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Image Quality Factors Influencing Selfie Preference: The Role of Skin Color

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ABSTRACT

This study investigates how image quality attributes affect selfie evaluations. Selfies were captured using five smartphone camera models under three different lighting conditions (5000, 4000, and 2500 K) and participants rated their selfie preferences using 7-point Likert scale scores. In addition to preference, participants evaluated 10 descriptive keywords related to image quality. Principal component analysis revealed that skin color was the most influential factor in determining selfie preference, as reflected in keywords related to hue and naturalness. A comparison with measured skin color datasets showed that smartphone cameras generally captured brighter and more saturated skin colors than actual measurements.

1 | Introduction

Image quality plays an important role in most image processing applications. In the field of signal processing, image quality refers to the accuracy with which imaging systems capture, process, store, compress, transmit and display image signals, whereas color science emphasizes the weighted combinations of visually significant attributes of an image [1–4]. Depending on the context, different aspects of image quality are prioritized. For example, signal processing focuses on technical accuracy, whereas color science highlights the visual attributes influencing human perception.

Traditional image quality assessments have primarily relied on both subjective and objective assessment methods [3]. These assessments typically focus on attributes such as sharpness, noise, blurring and compression artifacts, often using images of natural landscapes or architectural scenes as stimuli [4]. More recently, image esthetic assessment (IAA) has emerged as a computational approach to distinguish high-quality images from low-quality ones by incorporating human-perceived esthetics based on photographic composition and visual appeal [5]. However, when it comes to images featuring people, the "concerned area," typically the face, has been shown to significantly influence color preferences [6] This is because skin color is both physiologically distinctive and a well-known memory color. In many cases, observers lack knowledge of the original color or texture of the scene and instead rely on memory color, a phenomenon in which prior experience or knowledge influences color perception [7]. People tend to prefer skin tones that align with internal expectations [8, 9]. Research has shown that memory colors tend to be more saturated than their actual appearance and that observers associate specific color ranges with familiar objects [7, 10–12]. Other studies have explored color preference using familiar real-world objects, artworks or color patches, rather than photographic images, such as ripe bananas or Caucasian skin Hands and fruits in still life paintings showed that memory colors shifted toward higher chroma [8, 13, 14].

In addition to its role in color accuracy and image quality, skin color has been studied extensively as a memory color and perceptual cue related to cultural norms and individuality. People prefer skin colors that are typically slightly lighter, redder or more saturated than the actual tone, especially for facial images.

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These preferences vary across cultures and demographics, where East Asian culture and female observers tend to prefer lighter skin [9, 15]. Although such socio-cultural aspects are beyond the scope of this study, they provide useful context for interpreting results related to facial color preference.

With the rapid advancement of smartphone cameras, selfies, or self-portrait photographs that emphasize facial features over background elements, have become a dominant form of everyday photography. Selfies now serve not only as personal records but also as entertainment content for social media platforms [16–18]. Large-scale social and cultural analyses described selfies as a widespread practice of self-fashioning and performative image sharing, reflecting platform conventions and audience engagements [17]. Survey and correlational studies further indicate that selfie participation is driven by multidimensional motivations, such as self-presentation, self-branding, archiving, social feedback, and enjoyment, emphasizing the entertainment and social-reward context in which selfies are produced and evaluated [16, 18].

Typically, selfies are taken with a smartphone's front-facing camera and are instantly reviewed on the device's display. While the act of taking a selfie is straightforward, defining what constitutes the “best shot” remains unclear. This uncertainty arises from the complex interplay between camera characteristics and display expressions, both of which influence how selfie quality is perceived.

While selfie research has predominantly examined social, cultural and psychological dimensions, relatively few studies have addressed selfies from a perceptual or technical perspective relevant to image quality, including skin color databases, population differences in preferred facial color and display, or illuminant effects [9, 15, 19–22]. Unlike traditional photography, where background composition and overall structure are key, selfies prioritize facial appearance, making facial expression, and color-related factors especially critical in quality evaluation. Moreover, because selfies are a unique image type in which the photographer is also the subject, a specialized approach to evaluating selfie image quality is necessary. To address this gap, this study aims to identify the key factors that determine selfie image quality, with particular focus on how visual attributes and lighting conditions influence user preference. Rather than directly comparing camera-captured images with participants' measured skin colors, the study concentrates on the evaluation criteria most related to selfies.

2 | Method

In this study, selfie images were collected from individual participants. To simulate various selfie-taking conditions, three light settings were used. After capturing the images, interviews were conducted to gather keywords related to selfie image evaluation. Frequently mentioned keywords were compiled and organized into groups based on similar meanings, and these were used as evaluation criteria. In addition to keyword-based assessments, participants were also asked to provide preference scores for their selfies. Although selfies were captured using multiple smartphone camera modes, all evaluations were performed on a single reference monitor in a dark room.

2.1 | Obtaining Selfie Images

In this study, selfie images were captured using the front cameras of smartphones. Four different smartphone cameras, Camera A, Camera B, Camera C, and Camera D, were used. For Camera A, two color mode options, natural and warm, were included. Regarding camera capture settings, all smartphones were used in the default photo mode with user-controllable features disabled. For example, night mode, skin-tone refinement, face contouring, or smoothing functions were disabled. No third-party filters were applied. Exposure, shutter speed and auto white balance remained as the default setting which reflects typical user behavior.

