Towards Adjacency-Aware Categorical Color Palettes: Algorithm, Evaluation, and User Preferences

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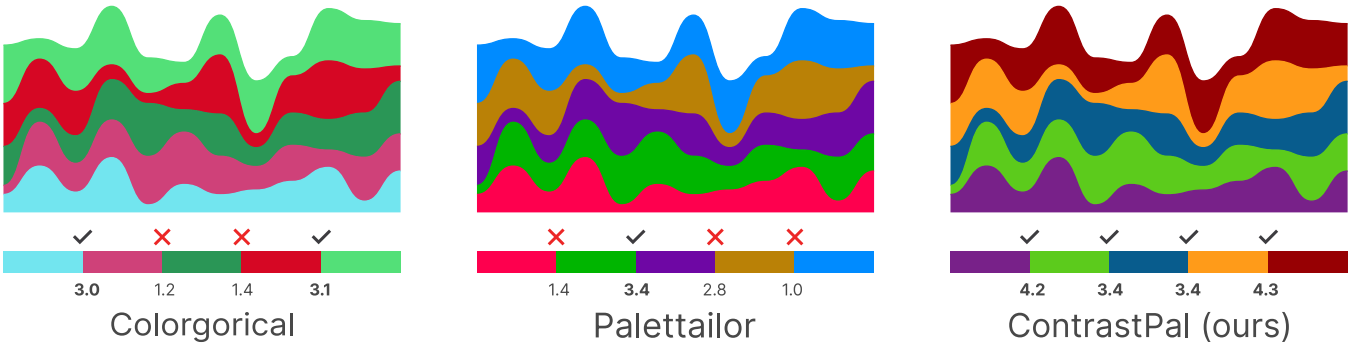


Figure 1: Results of three color palette generation approaches applied to data visualizations with adjacent color blocks: (left) Colorgorical, (center) Palettailor, (right) ContrastPal. ContrastPal integrates adjacent contrast into its optimization strategy, promoting distinguishability of adjacent color blocks in alignment with WCAG guidelines (contrast ≥ 3.0).

Abstract

As data complexity increases, so does the need for effective color encoding in visualizations. Existing palette generation tools optimize global discriminability but overlook adjacent luminance contrast, limiting legibility in stacked bar charts, pie charts, and similar visualizations. As a first step toward adjacency-aware palette optimization, we extend an established categorical palette generation algorithm with an adjacent luminance contrast term, integrated alongside color distance and name difference via Simulated Annealing and aligned with WCAG accessibility guidelines. A benchmark evaluation against two established optimizations shows that incorporating adjacent contrast maintains comparable discriminability while significantly improving WCAG contrast adherence. An exploratory preference study provides initial evidence that resulting palettes remain aesthetically competitive. Our findings indicate that adjacent luminance contrast can be jointly optimized with global color discriminability without meaningful trade-offs, laying the groundwork for studying its impact on chart reading performance and exploring more sophisticated aesthetics optimization.

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CCS Concepts

• **Human-centered computing** → **Visualization systems and tools**; **Empirical studies in visualization**.

Keywords

Color palette generation, discriminability, accessibility, adjacent color blocks, luminance contrast.

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1 Introduction

Categorical data visualizations rely on color to distinguish groups and datapoints, and choosing colors that support accurate and intuitive interpretation has been a longstanding objective in visualization research. A variety of approaches were introduced to optimize color palettes for different types of visualizations, typically optimizing towards overall distinguishability [10, 20, 31, 37] the visibility of small marks [15], or preservation of semantic information [3, 7, 36]. However, current optimizations neglect explicit distinguishability of neighboring segments which is central to common tasks in proportional visualizations such as stacked bar charts and pie charts [14]. Sufficient luminance contrast has been shown to improve legibility and accessibility of both text [5, 16, 34, 38] and

graphical marks and boundaries [8, 18, 23]. When adjacent colors in a visualization lack such contrast, viewers struggle to differentiate elements, reducing the effectiveness of the visualization [2, 25, 30].

