Perceptual Color Experience on Conventional and AR Displays across Color Gamut and Ambient Luminance

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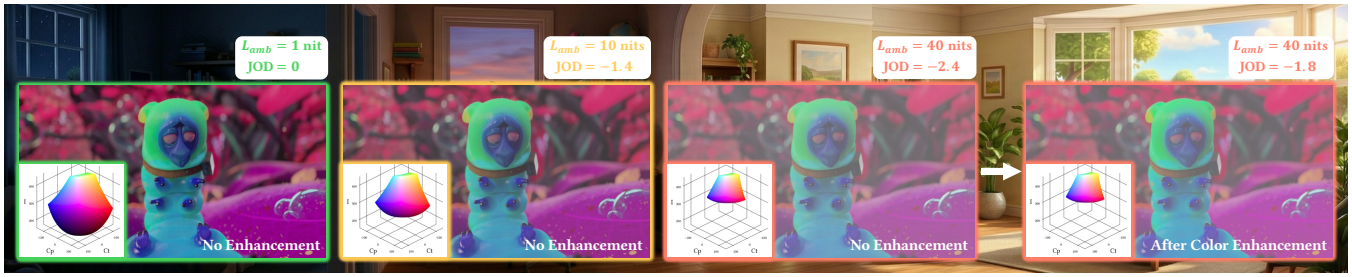

Fig. 1. Ambient light is ubiquitous in real-world viewing environments and can substantially alter display color appearance. Increasing ambient luminance shrinks the effective color gamut and degrades perceived color quality relative to a display's native capability. We systematically evaluate this effect across display characteristics and ambient conditions, and introduce color-enhancement algorithms that exploit unused display-gamut headroom for compensation. This figure shows a video presented on a display with Display P3 gamut and 280-nit peak luminance under three ambient luminance levels, L_{amb} = 1, 10, and 40 nits, together with a color-enhanced result at L_{amb} = 40 nits (rightmost). Insets visualize the effective color gamut in ICtCp color space [Dolby Laboratories 2016] after accounting for ambient light, with just-objectionable-difference (JOD) scores indicating perceived color quality. Because HDR/WCG imagery cannot be faithfully reproduced in PDF format, all images in this manuscript are tone- and gamut-mapped for illustration. Image credit: Netflix.

A display's color gamut defines the range of colors it can reproduce and is a key factor of perceptual color experience. Modern displays increasingly support high dynamic range (HDR) and wide color gamut (WCG), enabling brighter and more vivid color reproduction. In practical viewing environments, however, ambient illumination often shrinks the effective gamut and degrades perceived color quality relative to a display's native capability.

We study how color gamut, dynamic range, and ambient luminance jointly shape perceived color quality across conventional flat-panel and optical see-through augmented reality (OST-AR) displays. To this end, we gather a WCG HDR video dataset and develop a display-simulation pipeline that emulates diverse display capabilities and ambient conditions. Using this framework, we conduct a direct-view user study to collect preference data and derive a perceptual model that predicts perceived color quality from these factors. A second study evaluates model generalization to OST-AR viewing conditions and examines the effect of background pattern. To mitigate ambient-induced color degradation, we introduce three color-enhancement algorithms and validate them in a third study. Our findings provide practical guidance for display-system design aimed at improving real-world color experience.

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CCS Concepts: • **Computing methodologies** → **Mixed / augmented reality**; **Perception**; • **Human-centered computing** → **Displays and imagers**.

Additional Key Words and Phrases: Wide Color Gamut, High Dynamic Range, Color Perception, Perceptual Color Volume, Ambient Light

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1 Introduction

Wide-color-gamut (WCG) and high-dynamic-range (HDR) displays are increasingly deployed across televisions, monitors, mobile devices, and optical see-through augmented reality (OST-AR) systems. By expanding color-gamut coverage and dynamic range, these displays enable brighter and more vivid color reproduction. In practice, however, displays are commonly viewed outside ideal dark-room conditions. Ambient illumination introduces an additive light component, via panel reflection on conventional flat-panel displays or optical transmission in OST-AR displays, that reduces the effective color gamut and degrades perceived color quality relative to a display's native capability. As display technologies continue to evolve toward wider gamuts and higher brightness, understanding how display specifications and ambient conditions jointly shape perceptual color experience becomes increasingly important.

Prior work has examined visual quality using HDR/WCG images [Choudhury et al. 2021; Heckaman et al. 2007; Sakurai et al. 2008b] and videos [Athar et al. 2019; Mantiuk et al. 2024; Shang et al. 2023]. However, these studies generally consider limited color-gamut and dynamic-range configurations and do not characterize their interaction with ambient light. Recent work has studied various aspects of visual perception in OST-AR under ambient illumination, including brightness perception [Murdoch 2020], contrast perception [Kim et al. 2025], color appearance [Hassani and Murdoch 2019; Zhang et al. 2021a], and video artifact visibility [Chapiro et al. 2024]. Yet, the perceptual benefits of expanded display color capabilities across varying ambient conditions remain inadequately quantified.

In this research, we systematically study color experience across three interacting display and viewing factors: color gamut, dynamic range, and ambient luminance. To support this investigation, we collect a WCG HDR video dataset with broad color coverage and diverse content categories. We develop a display-simulation pipeline that combines tone mapping, gamut mapping, and an ambient-light model to emulate diverse display characteristics and ambient conditions on an HDR/WCG reference display. Using this framework, we conduct a direct-view study to measure perceptual preferences across display and ambient conditions and scale the responses into just-objectionable-differences (JODs) [Perez-Ortiz et al. 2019]. From these data, we establish a perceptual model that predicts perceived color quality from color gamut, dynamic range, and ambient luminance. In a follow-up user study, we evaluate how well the model generalizes from direct-view to OST-AR conditions and test how background structure affects perceived color quality.

To mitigate ambient-induced color-fidelity degradation, we introduce three color-enhancement algorithms that exploit unused display-gamut headroom for ambient compensation, and validate their perceptual benefits in OST-AR through a third user study. Our findings provide quantitative guidance for display-system design and practical methods for enhancing color experience in real-world viewing environments.[1] In summary, we contribute:

- A WCG HDR video dataset with broad color/luminance coverage;
- User studies quantifying how color gamut, dynamic range, and ambient luminance jointly shape perceived color quality across conventional flat-panel and OST-AR displays;
- A perceptual model predicting perceived color quality from display color gamut, dynamic range, and ambient luminance;
- Color-enhancement algorithms that exploit unused gamut headroom to compensate for ambient-induced color degradation.

2 Related Work

Color Representation and Color Gamut. Color appearance models, including CIECAM02 [Moroney et al. 2002], iCAM06 [Kuang et al. 2007], and appearance-based HDR encoding frameworks [Kunkel et al. 2013], model effects of viewing conditions, adaptation, and spatial context on perceived color attributes [Fairchild 2013]; ambient-adaptive systems further adjust rendering based on environmental illumination [Wu et al. 2019]. Display color reproduction is characterized through gamut and color-volume metrics, including discernible-color estimates and effects of flare, peak luminance, and diffuse white [Jiang et al. 2018, 2020; Masaoka et al. 2013; Wen 2006], as well as Gamut Rings for perceptual display comparisons [Masaoka et al. 2018, 2020, 2025; Smith et al. 2020]. Gamut-mapping methods transform colors between source and target gamuts while balancing hue preservation, lightness consistency, and contrast maintenance [Morovič 2008; Morovič and Luo 2001], spanning global compression/expansion [Xu et al. 2018a,b], spatially varying approaches [Bonnier et al. 2007; Farup et al. 2007; Kimmel et al. 2005], perceptually guided techniques [Zamir et al. 2014, 2019], and HDR/WCG content [Preiss et al. 2014; Sikudova et al. 2015]. Psychophysical evaluations reveal content- and method-dependent trade-offs [Dugay et al. 2008; Montag and Fairchild 1997]. These works provide foundations for representing, measuring, and transforming color.