To simulate different lighting conditions, three light settings were applied: 5000 K 500 lx, 4000 K 500 lx and 2500 K 200 lx. Lighting condition 5000 K 500 lx was selected to represent neutral, office-like illumination, 4000 K 500 lx to represent mixed-CCT indoor illumination, and 2500 K 200 lx to represent warm, dim ambient illumination commonly encountered in everyday settings. The illuminance and correlated color temperature (CCT) of each condition were measured using the Konica Minolta CL-200 and are summarized in Table 1, along with the corresponding light source. Measurements were taken at the position where the participant's face would be located during selfie capture. As shown in Figure 1a, the lighting setups were designed to replicate typical indoor environments where selfies are commonly taken and Figure 1b shows the spectral power distribution of the three light settings, normalized to the peak of the 5000 K 500 lx spectrum. The setup included fixed LED ceiling lights with relatively high CCT, typically used in office environments. In addition, Philips Hue smart bulbs were used to control illuminance, CCT and hue through a dedicated mobile application.

Selfies were obtained from 20 Korean participants in their 20s (7 males and 13 females), with an average age of 22.3. Each participant took selfies in front of a gray wall, to ensure a neutral background. They were instructed to include the MacBeth Color Chart in the background without any obstruction covering the chart. Figure 2 illustrates an example of a captured selfie. Participants had no restrictions for wearing or not wearing any foundation or skin-colored makeup during the selfie capture

TABLE 1 | Light settings: Correlated color temperature (CCT), illuminance, presence of LED ceiling light, and presence of Philips Hue smart bulbs.

No.	CCT (K)	Illuminance (lx)	LED ceiling lighting	Philips Hue bulbs
1	5000	500	O	O
2	4000	500	O	O
3	2500	200	X	O

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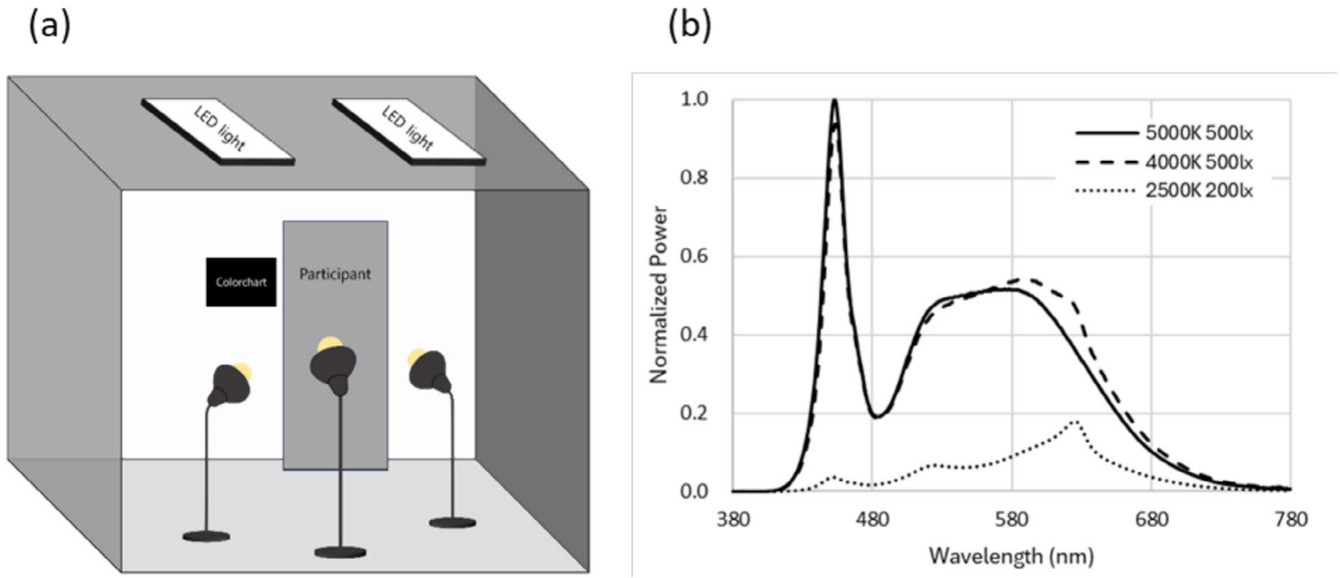

FIGURE 1 | (a) Lighting setup geometry and (b) spectral power distributions of the three light settings.

FIGURE 2 | Example of a selfie image.

session. The key point was to capture the selfie as if it were a selfie taken in typical real-life situations.

Participants were allowed to take as many photographs as they wished until they were satisfied with the resulting image. If multiple photographs were taken under the same condition, participants reviewed and selected the best one. The images were briefly reviewed on the smartphone only to check for issues such as blur or shaking, not for detailed quality assessment. In total, each participant captured 15 selfies, for all combinations of five smartphone camera models (Camera A with two mode options counted separately) and three light settings.

2.2 | Keyword Selection

To identify the image quality factors influencing selfie image perception, interviews were conducted immediately after participants took their selfies. The interviews were conducted in Korean and focused on participants' personal criteria for evaluating selfies. They were asked about the positive and negative aspects of the selfies they had just taken, as well as their general opinions on smartphone cameras.