To address this gap, we explore the integration of adjacent luminance contrast into established color discriminability optimization approaches [9, 20] that optimize for perceptual color distance [27] and color name difference [12]. In addition, our approach, *ContrastPal*, targets international accessibility guidelines [5] and covers both generating color palettes and assigning them to adjacent chart elements to maximize neighbor separability. We perform a benchmark evaluation of ContrastPal against the state-of-the-art palette generation approaches Colorgorical [9] and Palettailor [20], comparing palette discriminability and adjacent luminance contrast. Our results show that ContrastPal achieves substantially higher adjacent luminance contrast while matching both baselines in global palette discriminability, suggesting that adjacent luminance contrast can be jointly optimized without sacrificing global discriminability, though future work should investigate how adherence to WCAG contrast thresholds translates into measurable improvements in chart reading performance. In an exploratory crowdsourced aesthetics study, ContrastPal receives ratings comparable to Palettailor but lower than Colorgorical, which employs a more sophisticated aesthetics optimization. Our study reveals that excluding disliked colors constrains the solution space without improving aesthetics ratings, suggesting that closing the gap with more aesthetically optimized approaches like Colorgorical [9] requires exploring methods such as promoting preferred color pairs and understanding how such objectives interact with adjacent contrast optimization. Taken together, our work provides a foundation for adjacency-aware color palette optimization, and we open-sourced ContrastPal to support further research on adjacency-aware palette generation.

2 Related Work

A core requirement for categorical color palettes is that each color is perceptually distinct from all others [11], enabling viewers to reliably identify and differentiate data categories. Several approaches were introduced to address this by optimizing global pairwise color distance [27] across a whole palette [10, 19, 29, 41]. Gramazio et al. [9] and Lu et al. [20] further integrate color name difference [12] as a complementary discriminability metric, addressing perceptual grouping by hue similarity. However, high pairwise discriminability does not guarantee sufficient contrast where two colors meet. In visualizations such as stacked bar charts and pie charts, where viewers must judge boundaries and compare proportions between adjacent segments, global discriminability alone remains insufficient (cf. Figure 1). Several works have addressed spatial aspects of color optimization, each targeting a specific dimension of the problem. Lee et al. [15] optimize categorical color discriminability for map visualizations, weighting luminance and saturation contrast to improve visibility of small regions surrounded by larger ones. Lu et al. [21] optimize palettes for transparent overlapping displays such as histograms, where overlaid colors must remain distinguishable while preserving within-class association. Closer to our objective, Languenou [13] and Li et al. [17] assign higher priority to adjacent class pairs during optimization. However, both approaches assume a suitable input palette; if the starting colors lack sufficient contrast, the optimization is inherently limited in producing strong separation. Jointly generating and optimizing palettes for adjacent contrast thus remains an open challenge.

3 ContrastPal

We introduce ContrastPal, which formulates palette generation as a joint optimization problem balancing global palette discriminability with sufficient luminance contrast between adjacent colors.

3.1 Scoring Functions

In the following, we define the perceptual color metrics of our optimization approach, where c_i represents the i-th color of the ordered color palette M consisting of m colors; thus, $|M| = m$. Additionally, we define c_0 as the background color, which is not part of M. Our palette discriminability component follows established methods [9, 20] by adopting both color distance (CD) [27], an established metric calculated based on differences in lightness, chroma, and hue, and name difference (ND) [12], which estimates the likelihood of two colors being referenced by the same name. For instance, the colors `YellowGreen`, `rgb(154, 205, 50)` and `ForestGreen`, `rgb(34, 139, 34)` are perceptually different from each other, yet both are often referred to simply as `Green`. Unlike Colorgorical and Palettailor, we cap color distance scores at a sufficiency threshold of 10 [20] rather than maximizing pairwise separation, allowing the optimizer to prioritize diversity across all objectives. A palette's color distance score reflects its least distinguishable pair, while name difference is averaged across all pairs:

$$score_{CD}(M) = \min\left(10, \min_{0 \le i \ne j \le |M|} \Delta DE_{00}(c_i, c_j)\right) \tag{1}$$

$$score_{ND}(M) = \frac{1}{2|M|(|M|-1)} \sum_{0 \le i < j \le |M|} \mathrm{ND}(c_i, c_j) \tag{2}$$