Perceptual Color Quality Assessment. Prior perceptual studies have examined how color gamut and dynamic range affect image quality and preference. Paired-comparison studies showed that increasing display gamut volume generally improves preference, with diminishing returns and strong content dependence [Heckaman et al. 2007; Sakurai et al. 2008a,b]. Later work studied objective and subjective quality metrics for HDR/WCG images and videos [Choudhury and Daly 2020; Choudhury et al. 2021; Rousselot et al. 2019; Shang et al. 2023], and perceptual optimization of HDR rendering pipelines [Cao et al. 2024]. However, many studies focus on still images [Choudhury et al. 2021; Heckaman et al. 2007; Rousselot et al. 2019], while video evaluations often fix either gamut or dynamic range [Athar et al. 2019; Mantiuk et al. 2024]. Systematic evaluation is also limited by the lack of diverse, calibrated WCG HDR datasets: existing datasets are often domain-specific [Froehlich et al. 2014; Keller et al. 2024; Song et al. 2016] and sparsely cover high-chroma colors despite using WCG containers. Thus, perceived color quality across the joint space of color gamut, dynamic range, and ambient luminance remains under-characterized, particularly for dynamic content.

Visual Perception in OST-AR. OST-AR introduces additional complexity because virtual content is optically combined with real-world backgrounds. Prior work has examined color appearance shifts [Hassani and Murdoch 2019], brightness perception [Murdoch 2020], and contrast sensitivity in OST-AR systems [Livingston et al. 2009], highlighting the role of environmental light in color blending and contrast reduction. Recent studies further investigate background-dependent color appearance [Zhang et al. 2021a], color contrast enhancement [Zhang et al. 2021b], dichoptic and interocular effects [Erickson et al. 2022a; Wang et al. 2023], supra-threshold contrast perception [Kim et al. 2025], and transparency or color scission [Murdoch 2025]. Application-driven work has studied AR interface design and usability [Gabbard et al. 2020; Hou et al. 2025; Yamin et al. 2024], while reviews summarize broader perceptual challenges in AR [Cooper 2023; Erickson et al. 2022b]. Despite this progress, existing work largely focuses on isolated perceptual effects or application-specific scenarios. A unified empirical characterization of how display gamut, luminance, ambient illumination, and background structure jointly influence perceived color quality in OST-AR remains lacking, as does a clear connection between perceptual modeling for conventional and AR displays.

[1] Code, data, and model: yunxiangzhang.github.io/projects/color-perception/index.html

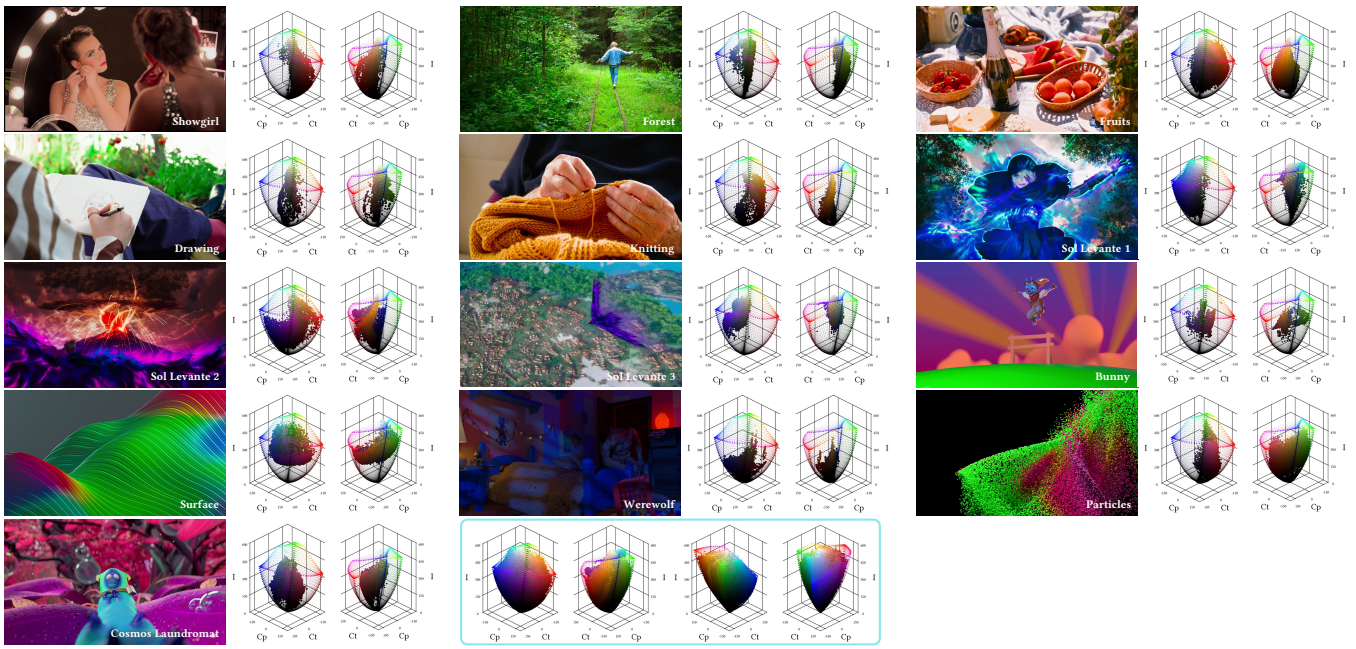

Fig. 2. *Our WCG HDR video dataset.* Each video clip is accompanied by its color distribution visualized in ICtCp color space [Dolby Laboratories 2016] from two azimuth angles, where I, Ct, and Cp denote luma, blue–yellow chroma, and red–green chroma, respectively. Video pixels are spatially subsampled with stride 64 and temporally subsampled at 2 FPS, then plotted as colored points. The dotted outer shell denotes the BT.2020 gamut boundary at 1,000-nit peak luminance and 0.001-nit black level, enclosing the reference color volume; our dataset covers 50% of this volume (see Appendix A.3 for details). The blue-boxed plots show the aggregated color distribution of the full dataset from four azimuth angles. Image credits: HdM Stuttgart, TU Ilmenau, Pexels, and Netflix.

3 Method

3.1 A Wide-Color-Gamut HDR Video Dataset

Recent advances in imaging and display technologies have accelerated the adoption of HDR/WCG media formats, driving a transition from legacy standards with limited color gamuts (e.g., BT.709 [ITU-R 2015b]) toward newer standards supporting substantially wider color reproduction (e.g., DCI-P3 [DCSS 2005] and BT.2020 [ITU-R 2015a]). However, the perceptual benefits of such expanded color capabilities remain inadequately quantified and understood.

Evaluating these benefits requires video content spanning a wide color gamut. Existing HDR video datasets, while often encoded in WCG containers (e.g., HDR10 uses BT.2020 color primaries), typically cover only part of the supported gamut. Many videos contain few high-chroma pixels, yielding effective coverage close to BT.709. Moreover, prior datasets frequently focus on homogeneous content domains, such as cinematic scenes [Froehlich et al. 2014] or casual footage [Keller et al. 2024; Song et al. 2016]. This content bias leads to uneven color distributions, with certain hues or luminance ranges being underrepresented or absent.