From the interview, frequently mentioned keywords were collected and grouped based on semantic similarity. For example, expressions such as "look alive" and "has vitality" were merged under the keywords "look lively". No formal data coding was applied. Instead, the categorization was based on intuitive and semantic similarities across participant responses. Keywords were then organized into four broader themes—hue, naturalness, contrast and texture—based on the shared perceptual interpretations. A total of 10 keywords were selected from four categories. The final keywords included: "look like skin color," "skin color looks natural," "look lively," "look natural," "look real," "big contrast," "big lightness difference," "look smooth," "clear details," and "looks sharp." Additionally, "preference" was included as it was the most frequently mentioned term in image evaluations. Table 2 presents the categorized keywords used for selfie image assessment.

2.3 | Keyword Evaluation

All evaluations were conducted on a 27-in. EIZO ColorEdge CG279X display set to DCI-P3 gamut with a maximum luminance of 284 cd/m^2. The experiment was conducted in a dark

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TABLE 2 | Categories and collected keywords.

Category	Keyword
Hue	Looks like skin color
	Skin color looks natural
	Looks lively
Naturalness	Looks natural
	Looks real
Contrast	Big contrast
	Big lightness difference
Texture/detail	Looks smooth
	Clear details
	Looks sharp
Preference	Preference

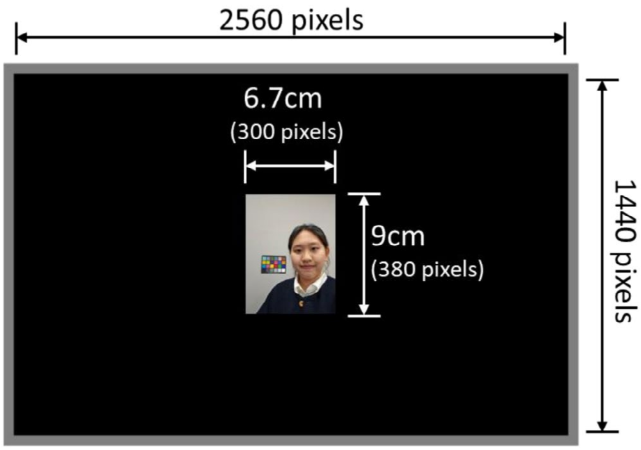

FIGURE 3 | Example of stimuli on display.

room. As shown in Figure 3, each selfie was shown on the display at a fixed size of 300 pixels by 380 pixels, centered on a neutral background. This size was designed to match the size of a photograph viewed on a typical smartphone screen.

Twenty participants each evaluated their own 15 selfies (five camera modes × three light settings). For every image, participants rated 10 descriptive keywords and overall preference on a 7-point Likert scale, where one represented very unsatisfied and seven represented very satisfied. Image order was randomized per participant. The distance between the participant and the display was 60 cm.

3 | Results

3.1 | Principal Component Analysis

The relationships between the keywords were analyzed using principal component analysis (PCA), which is useful for identifying important components that explain the variance in the data. Figure 4 presents the proportion of variance explained by each principal component and the cumulative explained variance. Based on this plot, we selected the first three components—Principal Components 1, 2, and 3—which together accounted for approximately 68.6% of the total variance. The remaining components explained only a small portion of the total variance and therefore were not included in further analysis. The values corresponding to these components are presented in Table 3. Keywords with absolute loading of 0.400 or higher were considered primary contributors to each principal component, whereas keywords with smaller but consistent loadings were treated as secondary contributors and interpreted together based on their semantic similarity.

Keywords such as “looks natural,” “skin color looks natural,” “looks like skin color,” and “looks real” closely align with principal component 1. These keywords belong to hue and naturalness categories. For principal component 2 the keywords “big contrast” and “big lightness difference” are strongly associated.

Based on the coefficient values of each principal component, the keywords were reorganized into three distinct categories. Principal component 1 is primarily associated with skin color, indicating that keywords related to natural-looking skin color are strongly aligned with this component. Principal component 2 emphasizes contrast, reflecting the impact of tonal differences and brightness variation on image perception. Lastly, principal component 3 represents smoothness, which is the characteristic related to texture and fine details in selfie images.

The keyword “preference” has the highest coefficient value for principal component 1, indicating a strong association with skin color. Although “preference” also has some relation to principal component 3 (smoothness), it is less correlated with principal component 2 (contrast). These results suggest that skin color plays a crucial role in determining preference. Therefore, improving skin color reproduction is essential for enhancing selfie image preference.

To further confirm the relationship between average preference and keywords, the Pearson correlation coefficient was calculated. This analysis was conducted to evaluate whether specific perceptual attributes were significantly associated with overall preference, independent of the PCA structure. As shown in Table 4, keywords related to hue and naturalness, such as “looks like skin color,” “skin color looks natural,” “looks natural,” and “looks real,” showed the highest correlations with preference scores. This supports the result that skin color plays a major role in selfie preference, reinforcing the findings from the PCA with a separate statistical perspective.

