].

6 Future Work and Conclusions

Several constraints in our current study shape directions for future research. First, some Study 2 subgroups (e.g., blue-yellow and combined red-green CVD) had small samples, which may limit detection of subtype-specific effects. Second, although we used red/green simulations to select stimuli, our Study 2 and 3 populations included participants with rarer CVD types (e.g., blue-yellow deficiency, monochromacy). While many design challenges generalized, our visualizations were not explicitly chosen to target their interference patterns. Some issues may stem from problematic hues beyond red/green (e.g., cyan, yellow), low contrast, or limited redundancy. Future work should broaden stimulus selection to cover a wider range of perceptual risks and CVD profiles. More broadly, accessibility is also shaped by factors such as aging, literacy, and culture, while we recruit English-speaking, high school-educated participants from Western nations. We also relied on subjective measures (Likert-scale ratings and interviews) to capture perceptual and emotional responses. While objective metrics (e.g., task accuracy or response time) could complement these insights, they were beyond the scope of this study. Future work should incorporate such measures to triangulate self-reported findings.

Another limitation in this work is that we do not to test palette-corrected versions of our stimuli, such as those produced by modern color correction algorithms [38, 58]. As discussed in Sec. 2.3, CVD color correction is a complex and evolving area, requiring careful trade-offs between discriminability, perceptual similarity, and aesthetic fidelity. While the current work focuses on establishing novel baselines (we thus consider corrective model testing out of scope), this limits conclusions we can make about the real-world effectiveness of current tools; we plan to perform such investigations in the future. Finally, our focus on static charts also leaves open questions about animated and interactive visualizations.

Overall, this work advances inclusive visualization research by empirically comparing simulated and real-world CVD experiences across functional, affective, and interpretive dimensions. While simulated filters preserved overall color contrast patterns [42] and captured some perceptual shifts, they often overstated usability, missed the interpretive effort required of CVD participants [47], and failed to reveal deeper issues such as missing structural cues or redundant encodings—that are critical for interpretation [45, 81]. Instead, CVD participants consistently described color as fragile, relying on instead on structure, shape, and text. However, this finding emerged in the context of visualizations that included at least low levels of perceptual interference; whether well-designed, dichromat-accessible palettes restore greater trust in color remains an open question for future work. Our findings emphasize that effective accessibility requires multi-channel design and real-user evaluation. We also found that interference level alone does not predict difficulty: high-interference charts often triggered issues, but low and medium charts also caused confusion when lacking redundancy or structural support. Ultimately, accessibility should not be retrofitted, but built in from the start. By prioritizing structure, redundancy, and user-centered evaluation, we can design visualizations that are not only accessible but interpretable and meaningful to all.

Supplemental Materials

All supplemental materials are available at `https://osf.io/ymucn/`, released under a CC BY 4.0 license. In particular, they include: (1) Excel files containing the aggregated data for collected measures, (2) study stimuli along with the corresponding source data visualizations, (3) a description of the annotation taxonomy, (4) analysis results (factor loadings, chi-squared, regression coefficients, significance, Cohen's f-squared), (5) demographic data of participants, and (6) a full version of this paper with all appendices.

Figure Credits

Visualizations used across Figures 1, 2, 3, 6, 7: *Shanghai*– Wendy Shija, Tableau Public, July 2021. *Climate Change*– Verisk Analytics, Maplecroft, November 2018. *Adore You*– Nadieh Bremer, Visual Cinnamon, September 2020. *Poppy*– Valentina D'Efilippo, Behance, November 2014. *Guns in America*– Joyce Ma, Visual Capitalist, September 2024. *Fall Leaves*– Chris Love, Tableau Public, January 2019. *Children's Lives*– Beautiful News, Information is Beautiful, February 2020. *Timeline of History*– Leonard Eisenberg, Evogeneao, February 2013. *Food and Wine Pairing Grid*– Madeline Puckette, Wine Folly, February 2014. *A Mixed Recovery*– Jeremy Ashkenas and Alicia Parlapiano, New York Times, June 2014. *Burger vs. Chinese*– Matt Daniels, The Pudding, February 2018. *Doodle Timeline*– Wendy Shija, IronViz Tableau Public, February 2022. *Satellites in Space*– Nadieh Bremer, Visual Cinnamon, September 2020. *Sustainable Development Goals*– UN SDG Action Campaign, Tableau Public, June 2017. *Nuclear Slowdown*– Valerio Pellegrini, Behance, May 2017.

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