We gather a WCG HDR video dataset with diverse content and broad color coverage by combining selected videos from existing sources with newly created content. As illustrated in Figure 2, the dataset consists of 13 video clips spanning cinematic scenes, user-generated content, animated films, and simple graphics. It includes both real-world scenes and non-photorealistic renderings, with memory colors such as human faces, fruits, and greenery. We use the ICtCp color space [Dolby Laboratories 2016], recommended by the International Telecommunication Union (ITU) for HDR/WCG imagery [ITU-R 2025], to visualize color distributions.

Content sources: *Fruits* is from Pexels[2]; *Sol Levante* and *Cosmos Laundromat* are from Netflix Open Content[3]; *Showgirl* is from HdM-HDR-2014 [Froehlich et al. 2014]; *Forest*, *Knitting*, and *Drawing* are from AVT-VQDB-UHD-2-HDR [Keller et al. 2024]; and the remaining clips are created in Blender. All videos are manually mastered to the BT.2020 gamut using DaVinci Resolve[4] to enhance colorfulness while preserving a natural appearance. When necessary, videos are resampled/cropped to 1080p. All videos are encoded using HEVC with BT.2020 primaries, perceptual quantizer (PQ) electro-optical transfer function (EOTF), 10-bit quantization, and no chroma subsampling. Additional dataset details are provided in Appendix A.

3.2 Display Simulation

Studying user preferences across display and ambient conditions without building each hardware setup requires accurate emulation on a reference display. We introduce a display-simulation pipeline that integrates tone-mapping operators (TMOs), gamut-mapping algorithms (GMAs), and ambient-light modeling to convert source BT.2020 RGB videos to target conditions. Many TMOs [Eilertsen et al. 2017] and GMAs [Morovič and Luo 2001] have been proposed in the literature, with relative performance depending on content

[2]https://www.pexels.com/
[3]https://opencontent.netflix.com/
[4]https://www.blackmagicdesign.com/products/davinci-resolve/

and application-specific constraints. As our goal is not to compare or introduce new tone- or gamut-mapping methods, we adopt established methods that follow ITU recommendations and common display-pipeline practice. A comprehensive evaluation of alternative TMOs and GMAs is beyond the scope of this work. Figure 13 (Appendix) illustrates the processing stages.

Given a display-encoded frame I_{disp}, we first apply PQ decoding to recover linear BT.2020 RGB, denoted as I_{in}. This linearized frame then undergoes tone mapping, gamut mapping, and ambient-light simulation, producing a linear output I_{out} for the target condition.

3.2.1 Tone Mapping. We follow the ITU recommendation for HDR-to-SDR conversion [ITU-R 2021] and adopt the tone curve proposed by Chen et al. [2023]. As shown by Chen et al. [2025], using a fixed tone curve across peak luminance levels can introduce substantial contrast distortions, particularly under strong dynamic-range compression. We therefore use the optimization framework of Tariq et al. [2023] to perform scene-adaptive tone-curve adjustment.

Given the target display with black level L_{min} and peak luminance L_{max}, our TMO proceeds in four stages: tone extraction, tone mapping, color correction, and black-level simulation. Implementation details of our TMO are provided in Appendix B.

3.2.2 Gamut Mapping. Following ITU guidance on gamut conversion, we implement two GMAs: an RGB-space soft-clipping method (**RGB-SC**) [ITU-R 2017] broadly supported on hardware platforms, and an ICtCp-space constant-hue-luminance method (**ICtCp-CHL**) [Morovič 2008] that preserves hue and luminance.

RGB-SC. Given the target color gamut G_{target}, defined by its RGB primaries and white point, and the tone-mapped linear BT.2020 RGB frame I_{TM}, **RGB-SC** proceeds as follows:

(1) Apply the BT.2020-to-G_{target} transform to convert I_{TM} into linear RGB values expressed in the target color space.

$$I_{\text{RGB}} = \mathcal{M}_{\text{BT.2020}\to G_{\text{target}}}(I_{\text{TM}}), \quad \text{[Color-Space Transform]} \tag{1}$$

(2) Soft-clip I_{RGB} using the knee function $\mathcal{S}(\cdot\,;\theta_{\text{GM}})$ introduced by MacDonald et al. [2002]. The function is parameterized by $\theta_{\text{GM}} = (\kappa, C^{\text{s}}_{\text{max}}, C^{\text{t}}_{\text{max}})$, where $C^{\text{s}}_{\text{max}}$ and $C^{\text{t}}_{\text{max}}$ specify the maximum input and output values, and $\kappa \in [0,1]$ controls the knee position $C_{\text{start}} = \kappa\, C^{\text{t}}_{\text{max}}$ (see Figure 15 in the appendix). Compared to hard clipping, this approach provides a smooth transition near the target gamut boundary, maintaining most in-gamut colors unchanged while mitigating contrast compression in high-chroma areas [Braun and Fairchild 1999]. The knee-function formulation is provided in Appendix C.

$$\tilde{I}_{\text{RGB}} = \mathcal{S}(I_{\text{RGB}};\theta_{\text{GM}}), \quad \text{[RGB Soft-Clipping]} \tag{2}$$

(3) Transform $\tilde{I}_{\text{RGB}}$ back to linear BT.2020 RGB.

$$I_{\text{GM}} = \mathcal{M}_{G_{\text{target}}\to\text{BT.2020}}(\tilde{I}_{\text{RGB}}), \quad \text{[Color-Space Transform]} \tag{3}$$

Given the same inputs, **ICtCp-CHL** proceeds as follows:

(1) Transform I_{TM} into ICtCp cylindrical coordinates as I_{LCh}, where L, C, and h denote luminance, chroma, and hue.

$$I_{\text{LCh}} = \mathcal{M}_{\text{BT.2020}\to\text{ICtCp}}(I_{\text{TM}}), \quad \text{[Color-Space Transform]} \tag{4}$$

(2) Soft-clip the chroma component C along lines of constant hue and luminance using the same knee function $\mathcal{S}(\cdot\,;\theta_{\text{GM}})$. Unlike **RGB-SC**, the parameters $C^{\text{s}}_{\text{max}}(L,h)$ and $C^{\text{t}}_{\text{max}}(L,h)$ are hue- and luminance-dependent; they represent the maximum chroma for the source (BT.2020) and target (G_{target}) gamuts at each (L,h). These values are obtained from precomputed 2D lookup tables (LUTs) that map (L,h) to the corresponding gamut-boundary chroma.

$$\tilde{C} = \mathcal{S}(C;\theta_{\text{GM}}), \tilde{I}_{\text{LCh}} = [L,\tilde{C},h], \quad \text{[Chroma Soft-Clipping]} \tag{5}$$

(3) Transform $\tilde{I}_{\text{LCh}}$ back to linear BT.2020 RGB.

$$I_{\text{GM}} = \mathcal{M}_{\text{ICtCp}\to\text{BT.2020}}(\tilde{I}_{\text{LCh}}), \quad \text{[Color-Space Transform]} \tag{6}$$

3.2.3 Ambient-Light Modeling. Ambient-light influence on display viewing is commonly modeled in linear colorimetric spaces to preserve physical accuracy. For example, prior work models the optical blending of display emission and background illumination in CIE 1931 XYZ color space [Chapiro et al. 2024]. Our pipeline operates in linear BT.2020 RGB, enabling analogous simulation of ambient light reflected from flat-panel displays or transmitted through OST-AR optics. We assume diffuse ambient illumination and, for flat-panel displays, approximate the display as a diffuse surface with uniform reflectance. Under this assumption, the eye-reaching ambient contribution can be modeled as an additive term:

$$I_{\text{out}} = I_{\text{GM}} + I_{\text{amb}}, \quad \text{[Ambient-Light Simulation]} \tag{7}$$

where I_{amb} denotes the ambient light reaching the observer's eyes after accounting for panel reflectance (flat-panel) or optical transmittance (OST-AR), rather than the incident ambient luminance. This model excludes glossy or spatially varying reflections, such as those produced by localized light sources.