To maintain hue discriminability at low luminance levels [2], we additionally include a minimal luminance score capped at a threshold of 30. According to international WCAG standards, graphical elements like adjacent color blocks in pie charts or stacked bar charts must have a minimum contrast of 3 to ensure accessibility and readability [5]. Analogous to color distance, we define a palette's adjacent contrast (AC) score as the minimum luminance contrast of its adjacent color pairs, capped to a sufficiency threshold of 3 and define the adjacent contrast score of a palette as the minimum luminance contrast of all adjacent color pairs:

$$score_{AC}(M) = \min\left(3, \min_{0 < i \le |M|} AC(c_i, c_{i+1})\right) \tag{3}$$

Prior work indicates that dark yellow-greenish colors are widely disliked across cultures [33, 39]. Gramazio et al. [9] defined this strongly disliked color space as consisting of colors of the CIE LCh color space whose luminance values fall within the range of $L \in [35, 75]$ and hue values of $H \in [85°, 114°]$. Following Gramazio et al. [9] and Lu et al. [20], we include a preference term that penalizes palettes containing colors from this disliked range.

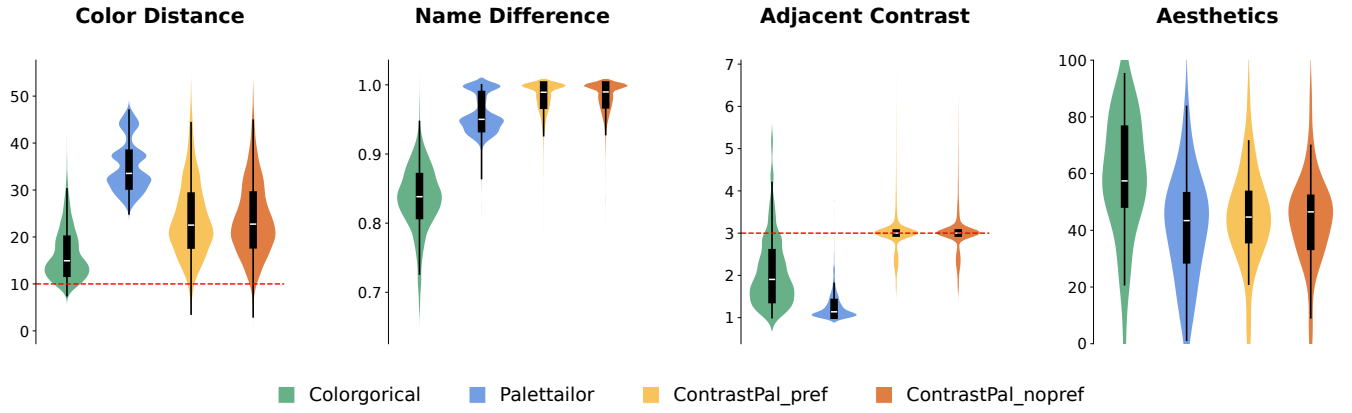


Figure 2: Results of benchmark evaluation and aesthetics study across different optimization approaches. The plots illustrate the minimum color distance per palette (outer left), mean name difference per palette (mid left), minimum adjacent contrast (mid right), and aesthetics ratings (outer right). The red dashed lines indicate thresholds for sufficient values of color distance [20] and adjacent contrast [5].

3.2 Annealing-Based Optimization

We employ Simulated Annealing [35] following Lu et al. [20], a probabilistic optimization technique that starts from a random solution and iteratively perturbs it, initially accepting suboptimal solutions to explore the search space broadly, then gradually narrowing toward the best-found solution as a temperature parameter decreases. Starting from a randomly initialized palette, each iteration perturbs each color's RGB components by a random value within ±10 and evaluates the resulting palette using a weighted linear combination of the scoring functions. We adopt the cooling rate (0.999) and end temperature (0.001) from Lu et al. [20], and set the initial temperature to 100 with a maximum of 50,000 iterations based on parameter exploration.