3.2 | Preference Scores Across Camera Models and Lighting Conditions

The preference scores for each camera and light setting are summarized and illustrated in Figure 5a. The results indicate that preference scores varied depending on the camera model and lighting conditions. Among the cameras, Camera C received the highest overall average preference score (4.48), followed by

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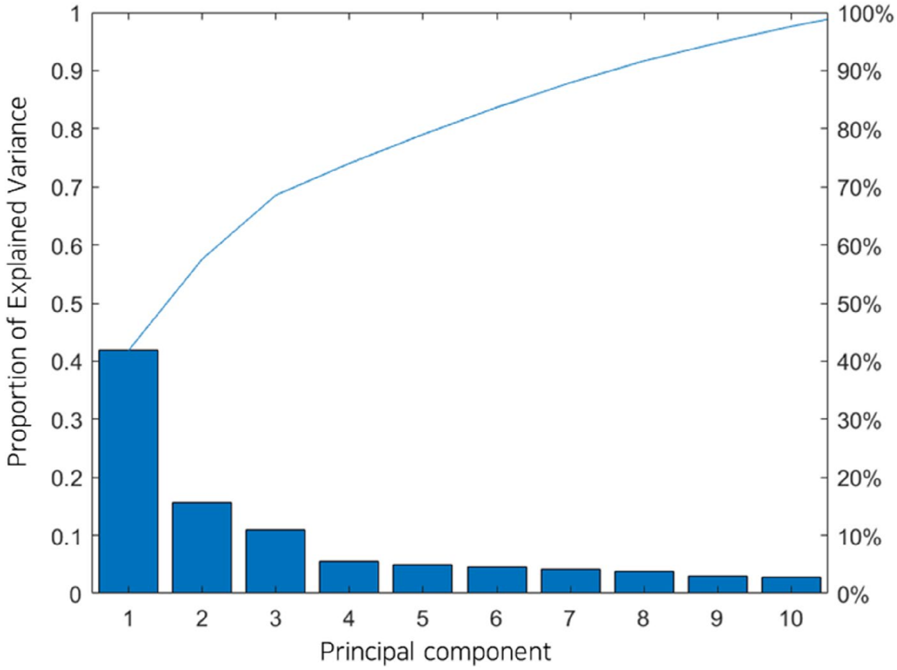

FIGURE 4 | Scree plot showing the proportion of explained variance (bar) and cumulative explained variance (line) for each principal component.

TABLE 3 | Coefficient values of each keyword for principal components 1, 2, and 3.

Component groups	Keywords	Principal component 1	Principal component 2	Principal component 3
Skin color	Looks natural	**0.432**	−0.164	−0.150
	Skin color looks natural	**0.413**	−0.097	−0.065
	Looks like skin color	**0.410**	−0.166	−0.187
	Looks real	**0.257**	−0.091	−0.176
Contrast	Big lightness difference	0.103	**0.639**	0.107
	Big contrast	0.083	**0.554**	0.110
	Looks sharp	0.263	**0.319**	−0.098
Smoothness	Looks smooth	0.126	−0.022	**0.658**
	Looks lively	0.286	0.037	**0.392**
	Clear details	0.205	0.296	**−0.459**
Preference	Preference	**0.428**	−0.145	**0.276**

Note: Bold values indicate high absolute loadings.

Camera D (4.18) and Camera A (warm mode, 4.03). Camera B received a score of 3.97, while Camera A (natural mode) received the lowest score of 3.72. Although Camera C had the highest overall average preference score across all lighting conditions, it was not consistent across individual settings. Under the 2500 K 200 lx condition, Camera C received the highest score (5.05). However, under 5000 K 500 lx, Cameras A (warm mode) and D both received the top score (4.95), while under 4000 K 500 lx, Camera B had the highest preference (3.85). These variations suggest that camera performance interacts with lighting conditions, and no single camera was preferred consistently across all environments. Figure 5a summarizes the preference scores for each camera-lighting combination.

Regarding lighting conditions, overall average preference scores for each setting are shown in Figure 5b. The 5000 K 500 lx setting had the highest preference score (4.74), followed by 2500 K 200 lx (4.07). The 4000 K 500 lx setting was the least preferred, with a score of 3.42, which falls below the neutral midpoint of 3.5.

A one-way analysis of variance (ANOVA) was conducted to examine the effects of camera model and lighting condition on preference scores. The effect of camera model was not statistically significant, $F(4, 10) = 0.42$, $p = 0.789$, indicating no meaningful differences in preference across the five camera models. The mean preference scores with standard error for each camera were as follows: Camera A-natural ($M = 3.72$, $SE = 0.45$),

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TABLE 4 | Correlation coefficient for preference scores and each keyword.

Category	Keywords	Preference score
Hue	**Looks like skin color**	**0.866**
	Skin color looks natural	**0.858**
	Looks lively	−0.182
Naturalness	**Looks natural**	**0.805**
	Looks real	**0.825**
Contrast	Big contrast	−0.345
	Big lightness difference	−0.136
Texture/detail	Looks smooth	0.264
	Clear details	0.188
	Looks sharp	0.378

Note: Bold values indicate strong correlations ($r > 0.800$).

Camera A-warm ($M = 4.03$, $SE = 0.53$), Camera B ($M = 3.97$, $SE = 0.28$), Camera C ($M = 4.48$, $SE = 0.40$), and Camera D ($M = 4.18$, $SE = 0.46$). In contrast, lighting conditions had a significant effect on preference, $F(2, 12) = 11.42$, $p = 0.0017$. The mean preference scores under each lighting condition were: 5000 K ($M = 4.74$, $SE = 0.09$), 2500 K ($M = 4.07$, $SE = 0.29$), and 4000 K ($M = 3.42$, $SE = 0.15$). A post hoc comparison indicated that the difference between 5000 K 500 lx and 4000 K 500 lx settings was statistically significant ($p = 0.0012$), while no significant differences were observed between other pairs, as illustrated in Figure 5b.