3.3 Direct-View User Study

Utilizing the display-simulation pipeline, we conduct a direct-view user study to measure perceived color quality across systematically varied color gamuts, dynamic ranges, and ambient luminance levels.

Participants. We recruited 41 participants (ages 22–48; 18 female), all of whom had normal or corrected-to-normal vision and passed a color-vision screening using the Ishihara test. The study protocol was approved by an Institutional Review Board (IRB), and all participants provided written informed consent prior to participation.

Hardware. For accurate wide-gamut color reproduction, we used a 31.1" EIZO CG3145 display with DCI-4K resolution, 60 Hz refresh rate, contrast ratio up to 1,000,000:1, 1,000-nit peak luminance, 10-bit color depth, and over 99% DCI-P3 coverage. It was calibrated to BT.2020 primaries and a D65 white point using a Konica Minolta CS-2000 spectroradiometer. A chin rest aligned observers with the display and fixed the viewing distance at 114.3 cm (0.875 diopters, D), yielding a $32.0^\circ \times 18.3^\circ$ field of view. Videos were upsampled from 1080p to 4K UHD via 2×2 pixel replication and center-aligned on the display, yielding an effective angular resolution of 59.0 pixels per degree (ppd), consistent with 20/20 visual acuity (60 ppd). Figure 4 (right) illustrates the hardware configuration.

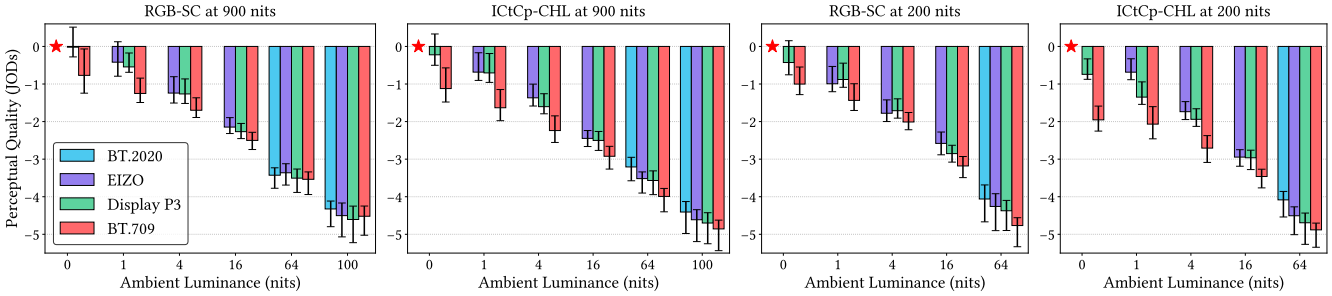

Fig. 3. *Direct-view user study results.* Perceptual quality plotted against ambient luminance for each color gamut. Panels correspond to peak-luminance × GMA conditions. Error bars indicate 95% confidence intervals. The red star marks the block-wise reference condition (EIZO, zero ambient, **RGB-SC**).

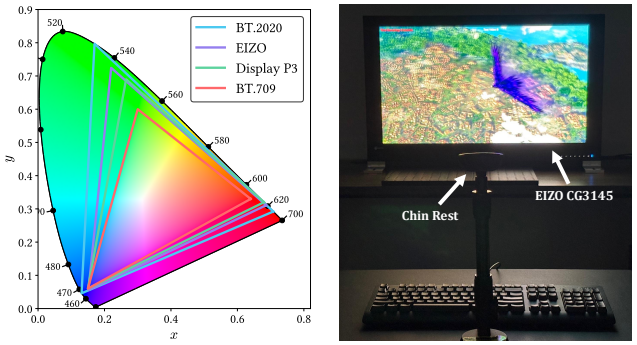

Fig. 4. *Direct-view user study setup.* EIZO native gamut shown in the CIE 1931 *xy* chromaticity diagram (left) and hardware configuration (right).

Stimuli. We selected 9 scenes: *Showgirl*, *Sol Levante 1–2*, *Bunny*, *Forest*, *Particles*, *Knitting*, *Werewolf*, and *Surface*. Each video was tone-mapped to two peak luminance levels, 200 and 900 nits, with a black level of 0.001 nit using the TMO in Section 3.2.1. The tone-mapped videos were mapped to four color gamuts of decreasing size, BT.2020, EIZO, Display P3[5], and BT.709 (Figure 4, left), using the GMAs in Section 3.2.2. As all gamuts share a D65 white point, chromatic adaptation was not required. Ambient light reaching the observer's eyes was modeled as D65 white with luminance L_{amb}. To guide the selection of ambient levels, we define additive contrast as:

$$c_{\text{add}} = (L_{\max} + L_{\text{amb}})/(L_{\min} + L_{\text{amb}}), \quad \text{[Additive Contrast]} \quad (8)$$

We estimated additive contrast for representative display models under typical indoor and outdoor lighting [Zhang et al. 2023], assuming 1–5% panel reflectance for flat panels and 20–90% optical transmittance for OST-AR (see Appendices D.1 and D.2 for details). Based on these estimates and a pilot study with two expert participants, we sampled six eye-reaching ambient luminance levels for L_{amb}: 0, 1, 4, 16, 64, and 100 nits. The 0-nit condition isolates intrinsic perceptual differences across color gamuts under near-dark viewing. Although the EIZO display cannot reproduce the full BT.2020 gamut, more than 93% of the ambient-blended BT.2020 gamut falls within the EIZO gamut for L_{amb} = 64–100 nits, enabling its simulation. In total, this yielded 648 stimuli: 9 scenes × 2 GMAs × 36 conditions. Appendix D.3 details the stimuli selection process.

[5]Display P3 shares the same RGB primaries as DCI-P3 but uses a D65 white point.

Procedures. We used a two-interval forced-choice (2IFC) protocol. Each trial included a reference video and two test videos, and participants were instructed to select the test video that better matched the reference in color fidelity. The reference was always presented first. Participants could toggle between the three videos in any order and as many times as needed, but were required to view all three at least once before responding. To prevent direct visual comparisons across conditions, we inserted a 500-ms gray screen at the mean luminance of the incoming stimulus between video switches, which also provided sufficient adaptation time prior to each stimulus onset [Hayhoe et al. 1987]. A 15-second trial timer was displayed to discourage excessively long trials but was not enforced. Participants completed an 18-trial training session prior to the main experiment.

We allowed comparisons across color gamuts, ambient luminance, and GMAs, but not across scenes or peak luminance, because color perception is luminance-dependent [Hunt 1952; Purdy 1931] and a single reference condition across multiple peak luminance levels would be ambiguous. For each scene–peak-luminance block, the reference was the stimulus with the largest effective gamut (EIZO, zero ambient, **RGB-SC**); its **ICtCp-CHL** counterpart was excluded to avoid ambiguity. Under this design, exhaustive pairwise comparison would require 10,854 trials. We instead used ASAP [Mikhailiuk et al. 2021] to adaptively schedule comparisons that maximize expected information gain, linking all conditions while reducing the study to 612 trials. To further reduce participant workload, the study was divided into three sessions of 204 trials, each covering three scenes. Participants were assigned to one session, rotated to balance scene coverage. The average completion time was 50.6 minutes.

Results. Pairwise comparison results were converted to a perceptual quality scale in just-objectionable-difference (JOD) units [Perez-Ortiz et al. 2019] using `pwcmp`.[6] Observers with an interquartile score above 1.5 were excluded as outliers (2 out of 41 participants). JOD differences map to observer preference probabilities (see Figure 17 in the appendix). The reference in each block was set to 0 JOD.