4 Evaluation

We evaluate ContrastPal along two dimensions. A benchmark evaluation compares palette discriminability, name difference, and adjacent luminance contrast against Colorgorical [9] and Palettailor [20]. Since aesthetics are a complementary objective in palette generation [9, 17, 40], we further conduct an exploratory crowdsourced study assessing the visual appeal of generated palettes.

4.1 Quantitative Evaluation

We compare ContrastPal against Colorgorical [9] and Palettailor [20] on three metrics: palette discriminability, name difference, and adjacent luminance contrast. For each method, we generate 4,000 palettes (1,000 each at representative sizes 4, 6, 8, and 10) to assess robustness across palette sizes. For ContrastPal, we test two variants: ContrastPal_pref (including the preference term that excludes disliked colors, resulting in 0 palettes containing disliked colors) and ContrastPal_nopref (excluding the preference term, resulting in 238/4,000 palettes containing up to two disliked colors) to isolate the effect of the preference objective.

4.1.1 Results. We observe consistent differences in discriminability metrics between approaches (Figure 2). Both ContrastPal variants achieve higher adjacent contrast ($M = 3.0$, $SD = .52$) compared to Colorgorical ($M = 1.9$, $SD = .82$) and Palettailor ($M = 1.14$, $SD = .3$), while maintaining comparable name difference scores. Color distance is lower than Palettailor ($M = 22.5$ and $M = 22.7$ vs. 33.5) but exceeds Colorgorical ($M = 14.9$), while all four approaches remain above the perceptual distinctness threshold of 10. An ART ANOVA confirms a main effect of Approach for all three metrics ($p < .001$, η_p^2 ranging between .68 and .72 indicating strong effect size [4]), and post-hoc comparisons reveal that all pairwise differences are significant except between the two ContrastPal variants ($p \geq .25$; see Table A1 and Table A2 for detailed tables). Interactions with PaletteSize are reported in the appendix.

4.2 Crowdsourced Aesthetics Study

To evaluate the aesthetic appeal of ContrastPal's generated palettes, we used a within-subjects design in which each participant rated palettes produced by four generation approaches. We generated 12 datasets with smoothly varying distributions (three per palette size: 4, 6, 8, 10) to avoid abrupt visual changes that could bias aesthetics ratings. Each dataset was rendered as a stacked area chart using palettes from Colorgorical, Palettailor, ContrastPal_pref, and ContrastPal_nopref, resulting in 48 stimuli. All charts used a consistent minimalist layout (400×400 px, unlabeled axes, no legend, and no gaps between areas).

We estimated sample size via an a priori power analysis using the average effect size reported in Palettailor's preference study [20]. Assuming Cohen's $d = 0.2$, $\alpha = 0.05$, and power $1 - \beta = 0.8$, the analysis suggested a minimum of 36 participants. We recruited 39 participants via Prolific (20 male, 19 female; $M_{age} = 37.69$, $SD = 11.31$). Compensation was £1.20 (approximately £9/hour based on pilot completion times). Participants were fluent English speakers, reported no color-vision deficiencies, and had not participated in our pilot. To ensure data quality, we restricted participation to workers with a 95–100% approval rate and at least 10 prior Prolific studies. All participants provided informed consent.