Given the absence of individual camera's colorimetric calibration and fixed white balance, the observed differences should be viewed as the net outcome of both device-specific processing and lighting conditions.

To examine whether gender influenced selfie preferences, an independent sample t-test was conducted. The average preference score for male participants was 3.88 (standard deviation = 0.31), while for female participants it was 4.18 (standard deviation = 0.84). The difference was not statistically significant $t(18) = -0.93$, $p = 0.365$, indicating that participant gender did not have a meaningful impact on selfie preference.

Overall, these findings confirm that certain lighting conditions, rather than camera models or participant gender, had a significant influence on selfie preference.

3.3 | Color Analysis in Selfie Images

To examine how color varies across different cameras and lighting conditions, RGB values of skin color were extracted from each selfie image. Skin color was sampled from left and right cheek areas of each selfie, as these regions are generally color-uniform and contain fewer wrinkles or blemishes, making them ideal for representative skin color analysis [19, 20]. A 10×10 pixel region was selected from each cheek, resulting in a total of 200 pixels per participant. The average RGB value of these pixels was used as the representative skin color for each individual.

In addition to skin color, white color samples were extracted from the same selfie images. The extraction of a white reference was necessary because the relationship between skin color and surrounding white color may influence the perceived skin color. White RGB values were obtained from the color chart in the background of each selfie, using a 10×10 pixel region.

To convert digital RGB values to CIELAB color space, the EIZO monitor was characterized using a gain-offset-gamma (GOG) model and an optimized 3x3 transformation matrix. For the monitor characterization, 100 RGB patches were used, including uniformly sampled colors (red, green, blue, cyan, magenta, yellow, gray) as well as random colors and skin colors. Color measurements were obtained using a CS-2000 spectroradiometer (Konica Minolta). The performance of the EIZO characterization model was evaluated by comparing the predicted CIE XYZ values with the measured values and the color difference was calculated using CIE ΔE^*ab. The resulting average ΔE^*ab was 1.17 with a maximum value of 4.78.

The digital RGB values from the camera were first converted to linear RGB and transformed into XYZ tristimulus values by the GOG model. Then, CIE XYZ values were transformed into CIELAB L*, a* and b* values referenced to the CIE standard illuminant D65 and the CIE 1931 2° standard observer. The L*-C* and a*-b* distributions are illustrated in Figure 6. To visualize the distribution of white patch and skin color data for each camera and light setting, a 95% confidence ellipse was plotted using eigenvalues and eigenvectors of the data covariance matrix. The ellipse represents the region where approximately 95% of the data points are expected to fall, assuming a bivariate normal distribution. The ellipse was calculated based on a chi-square of 2.4477, corresponding to the 95% confidence level in two dimensions. The black ellipses in Figure 6 represent white patches captured from each camera and beige ellipses represent skin colors.

Under the 5000 K lighting condition, all cameras produced similar skin color distributions and preference scores were consistently high. In contrast, under 4000 K lighting, the white reference from the color chart remained similar to that of 5000 K, but skin color showed higher chroma, resulting in lower preference scores. Similarly, under 2500 K lighting, skin color also showed increased chroma. However, in this condition, the white reference shifted toward a yellowish hue, which led to higher preference scores and a more natural appearance.

Additionally, skin color distributions under 4000 and 2500 K lighting were more widely dispersed in CIELAB color space compared to 5000 K lighting, indicating greater variability in skin color reproduction at lower color temperature conditions. As CCT of lighting conditions decreases, the captured colors tend to shift toward reddish or yellowish hues with increased chroma. This affects the overall color balance, particularly in the reproduction of white and skin colors. Lower chroma values