The scene-aggregated JOD scores are summarized in Figure 3, grouped by peak luminance and GMA. Error bars show 95% confidence intervals estimated from 500 bootstrap samples. Qualitatively, perceived color quality decreases as gamut size shrinks and ambient luminance increases, consistent with the reduction in effective

[6]https://github.com/mantiuk/pwcmp/

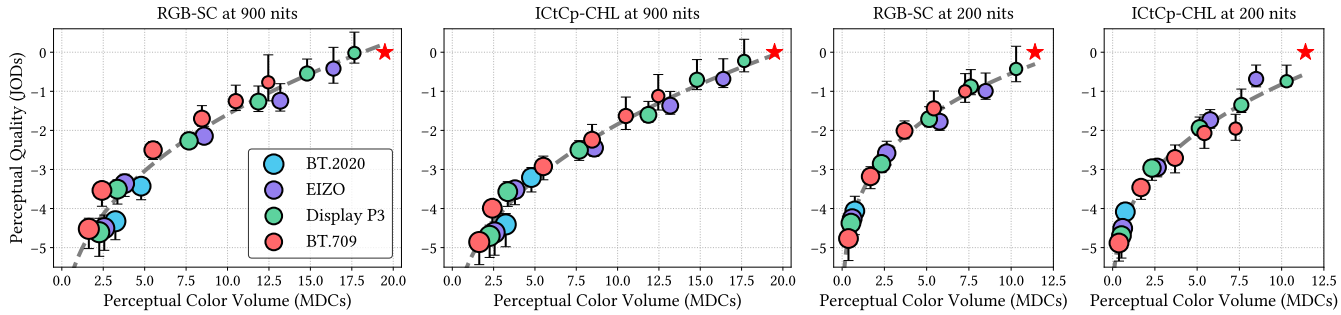

Fig. 5. *Analytical model relating perceptual color volume to perceived color quality.* JOD scores are plotted against the corresponding MDC values for all conditions studied in Section 3.3, separated by peak luminance and GMA. Dashed curves show the fitted models. Marker size increases with ambient luminance.

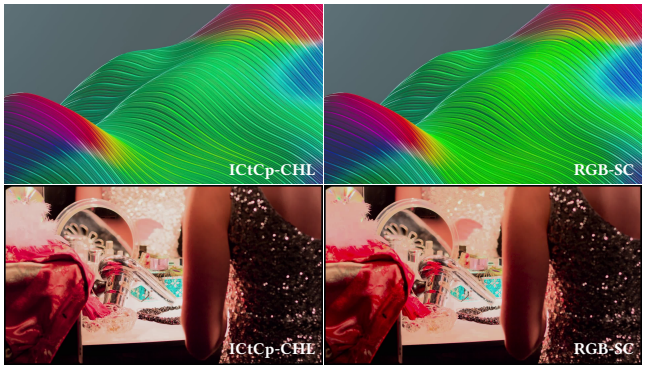

Fig. 6. *Comparison of GMAs.* When mapping to narrower gamuts, **ICtCp-CHL** strictly preserves hue but can substantially reduce chroma at certain hue angles, whereas **RGB-SC** allows hue shifts that retain higher chroma and was generally preferred in our study. The examples are BT.2020 content gamut-mapped down to BT.709. Image credit: HdM Stuttgart.

color gamut under both factors. In addition, perceptual differences between gamuts diminish with increasing ambient luminance.

An N-way analysis of variance (ANOVA) on JOD scores revealed significant main effects of ambient luminance, scene, color gamut, GMA, and peak luminance (all $p < .005$; full statistics in Table 5). Among these factors, ambient luminance accounted for the largest share of variance. A significant interaction between peak luminance and ambient luminance ($p < .001$) shows that the impact of ambient light depends on available display luminance, with the 900-nit condition partially mitigating ambient-induced degradation compared with the 200-nit condition. A significant color-gamut × ambient-luminance interaction ($p < .001$) indicates that the perceptual advantage of wider gamuts diminishes as ambient luminance increases. The color-gamut × GMA interaction ($p < .01$) suggests that GMA performance depends on the target gamut. While **RGB-SC** generally outperforms **ICtCp-CHL**, this difference increases for narrower gamuts, where stronger gamut compression is required. This behavior reflects an inherent trade-off between hue preservation and chroma retention in the two GMA designs. **ICtCp-CHL** maps out-of-gamut colors toward the target gamut boundary along constant-hue-luminance directions in ICtCp color space, strictly preserving hue but potentially causing substantial chroma reduction at certain hue angles. In contrast, **RGB-SC** projects out-of-gamut colors to the closest points on the target gamut boundary in RGB color space, permitting hue shifts that help retain higher chroma, an outcome that was perceptually preferred in our study. Figure 6 illustrates the trade-off between **ICtCp-CHL** and **RGB-SC**.

3.4 Perceptual Model

To quantify ambient-induced gamut loss, as shown in Figure 13 (Appendix), we adopt Dolby's perceptual color volume (PCV) formulation [2023]. PCV operates in ICtCp color space, which is designed to be approximately linear in just-noticeable-difference (JND) units and perceptually uniform for HDR/WCG imagery. Following this formulation, we convert ICtCp coordinates to JND units and compute color volume in millions of distinguishable colors (MDCs) for all conditions studied in Section 3.3. Appendix A.3 details this step.

Correlation analysis showed strong agreement between MDC and JOD. For **RGB-SC**, we found linear (Pearson's $r = 0.868$, $p < .001$), rank-order (Spearman's $r = 0.902$, $p < .001$), and distance correlations ($r = 0.869$, $p < .001$); for **ICtCp-CHL**, we found Pearson's $r = 0.884$ ($p < .001$), Spearman's $r = 0.920$ ($p < .001$), and distance correlation $r = 0.884$ ($p < .001$). These results indicate that PCV provides a robust predictor of perceived color quality and motivate an analytical model mapping MDC to JOD. As shown in Figure 5, perceptual quality increases with PCV and gradually saturates as PCV approaches the reference condition, exhibiting a quasi power-law relationship. To model this behavior, we evaluated three candidate functional forms—power, logarithmic, and rational—fitted using nonlinear least squares. We compared the resulting models using Akaike Information Criterion (AIC) and adopted the power model.

Although peak luminance is incorporated into the MDC computation, Figure 5 suggests that the JOD–MDC relationship remains luminance-dependent. Because two peak-luminance settings are insufficient to robustly fit a unified model, we first fit separate models at each peak luminance and then interpolate their parameters in log-luminance space. The resulting unified model is defined as:

$$\begin{aligned} Q(V,L) &= k_1(L)\cdot V^{\,k_2(L)} + k_3(L), \quad L \in [L_{\max}^{\mathrm{SDR}}, L_{\max}^{\mathrm{HDR}}] \\ k_i(L) &= (1-\alpha)k_i^{\mathrm{SDR}} + \alpha k_i^{\mathrm{HDR}}, \qquad i \in \{1,2,3\} \\ \alpha &= \log(L/L_{\max}^{\mathrm{SDR}}) \,/\, \log(L_{\max}^{\mathrm{HDR}}/L_{\max}^{\mathrm{SDR}}) \end{aligned} \tag{9}$$