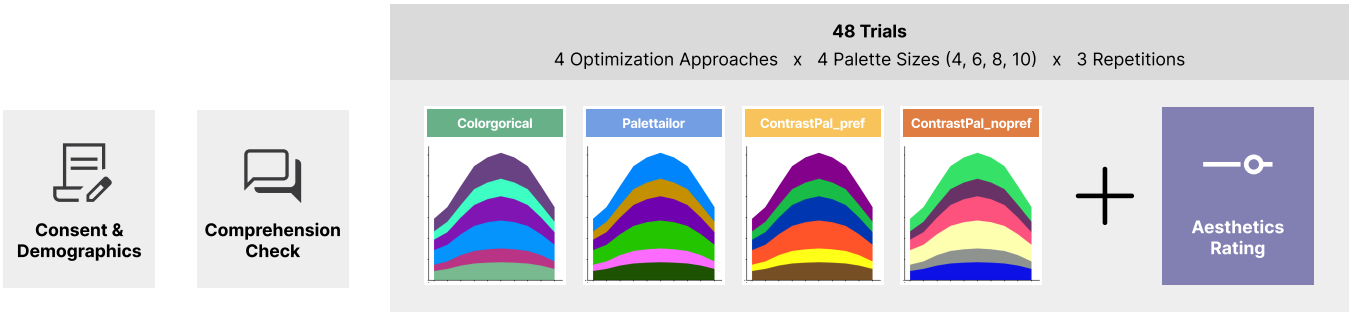


Figure 3: Overview of the aesthetics study procedure. After consent, demographic questions, and a comprehension check, participants rated the aesthetic quality of stacked area charts generated by four palette generation approaches. Each participant evaluated 48 stimuli (4 approaches × 4 palette sizes × 3 datasets) in randomized order using a continuous slider scale.

The study procedure is illustrated in Figure 3. After informed consent, demographics, and a comprehension check, participants rated 48 charts in randomized order across four blocks of 12. For each chart, they rated the statement *"I find the colors of this chart very aesthetically pleasing."* on a continuous visual analog scale from 0 to 100 without tick marks [22], phrased strongly to counteract acquiescence bias [6]. Attention checks between blocks required participants to place the slider at a specified endpoint.

4.2.1 Results. Colorgorical receives the highest aesthetics ratings ($M = 57.42$, $SD = 20.84$), followed by ContrastPal_nopref ($M = 46.50$, $SD = 15.22$), ContrastPal_pref ($M = 44.67$, $SD = 16.20$), and Palettailor ($M = 43.42$, $SD = 18.37$). An ART ANOVA confirms a significant and strong [4] main effect of Approach ($F(3, 570) = 43.94$, $p < .001$, $\eta_p^2 = .19$). Post-hoc comparisons show that Colorgorical is rated significantly higher than all other approaches ($p < .001$), which do not differ from each other (see Table A1 and A2 for details). To further assess equivalence between ContrastPal variants and Palettailor, we conducted Bayesian Wilcoxon signed-rank tests. Results provide substantial evidence that ContrastPal_pref and ContrastPal_nopref produce equivalent ratings ($BF_{10} = 0.252$), and substantial evidence for equivalence between ContrastPal_pref and Palettailor ($BF_{10} = 0.302$). Evidence for equivalence between ContrastPal_nopref and Palettailor is anecdotal ($BF_{10} = 0.884$), indicating a less conclusive result for this pair.

5 Discussion

Our benchmark results demonstrate that optimizing for adjacent luminance contrast does not inherently conflict with palette-level discriminability. ContrastPal achieves substantially higher adjacent contrast while maintaining comparable discriminability to both baselines. ContrastPal's lower color distance compared to Palettailor reflects our deliberate capping strategy rather than a cost of adjacent contrast optimization: once the sufficiency threshold of 10 is reached, the optimizer redirects effort toward other objectives instead of maximizing global pairwise differences. WCAG luminance contrast is correlated with the lightness component of CIEDE2000 [27], so enforcing adjacent luminance contrast tends to partially satisfy color distance requirements for adjacent pairs. From a practical perspective, adjacent contrast can be integrated as an additional scoring term into existing weight-based optimization frameworks [9, 20] without requiring architectural changes. Practitioners can incorporate the term whenever the target visualization contains adjacent color segments, such as stacked bar charts, pie charts, or treemaps, extending existing frameworks to adjacency-aware use cases. As a potential additional benefit, optimizing for luminance contrast may improve legibility for viewers with color vision deficiencies, since the most common forms primarily impair chromatic discrimination while leaving luminance perception largely intact [1].

Our exploratory study provides, to our knowledge, the first empirical evidence that excluding culturally disliked colors [33, 39] does not improve perceived palette quality, an assumption embedded in existing tools [9, 20] but previously unvalidated. In contrast, Colorgorical, which optimizes for preferred color pairings [9], achieved significantly higher preference ratings than all other methods. Colorgorical defines pair preference based on cool colors that differ in lightness and are similar in hue [9, 26], which inherently favors perceptually similar colors, producing aesthetically preferred but less discriminable palettes. This is reflected in our benchmark results, where Colorgorical exhibited the lowest adjacent contrast and color distance among all tested methods. These results indicate a potential tension between sophisticated aesthetics optimization and discriminability that motivates further investigation into how to adequately balance competing objectives.