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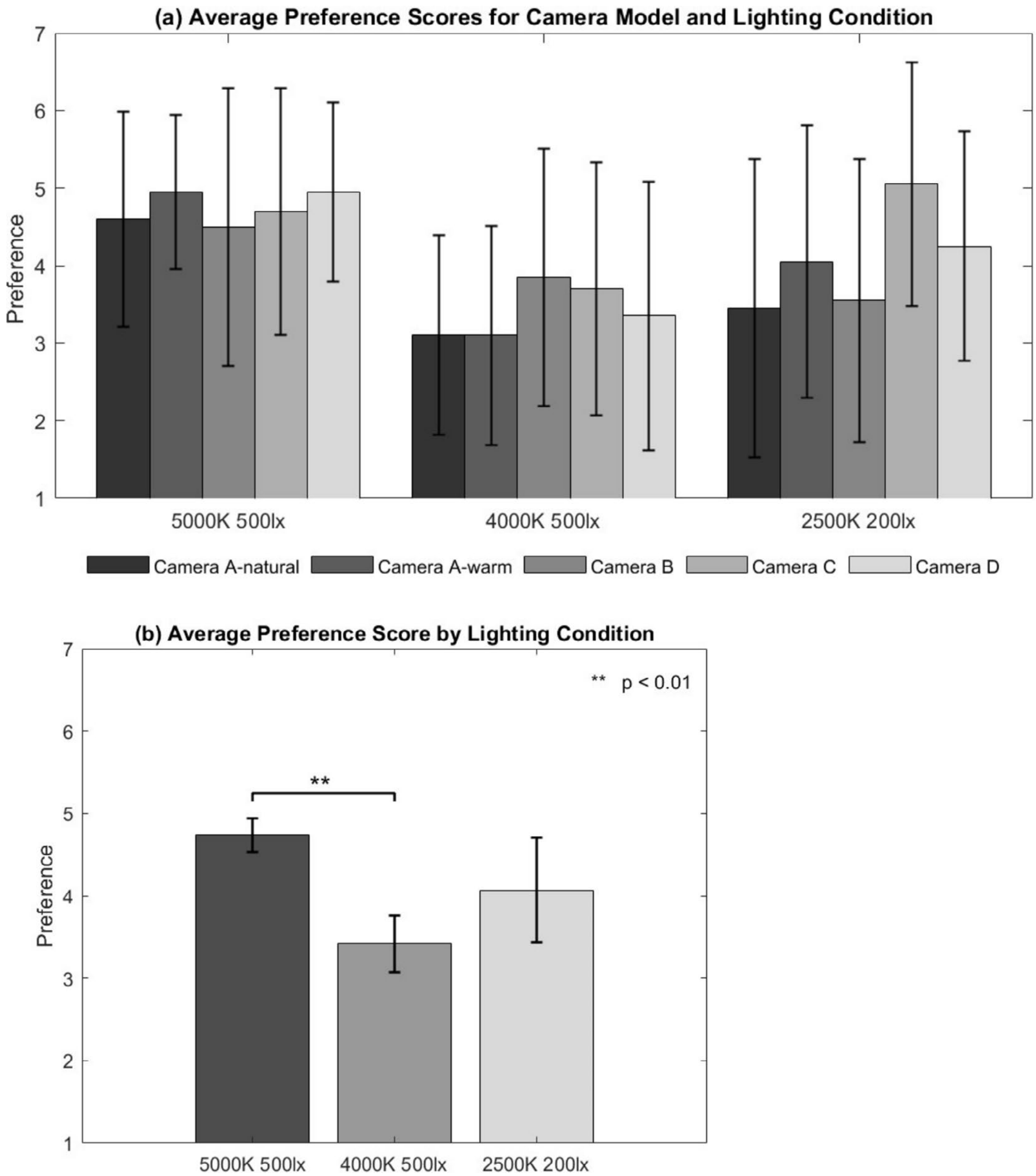

FIGURE 5 | (a) Average preference scores for each camera model and lighting condition, and (b) average preference scores by lighting condition, showing a significant difference between 5000 K 500 lx and 4000 K 500 lx ($p < 0.01$).

for skin colors were generally preferred, as observed under 5000 K lighting. In contrast, both 4000 and 2500 K lighting produced skin colors with higher chroma, but their resulting preference scores differed. Under 2500 K lighting, the white reference shifted toward a yellowish hue with higher chroma, making the skin color appear more natural. In contrast, under 4000 K lighting, the white reference remained the same as that of the 5000 K condition while skin colors appeared to have higher chroma, resulting in lower preference scores.

Such color changes were likely caused by the auto white balance algorithm, which adjusts white regions to match how they are perceived by human vision—for example, allowing them to appear slightly yellowish in scenes with low color temperature. These results highlight the importance of white balance strategies in selfie image quality, as they directly influence the color reproduction of the skin region.

3.4 | Comparison of Captured Skin Colors With Measured Skin Color Data

A previous study collected skin color data from Caucasians, Chinese, Kurdish and Thai participants, while another study gathered skin color data from Korean participants [19, 20]. In this study, the camera-captured skin colors were compared with these previously measured datasets. For the measured datasets, the average values are used.

As shown in Figure 7a, the skin color data from five ethnic groups was clustered within a similar region on the CIELAB L*-C* plane, near L* = 60 and C* = 20. However, the camera-captured skin colors were positioned at higher L* and C* values. Despite variations among different cameras, all captured skin colors were located within the range of L* = 70 to 80 and C* = 20 to 30. This suggests that cameras tend to capture skin colors as