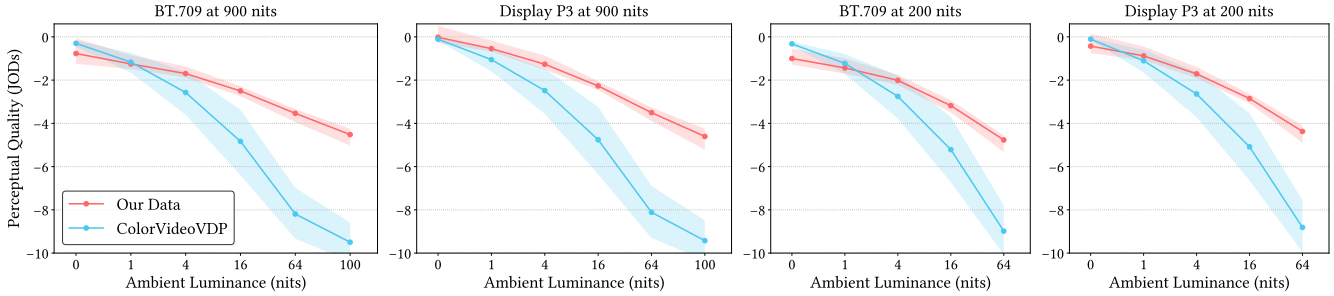

Fig. 7. *Evaluation of ColorVideoVDP on direct-view study stimuli.* Comparison of our user-study measurements with ColorVideoVDP [Mantiuk et al. 2024] predictions, both aggregated across scenes. Panels correspond to peak-luminance × gamut conditions. Shaded bands indicate 95% confidence intervals.

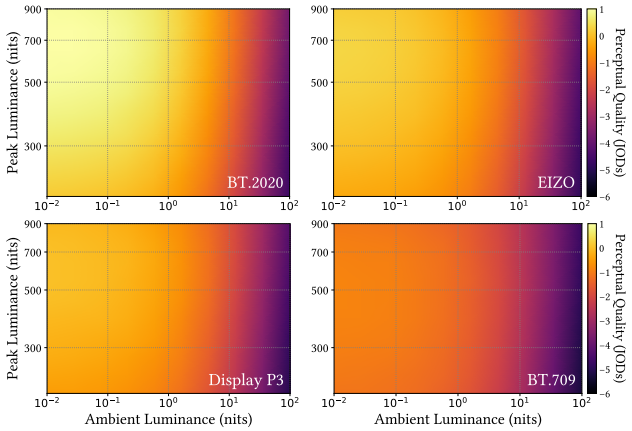

Fig. 8. *Model-predicted color quality across display and ambient conditions.* The fitted model for **RGB-SC** is evaluated across ambient luminance and peak luminance and visualized as JOD heatmaps for four color gamuts.

where Q and V denote perceived color quality (JOD) and perceptual color volume (MDC). $L_{\max}^{\mathrm{SDR}}$ and $L_{\max}^{\mathrm{HDR}}$ denote the two peak-luminance levels: 200 nits for SDR and 900 nits for HDR.

Separate models were fit for the two GMAs. The model achieved a root-mean-square error (RMSE) of 0.237 and a coefficient of determination $R^2 = 0.973$ for **RGB-SC**, and an RMSE of 0.216 and an R^2 of 0.976 for **ICtCp-CHL**. The fitted JOD–MDC relationships are shown as dashed curves in Figure 5. The unified model is visualized as JOD heatmaps across ambient luminance and peak luminance in Figure 8. Details on model selection and fitted model parameters (k_i^{SDR} and k_i^{HDR}, $i \in \{1, 2, 3\}$) are provided in Appendix E.

To position our model relative to prior metrics, we evaluate ColorVideoVDP [Mantiuk et al. 2024], a state-of-the-art visual difference predictor for HDR/WCG videos, on our direct-view study stimuli. ColorVideoVDP accounts for the physical display and viewing configuration, including resolution, dynamic range, viewing distance, and ambient illumination, and reports predictions in JOD units. We evaluate both peak-luminance levels for the BT.709 and Display P3 gamuts using **RGB-SC**-mapped stimuli. Compared to our model, ColorVideoVDP exhibits substantially larger errors relative to the user-study measurements: RMSE is 2.64 vs. 0.24.

As shown in Figure 7, ColorVideoVDP underestimates perceptual differences between BT.709 and Display P3 under near-dark conditions, while substantially overestimating ambient-induced quality degradation as ambient luminance increases. Its predictions also exhibit considerably larger variation across scenes. One possible explanation is that ColorVideoVDP was primarily calibrated on distortions such as light-source nonuniformity, reduced clarity and contrast, and chroma subsampling, rather than perceptual differences induced by systematically varying display gamut and ambient illumination. This comparison is nonetheless limited to two gamuts, two peak-luminance levels, and the stimuli from our direct-view study. A broader evaluation across video content, display characteristics, and viewing conditions is therefore needed to determine whether these failure modes generalize.

3.5 Color Enhancement

The preceding sections show that increasing ambient luminance rapidly shrinks the effective color gamut and degrades perceived color quality relative to a display's native capability. To mitigate this ambient-induced degradation, we introduce three color-enhancement algorithms: an RGB-space color expansion method (**RGB-CE**), a Schlick-style color correction method (**Schlick-CC**) [Schlick 1995], and an ICtCp-space chroma expansion method (**ICtCp-CE**). Rather than attempting to recover the original content colors, these methods aim to better utilize available display gamut to improve color quality while maintaining a natural appearance.

RGB-CE and **Schlick-CC** operate in RGB space and require minimal computation, making them suitable for resource-constrained display pipelines. **RGB-CE** is the most lightweight, as it can be implemented as a simple linear transformation, whereas **Schlick-CC** additionally requires a cross-channel maximum operation. **ICtCp-CE** works in the more perceptually uniform ICtCp color space and preserves hue, but requires a computationally intensive LUT-based implementation. In addition, **Schlick-CC** and **ICtCp-CE** incorporate an ambient term, which enables controllable ambient-aware enhancement. When additive contrast c_{add} is very low, fully compensating for the ambient contribution may introduce chromatic artifacts and distort natural color appearance. We therefore compensate only partially by defining the compensated ambient level L_{comp}. Together, these methods span lightweight RGB manipulations to



Fig. 9. *Comparison of color-enhancement algorithms.* The original BT.709 content (a) is shown at 280-nit peak luminance. For (b)–(e), 40-nit ambient luminance is simulated. For the enhancement algorithms (c)–(e), the output display is assumed to have a Display P3 gamut. Image credits: Pexels and Netflix.

perceptually constrained chroma expansion, trading computational costs against visual quality and controllability.

RGB-CE. Given the target black level $L_{\min}$, peak luminance $L_{\max}$, and linear RGB input I_{RGB} in the target color space G_{target}:

(1) Compute the luminance component Y from I_{RGB} using the RGB-to-XYZ transform of G_{target}.

$$I_{\mathrm{XYZ}} = [X, Y, Z] = \mathcal{M}_{G_{\mathrm{target}}\to\mathrm{XYZ}}(I_{\mathrm{RGB}}), \quad \text{[Luminance]} \tag{10}$$

(2) Perform color expansion with scaling factor $s \in [1, 2]$.

$$\tilde{I}_{\mathrm{RGB}} = s\, I_{\mathrm{RGB}} + (1 - s)Y, \quad \text{[Color Expansion]} \tag{11}$$

(3) Clip the expanded RGB values to the valid dynamic range.

$$I_{\mathrm{CE}} = \left[\tilde{I}_{\mathrm{RGB}}\right]_{L_{\min}}^{L_{\max}}, \quad \text{[RGB Clipping]} \tag{12}$$

where $[\cdot]_{L_{\min}}^{L_{\max}}$ denotes element-wise clipping.