5.1 Limitations and Future Work

Our evaluation assessed adjacent contrast computationally but did not investigate whether WCAG adherence translates into measurable improvements in chart reading performance. While prior work demonstrates that luminance contrast impacts visual search time [24, 28], future studies should examine how the WCAG threshold relates to response error and time in proportional visualizations. Our exploratory aesthetics study indicates that excluding disliked colors does not improve preference ratings, while Colorgorical's more sophisticated preference optimization achieves higher ratings at the cost of lower discriminability. Future work should systematically vary aesthetics strategies, such as preferred color pairs [9], color harmony models [17], or image-extracted palettes [41], measuring their interaction with both palette discriminability and adjacent contrast. Finally, our optimizer assumes a

fixed linear adjacency structure. Extending the approach to circular cases (e.g., pie charts), graph-based structures (e.g., node-link diagrams), and data-dependent adjacency changes remains open. Similarly, mark size effects on perceivability [20, 32] are not yet accounted for and should inform future data-aware weighting of adjacent contrast by segment size. While our approach and existing tools [9, 20] allow users to set weights for competing objectives, it remains underexplored how to transparently communicate whether specific optimization goals were actually met, and how deprioritizing objectives such as WCAG adherence may impact the suitability of the resulting visualization for concrete reading tasks.

6 Conclusion

We introduced adjacent luminance contrast as an optimization objective for categorical color palettes and demonstrated that it can be jointly optimized with global discriminability without meaningful trade-offs. Our exploratory aesthetics study indicates that simple color filtering does not affect aesthetics ratings or discriminability, suggesting that more sophisticated approaches are needed to close the aesthetic gap with preference-aware methods. This work establishes that adjacency-aware optimization is feasible without sacrificing discriminability, enabling future work to investigate how aesthetics optimization interacts with adjacent contrast objectives, and whether WCAG-aligned contrast thresholds improve chart reading performance.

Open Science & Transparency

Algorithm, datasets, and analysis scripts are available on osf.io. Claude was used for grammar and style editing; authors reviewed all content and take full responsibility for the final manuscript.

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A Appendix

Table A1: ART ANOVA results for palette discriminability metrics and aesthetics ratings. Df: degrees of freedom; Df.res: residual degrees of freedom; F: F-statistic; p: p-value; η_p^2: partial eta squared.

Factor	Df	Df.res	F	p	η_p^2
Color Distance					
Approach	3	15984	12049.47	<.001	.69
PaletteSize	3	15984	8449.68	<.001	.61
Approach × PaletteSize	9	15984	127.38	<.001	.07
Name Difference					
Approach	3	15984	13872.75	<.001	.72
PaletteSize	3	15984	2031.81	<.001	.28
Approach × PaletteSize	9	15984	439.34	<.001	.2
Adjacent Luminance Contrast					
Approach	3	15984	11082.6	<.001	.68
PaletteSize	3	15984	967.23	<.001	.15
Approach × PaletteSize	9	15984	329.13	<.001	.16
Aesthetics Ratings					
Approach	3	570	43.94	<.001	.19
PaletteSize	3	570	2.93	.033	.02
Approach × PaletteSize	9	570	1.34	.213	.02