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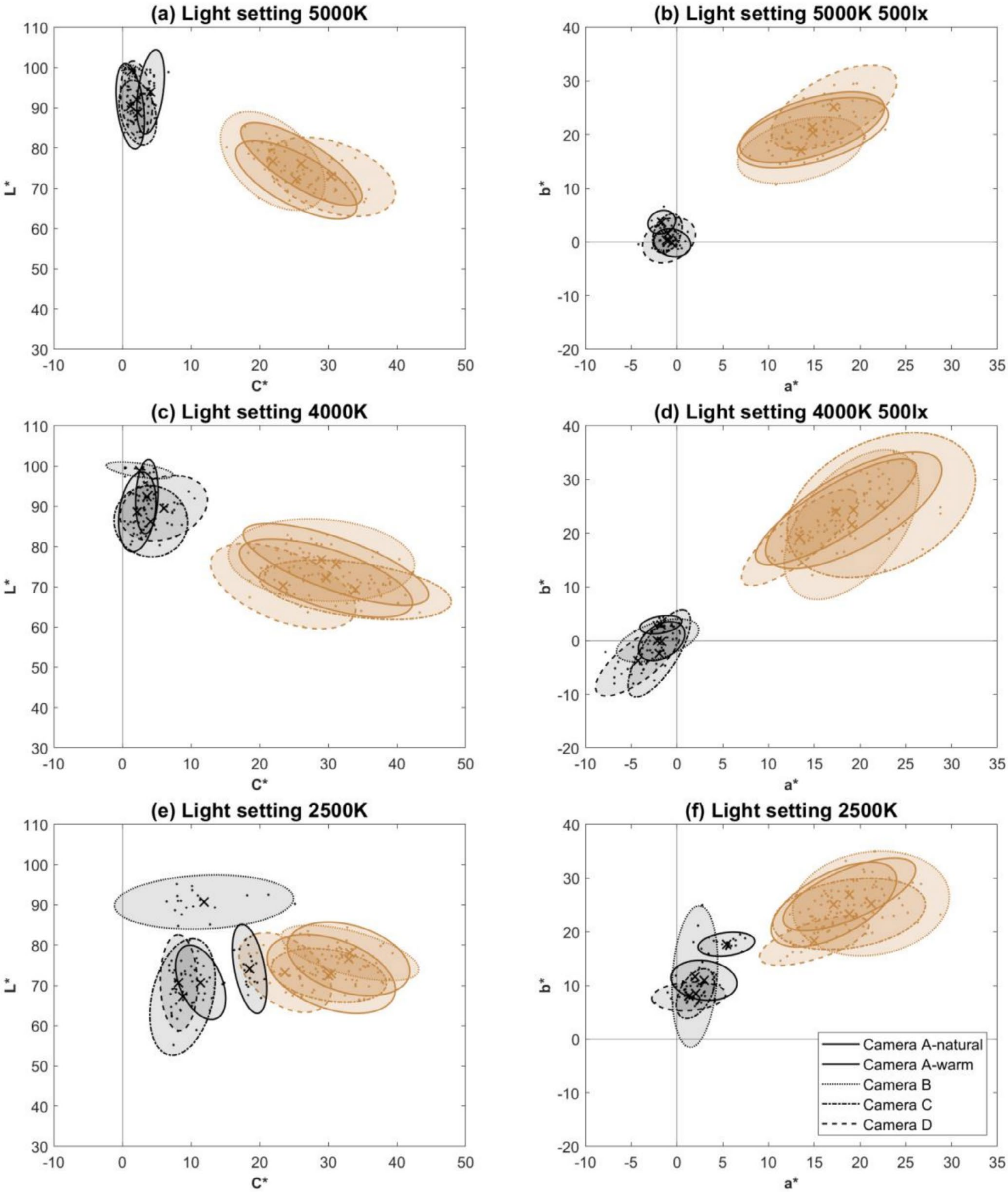

FIGURE 6 | White patch and skin color regions compared under different lighting conditions: (a) CIELAB L*-C*, 5000 K lighting (b) CIELAB a*-b*, 5000 K lighting (c) CIELAB L*-C*, 4000 K lighting (d) CIELAB a*-b*, 4000 K lighting (e) CIELAB L*-C*, 2500 K lighting (f) CIELAB a*-b*, 2500 K lighting (black lines: White patch regions, brown lines: Skin color regions).

brighter and with slightly higher chroma than the actual measured skin colors.

Figure 7b presents a comparison between the previously measured skin color dataset and the camera-captured skin color on the CIELAB a*-b* plane. The measured skin colors from all ethnic groups had a similar a* value near 10, while b* ranged from approximately 14–18. In contrast, the camera-captured skin colors exhibited a wider distribution across both a* and b* values. Despite this variation, the hue of camera-captured skin

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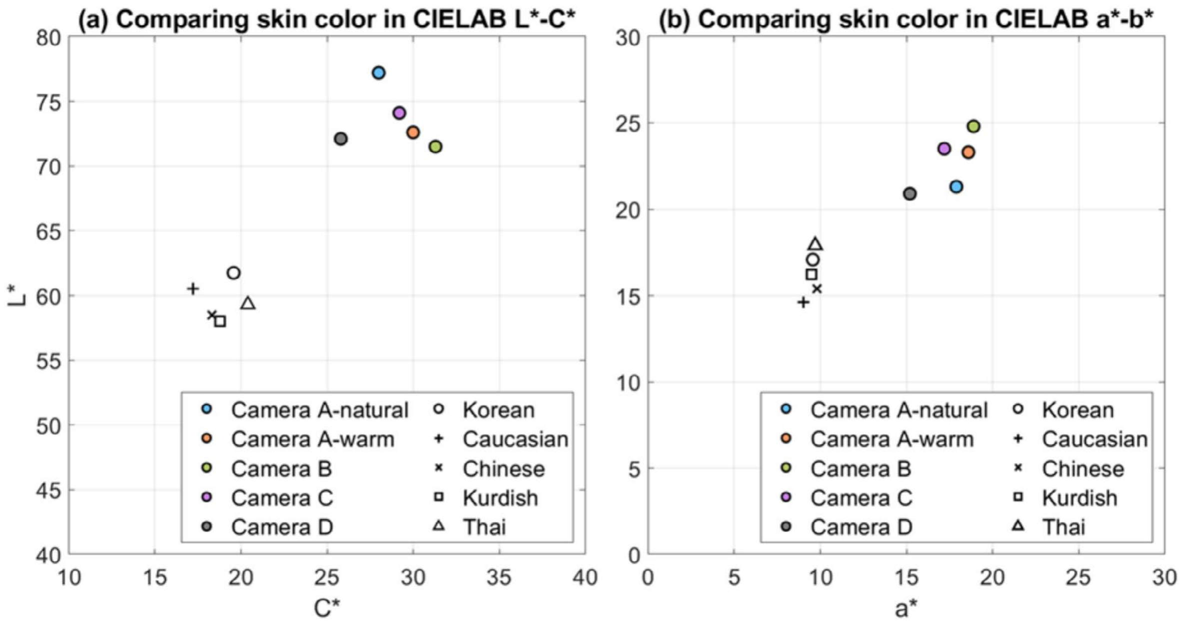