Schlick-CC. Given the same inputs as **RGB-CE** and the compensated ambient term L_{comp}, **Schlick-CC** proceeds as follows:

(1) Similar to the tone-extraction step in tone mapping, extract the input tone as the channel-wise maximum of I_{RGB}. While different luminance proxies can be used, recent work shows that the maximum RGB channel helps avoid out-of-gamut clipping and associated color distortions [Burke et al. 2020].

$$T_{\mathrm{RGB}} = \max(I^R_{\mathrm{RGB}}, I^G_{\mathrm{RGB}}, I^B_{\mathrm{RGB}}), \quad \text{[Tone Extraction]} \tag{13}$$

(2) Apply Schlick-style color correction [1995] to scale the RGB channels while preserving their relative ratios.

$$\tilde{I}_{\mathrm{RGB}} = ((T_{\mathrm{RGB}} + L_{\mathrm{comp}})/T_{\mathrm{RGB}})\, I_{\mathrm{RGB}}, \quad \text{[Color Correction]} \tag{14}$$

(3) Remove L_{comp} and clip to the valid dynamic range.

$$I_{\mathrm{CE}} = \left[\tilde{I}_{\mathrm{RGB}} - L_{\mathrm{comp}}\right]_{L_{\min}}^{L_{\max}}, \quad \text{[RGB Clipping]} \tag{15}$$

ICtCp-CE. Given the same inputs as **Schlick-CC**:

(1) Transform I_{RGB} and $I_{\mathrm{RGB}} + L_{\mathrm{comp}}$ into ICtCp color space and express them in cylindrical coordinates.

$$\begin{aligned} I_{\mathrm{LCh}} &= [L, C, h] = \mathcal{M}_{G_{\mathrm{target}}\to\mathrm{ICtCp}}(I_{\mathrm{RGB}}), \\ \tilde{I}_{\mathrm{LCh}} &= [\tilde{L}, \tilde{C}, \tilde{h}] = \mathcal{M}_{G_{\mathrm{target}}\to\mathrm{ICtCp}}(I_{\mathrm{RGB}} + L_{\mathrm{comp}}), \end{aligned} \tag{16}$$

(2) Query the maximum allowable chroma $C^{\mathrm{t}}_{\max}$ at $(\tilde{L}, h)$ within the effective gamut under ambient level L_{comp} from precomputed 2D LUTs, and expand chroma toward this boundary.

$$C_{\mathrm{out}} = \min(C, C^{\mathrm{t}}_{\max}(\tilde{L}, h)), \quad \text{[Chroma Expansion]} \tag{17}$$

(3) Transform $[\tilde{L}, C_{\mathrm{out}}, h]$ back to the target RGB space G_{target} and remove the compensated ambient term L_{comp}.

$$I_{\mathrm{CE}} = \mathcal{M}_{\mathrm{ICtCp}\to G_{\mathrm{target}}}([\tilde{L}, C_{\mathrm{out}}, h]) - L_{\mathrm{comp}}, \tag{18}$$

Figure 9 visually compares the enhancement results. Additional details on the parameter settings are provided in Appendix F.

4 Evaluation

Visual perception in OST-AR differs from conventional direct-view displays because virtual content can appear at different focal depths from the real-world background and is optically blended with environmental light, producing transparency-like appearances [Chapiro et al. 2024]. Prior work suggests that observers may partially discount either display-emitted or environmental light in brightness [Murdoch 2020] and color perception [Zhang 2022], consistent with scission effects [Metelli 1974]. We therefore construct an OST-AR viewing setup to evaluate how well the model derived from direct-view data (Section 3.4) generalizes to OST-AR conditions, and to test whether background structure modulates perceived color quality. We also quantify the perceptual benefits of the color-enhancement algorithms introduced in Section 3.5 under OST-AR viewing.

Hardware. We used two 31.1" EIZO CG3146 displays, which share the specifications of the EIZO CG3145, to present virtual content, and a 76" DynaScan DK751DH5 display to present the background. The EIZO displays were placed to the left and right of the observer. Two neutral-response beam splitters (Edmund Optics) were placed in front of the observer and oriented at 45° toward the EIZO displays, forming an optical see-through setup. The beam splitters reflected 80% of the EIZO-emitted light toward the observer and transmitted 20% of the DynaScan-emitted light. Because the DynaScan has a black level of nearly 0.5 nits, we placed a neutral-density (ND) filter between it and the beam splitters to enable near-dark backgrounds. The system produced effective viewing distances of 83 cm (1.20 D) for the virtual content and 210 cm (0.476 D) for the background, i.e., a 0.724 D separation between the virtual and background planes. Prior work has shown this separation to be sufficient for clear depth

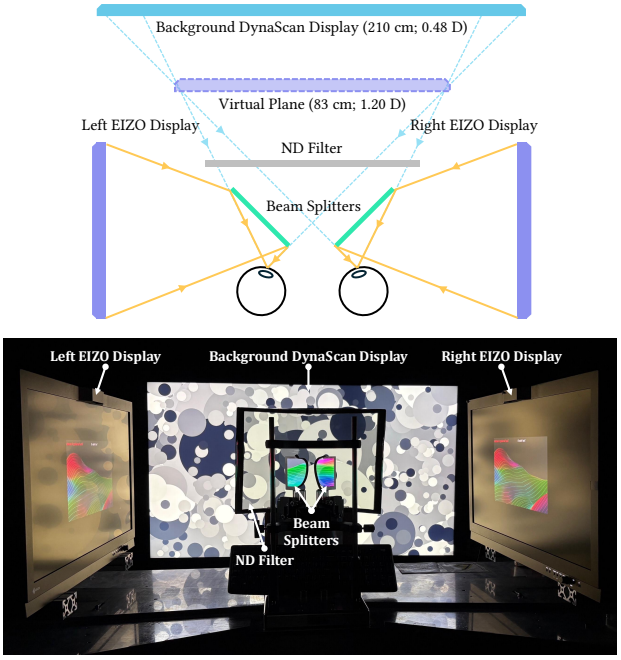

Fig. 10. *OST-AR system configuration and viewing setup.* Top: schematic of our OST-AR viewing system. Bottom: photograph of the implemented setup.

separation [Chapiro et al. 2024]. The setup created a field of view of $46° \times 26°$ and an effective angular resolution of 44.2 ppd, consistent with commercial AR devices. All three displays were calibrated using a CS-2000 spectroradiometer through the complete optical path, including the beam splitters and ND filter, such that the calibration accounted for the optical effects introduced by the hardware setup. Figure 10 illustrates the resulting OST-AR system configuration.

4.1 Perceived Color Quality under OST-AR Viewing

A second user study with 18 participants was conducted to evaluate model generalization to OST-AR and examine background effects.

Stimuli. We selected 4 scenes from Section 3.3: *Showgirl*, *Surface*, *Forest*, and *Sol Levante 1*. Each video was tone-mapped to two peak luminance levels, 200 and 800 nits, with a 0.001-nit black level. The tone-mapped videos were mapped to two color gamuts, Display P3 and BT.709, using **RGB-SC**. Before presentation, video luminance values were scaled by 1.25 to compensate for the 80% beam-splitter reflectance. We sampled four ambient levels for L_{amb}: 0.01, 5, 25, and 100 nits. Two backgrounds were used (Figure 16, Appendix): *flat* (uniform D65 white) and *leaves* (a high-contrast pattern following Chapiro et al. [2024]). This yielded 128 stimuli in total: 4 scenes × 32 conditions. Appendix G describes the stimuli selection process. The same 2IFC and ASAP study procedure as explained in Section 3.3 were adopted to schedule pairwise comparisons. Comparisons were allowed across color gamuts, ambient luminance, and backgrounds, but not across scenes or peak luminance. The block-wise reference was set to the Display P3, 0.01-nit ambient, *flat* condition.