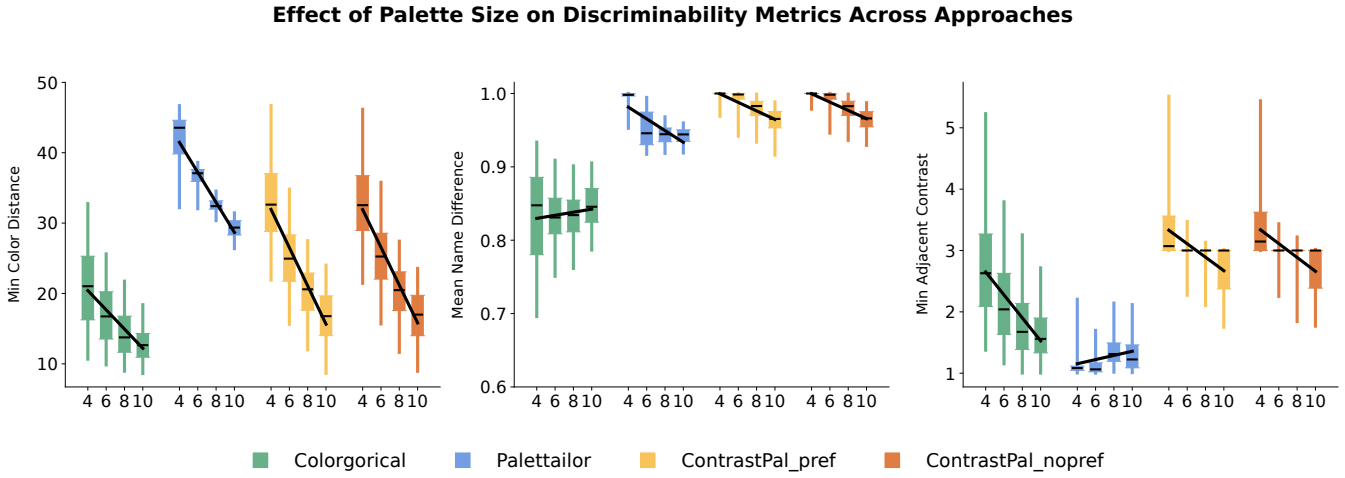


Figure A1: Results for each color metric across different optimization approaches, grouped by PaletteSize, confirming PaletteSize as a confounding variable: minimum color distance (left), mean name difference (center), and minimum adjacent contrast (right). The bars represent the median values, with lighter-colored error bars indicating the 95% confidence interval. Solid black lines show regression trends across palette sizes.

Table A2: Key Tukey-adjusted EMM pairwise comparisons. Δ denotes the estimated mean difference (first minus second approach); positive values indicate higher scores for the first approach. Estimates are reported on the analysis scale.

Metric & Pairwise Comparison	Δ	SE	df	t	p
Color Distance					
ContrastPal_pref – Palettailor	-6195.66	57.18	15984	-108.35	< .001
ContrastPal_pref – Colorgorical	4623.67	57.18	15984	80.86	< .001
ContrastPal_pref – ContrastPal_nopref	-59.31	57.18	15984	-1.04	.73
ContrastPal_nopref – Palettailor	-6136.34	57.18	15984	-107.31	< .001
ContrastPal_nopref – Colorgorical	4682.98	57.18	15984	81.89	< .001
Name Difference					
ContrastPal_pref – Palettailor	4625.27	54.27	15984	85.22	< .001
ContrastPal_pref – Colorgorical	9471.64	54.27	15984	174.51	< .001
ContrastPal_pref – ContrastPal_nopref	17.93	54.27	15984	0.33	.99
ContrastPal_nopref – Palettailor	4607.34	54.27	15984	84.89	< .001
ContrastPal_nopref – Colorgorical	9453.71	54.27	15984	174.18	< .001
Adjacent Luminance Contrast					
ContrastPal_pref – Palettailor	8975.31	58.61	15984	153.13	< .001
ContrastPal_pref – Colorgorical	4868.53	58.61	15984	83.06	< .001
ContrastPal_pref – ContrastPal_nopref	-108.83	58.61	15984	-1.86	.25
ContrastPal_nopref – Palettailor	9084.13	58.61	15984	154.99	< .001
ContrastPal_nopref – Colorgorical	4977.35	58.61	15984	84.92	< .001
Aesthetic Ratings					
ContrastPal_pref – Palettailor	20.1	14.4	570	1.39	.5
ContrastPal_pref – Colorgorical	-129.5	14.4	570	-8.99	< .001
ContrastPal_pref – ContrastPal_nopref	10.4	14.4	570	0.73	.887
ContrastPal_nopref – Palettailor	30.5	14.4	570	2.12	.15
ContrastPal_nopref – Colorgorical	-119.0	14.4	570	-8.26	< .001