FIGURE 7 | Comparison of average skin color captured by camera and average measured skin color from previous studies plotted on (a) CIELAB L*-C* and (b) CIELAB a*-b*.

color appeared to be similar to that of the measured skin color. It should be noted that the measured skin color dataset used for comparison was obtained from different subjects and under different measurement conditions than those used in this study. Because the experiment was designed to assess how viewers evaluate selfies, comparisons with measured skin color datasets were treated as qualitative context. While direct correspondence was not established, camera-captured skin colors generally fell toward higher lightness and chroma than reported measurements, indicating an overall tendency.

4 | Discussion

This study focused on selfie preferences and examined how image quality factors, particularly those related to skin color reproduction, influence selfie evaluation. Unlike traditional photography, selfies are unique in that the subject and the evaluator are the same individual, making facial appearance and perceived naturalness particularly important in preference formation. Prior studies have shown that memory color effects are especially strong for facial skin colors, as observers have internal expectations for how skin color should appear [7, 10–12]. Our findings are consistent with this, as skin color was identified as the most influential factor in preference judgments based on principal component analysis and correlation results.

While previous selfie-related studies have primarily focused on social, cultural, or behavioral dimensions, relatively few have investigated the perceptual qualities of selfies [14–16, 18, 21, 22]. This study contributes to that literature by demonstrating that skin color and lighting play a central role in how users assess selfie quality. Among the tested lighting conditions, 5000 K lighting resulted in the highest preference scores, supporting the findings from previous color appearance studies suggesting that mid-to-high correlated color temperatures can enhance the perception of the naturalness of facial skin color on mobile displays [21, 22].

With respect to skin color rendering, the patterns observed here are consistent with the idea that device-level processing, for example, tone mapping or white balance strategies, can affect perceived facial color. However, detailed analyses were beyond the scope of this work. Notably, cameras that produced lighter and more saturated skin color tended to receive higher preference scores. This corresponds with previous findings showing that users often prefer skin colors that shift from actual measurements toward higher lightness and chroma [7, 10–12, 15].

Furthermore, the comparison between camera-captured skin colors and measured skin color datasets revealed that captured values were shifted toward higher L* and C*, aligning with the preference tendencies reported elsewhere [13–15]. This suggests that smartphone cameras may intentionally enhance facial appearance, possibly to meet implicit user expectation.

Taken together, these findings highlight the importance of skin color reproduction, not only for accuracy, but also for perceived attractiveness in selfie contexts [7, 10–12, 15]. Future research should examine how individual preferences vary with skin type and cultural background, and how camera algorithms might adaptively optimize rendering for personalized outputs. Additionally, further investigation into the effects of lighting conditions in selfie photography could provide deeper insights, particularly regarding white balance and its role in shaping skin color perception in selfies.

5 | Conclusion

This study focuses on selfie preferences and explores how image quality factors influence selfie evaluation. Unlike other types of photography, selfies are both captured and assessed by the same

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individual, making personal appearance evaluation and color reproduction especially important in preference formation. Through principal component analysis and statistical evaluation, the study identified skin color as a key determinant of selfie preference, with notable variation in preference scores observed across lighting conditions.

Among the lighting conditions, 5000 K lighting resulted in the highest preference score, while 4000 K lighting received the lowest. These findings strongly suggest that skin color reproduction, influenced by white balance algorithms, is a critical factor in enhancing selfie image quality.

Furthermore, a comparison between camera-captured skin colors and previously measured skin color datasets revealed a clear difference. While measured skin colors from various ethnic groups were generally clustered around $L^* = 60$ and $C^* = 20$, skin colors captured by smartphone cameras were positioned at higher L^* (70–80) and C^* (20–30) values.

Future research should further explore the relationship between preferred skin color and measured skin color, taking individual variation into account. Additionally, more studies on the effects of lighting conditions in selfie photography could offer deeper insights into optimizing smartphone camera settings and processing algorithms for improved selfie image quality.

Author Contributions

Conceptualization: H.H. and Y.K. Methodology: H.H. and Y.K. Material production: H.H. Material measurement and data curation: H.H. and Y.K. Validation: H.H. and Y.K. Formal analysis: H.H. and Y.K. Writing – original draft preparation: H.H. Writing – review and editing: H.H. and Y.K. Supervision: Y.K. Funding acquisition: Y.K. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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