Results. We applied the same JOD conversion and outlier-filtering procedures as in Section 3.3. The scene-aggregated JOD scores are

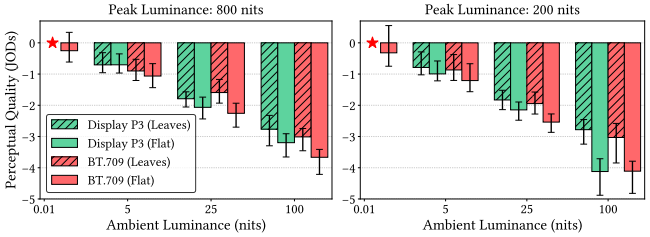

Fig. 11. *OST-AR color-quality study results.* Perceptual quality plotted against ambient luminance. Error bars show 95% confidence intervals. The red star marks the block-wise reference (Display P3, 0.01-nit ambient, *flat*).

shown in Figure 11. Consistent with the direct-view study, perceived color quality decreases with shrinking gamut size and increasing ambient luminance. We applied the model derived from direct-view data to predict results from this OST-AR study. Correlation analysis between model predictions and measured JOD scores for the *flat* background showed strong agreement: Pearson's linear correlation ($r = 0.990$, $p < .001$), Spearman's rank-order correlation ($r = 0.993$, $p < .001$), and distance correlation ($r = 0.992$, $p < .001$). These results suggest that the model derived from direct-view data transfers well to the controlled OST-AR conditions evaluated here.

An N-way ANOVA revealed significant main effects of ambient luminance, background pattern, color gamut, peak luminance, and scene (all $p < .05$; see full statistics in Table 8). Ambient luminance again accounted for the largest share of variance, indicating its dominant influence on perceived color quality under OST-AR viewing. The significant main effect of background type ($p < .001$) further suggests that background structure can affect the perceived color quality of virtual content: the *leaves* background produced substantially higher JOD scores than the *flat* background. We hypothesize that the high-contrast structure of the *leaves* background facilitates perceptual separation of the background from the virtual content, allowing observers to partially discount the ambient contribution. Previous work has observed similar effects in color-matching tasks [Hassani 2019]. A significant ambient-luminance and background-type interaction ($p < .001$) indicates that this effect becomes more pronounced with increasing ambient luminance.

These findings, however, should be interpreted within the scope of our controlled OST-AR setup. The beam-splitter system enables calibrated control of display gamut and background luminance, but does not reproduce the full optical characteristics of commercial AR headsets, such as spatial and spectral nonuniformity introduced by waveguides. Moreover, the two static backgrounds represent only a small subset of the complex and dynamic environments encountered in real-world AR. A broader evaluation across AR devices and more diverse, dynamic backgrounds is therefore needed to establish how well these findings generalize to real-world AR environments.

4.2 Color Enhancement under OST-AR Viewing

A third user study with 16 participants was conducted to evaluate the color-enhancement algorithms (Section 3.5) under OST-AR viewing.

Stimuli. We used the remaining 4 scenes: *Fruits*, *Drawing*, *Cosmos Laundromat*, and *Sol Levante 3*. We sampled 3 contrast levels

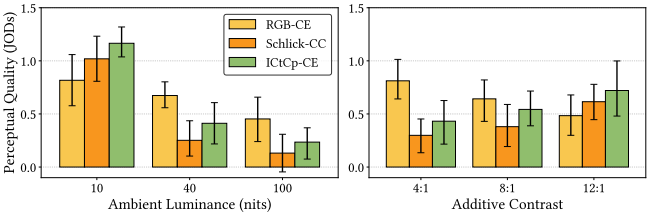

Fig. 12. *OST-AR color-enhancement study results grouped by L_{amb} and c_{add}.* In each block, the no-enhancement baseline was set to 0 JOD.

representative of OST-AR displays, 12:1, 8:1, and 4:1 [Chapiro et al. 2024], and 3 ambient levels, 10, 40, and 100 nits. Two combinations were excluded since they required impractical or infeasible peak luminance. Each video was tone-mapped to the specified peak luminance with a 0.001-nit black level, then mapped to the BT.709 gamut using **RGB-SC**. As in Section 4.1, video luminance was scaled by 1.25 before presentation, and the *flat* background was used.

Besides the three color-enhancement algorithms, we included a no-enhancement baseline in which no ambient-light compensation was applied. For the enhancement algorithms, the target display was assumed to have a Display P3 gamut, offering additional gamut headroom to compensate for ambient-induced color-fidelity losses. This setup reflects practical scenarios where visual content is mastered for a standard gamut such as BT.709, while display devices use custom color primaries that exceed these standards (e.g., the EIZO gamut shown in Figure 4, left). In total, this yielded 112 stimuli: 4 scenes × 28 conditions. Appendix H describes the stimuli selection process. We employed the same procedure as in Section 4.1, allowing comparisons only across enhancement methods. The block-wise reference was set to the original video without ambient light.

Results. The JOD scores are presented in Figure 12. In each block, the no-enhancement baseline was set to 0 JOD. All three methods consistently improved perceived color quality relative to the baseline. **ICtCp-CE** and **Schlick-CC** performed better at lower ambient luminance and higher additive contrast, whereas **RGB-CE** showed the opposite trend. **RGB-CE** and **Schlick-CC** operate directly in RGB color space and are more lightweight, making them suitable for resource-constrained display pipelines. **ICtCp-CE** requires a more compute-heavy LUT-based implementation but preserves hue and luminance, offering a more perceptually constrained solution when higher computational cost is acceptable. These results highlight a practical trade-off between visual quality and system efficiency.

An N-way ANOVA on JOD scores revealed significant main effects of all three factors ($p < .001$; full statistics in Table 10). Enhancement method accounted for the largest share of variance, confirming measurable perceptual improvements over the no-enhancement baseline. Significant scene × enhancement-method ($p = .029$) and viewing-condition × enhancement-method ($p = .031$) interactions further indicate that relative effectiveness depends on both scene content and the severity of ambient-induced color degradation.

These enhancement methods also have limitations. **Schlick-CC** uses a simple Schlick-style color correction, while more sophisticated methods may better preserve hue and produce more natural appearances [Artusi et al. 2018; Mantiuk et al. 2009]. **ICtCp-CE** explicitly preserves hue and luminance but relies on scene-dependent parameters, whose robustness across broader content remains to be evaluated. Future work could incorporate more advanced color correction and automatic, content-adaptive parameter selection.

5 Discussion and Future Work

This work has several practical applications. The model established in Section 3.4 enables color-quality comparisons across display specifications and viewing conditions; the color-enhancement algorithms introduced in Section 3.5 demonstrate how unused display-gamut headroom can mitigate ambient-induced color degradation; and our findings can inform display-system design by jointly considering peak luminance, color gamut, and expected ambient illumination.

Our work also has several limitations. While our studies provide a systematic characterization of the interactions between display and ambient conditions on perceived color quality, only limited sampling of this high-dimensional space was feasible. Future work may further refine this sampling. We assume a D65 ambient illuminant; while the model can be adapted to other illuminants, further validation is needed under chromatic illumination. Our controlled beam-splitter setup enables calibrated measurements but does not reproduce the full optical characteristics of commercial AR headsets, such as spatial and spectral nonuniformity introduced by waveguides. Moreover, the two static backgrounds represent only a small subset of complex, dynamic real-world environments. Finally, our stimuli are generated using specific tone- and gamut-mapping methods; alternative mappings may affect perceived color quality and warrant further evaluation.

Overall, we characterize how color gamut, dynamic range, and ambient luminance jointly shape perceived color quality across conventional and controlled OST-AR viewing conditions, and introduce a perceptual model and color-enhancement methods informed by these measurements. Our findings provide a foundation for perceptually adaptive display systems that jointly account for display capabilities and real-world viewing conditions.

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