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Personal Colour between Perceptual Space and Social Practice

Akihiro Kawase, Junji Adachi, Kako Nagashima

Abstract

Personal colour analysis has become a pervasive guide to self-presentation in East Asian beauty cultures, yet its authority rests on a largely qualitative diagnostic practice whose relation to colourimetric structure remains unclear. This study investigates how far contemporary personal colour, as practised by social media influencers, can be modelled within a perceptually uniform colour space. We compiled a dataset of 1,600 product entries corresponding to 1,193 unique lipsticks from five Japanese Instagram influencers who routinely classify cosmetics into personal colour categories. Of these, 1,229 items carried a single yellow- or blue-base label and 673 items carried a single seasonal label, which were used in the predictive models. For each product, the representative colour sample from the manufacturer's website was converted from sRGB to CIE L*a*b* coordinates and linked to two kinds of label: yellow-base versus blue-base, and the four seasonal types (spring, summer, autumn, winter). Gradient-boosted decision tree classifiers (XGBoost) were trained to predict these labels from L*, a* and b*. The yellow/blue task achieved an accuracy of .82 (chance level .50), with feature importance dominated by the b* (yellow-blue) component. The seasonal task, which has a four-way chance level of .25, reached a moderate accuracy of .65, with lightness L* emerging as the most informative feature and extensive overlap between all four seasons in the a*-b* plane. These findings suggest that influencer practice tracks a perceptually meaningful yellow-blue dimension, while seasonal categories operate as looser narrative constructs that combine lightness and hue in culturally elaborated ways. The study thus positions personal colour as a hybrid formation in which colour-scientific regularities underpin, but do not fully determine, popular regimes of aesthetic classification.

Keywords: Personal Colour, CIE L*a*b*, Statistical Analysis, Machine Learning

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Prof. Dr. Akihiro Kawase
Corresonding author
Faculty of Culture and Information Science
Doshisha University
kawase@dh.doshisha.ac.jp

M.A. Junji Adachi
Co-author
Graduate School of
Culture and Information Science
Doshisha University
adachi.junji@dh.doshisha.ac.jp

Kako Nagashima
Faculty of Culture and Information Science
Doshisha University
nagashima.kako@dh.doshisha.ac.jp

1. Introduction

1.1 Context and the Rise of Personal Colour

In the modern, highly competitive and digitalised world, the optimization of self-presentation has driven widespread interest in methods that guide individuals toward suitable aesthetic choices. The most popular of these is personal colour, a systematic approach rooted in colour harmony theory that helps individuals identify the group of colours that best complement their natural features, such as their inherent skin tone, eye colour, and hair colour (NPO Hojin Nihon Pasonaru Kara Kyokai 2001). In simple terms, personal colour aims to find a palette (a set of colours for clothing and cosmetics) that naturally enhances an individual's complexion, making them appear clearer and healthier.

The mechanism driving personal colour's social authority is strongly linked to modern consumption behaviour. The rapid growth of e-commerce and digital shopping has increasingly minimised opportunities for in-person fitting and consultation with sales staff, who traditionally provided expert styling advice (Ashar 2025). This market shift created a vacuum: consumers needed a standardised, objective guide to reduce the risk of purchasing unsuitable colours online. Personal colour filled this gap, becoming a highly trusted tool for risk management and strategic self-presentation. This trend is particularly evident in East Asia, where studies, such as one conducted on Japanese female university students, have revealed that the awareness of personal colour diagnosis is nearly 100%, with approximately 70% actively using these categories in their purchasing decisions (Tani, Watanabe and Okawa 2024). Personal colour's fundamental classification of colour is based on the underlying warmth or coolness (Undertone) of an individual's skin. This divides all colours into two primary bases: Yellow Base (Warm) and Blue Base

(Cool). These two primary bases are further segmented into four seasonal types based on two secondary colour characteristics: Brightness (how light or dark the colour is) and Chroma (how muted or vivid the colour is). For instance, the Yellow Base includes Spring (which is both Warm and characterized by high chroma/high brightness, making its colours vivid and light) and Autumn (which is Warm but characterized by low chroma/low brightness, making its colours muted and deep). Similarly, the Blue Base includes Summer (which is Cool but characterized by high brightness/low chroma, making its colours soft and pale) and Winter (which is Cool but characterized by low brightness/high chroma, making its colours vivid and dark).

The personal colour diagnosis is traditionally a qualitative process, performed by a trained colourist who conducts a subjective visual assessment by placing coloured drapes beneath the client's face (Kamiyama and Nagasaka 2004). This framework has attained high social authority and practical utility, actively guiding consumer purchasing decisions for cosmetics and fashion. Critically, however, despite this utility, the methodology of personal colour analysis is widely criticised for its lack of consistent, objective standards (Ippan Shadan Hojin Nihon Kara Kodineta Kyokai 2022). Researchers have pointed out that the classification often reflects the individual experience and visual judgment of the analyst, leading to significant variations in classification outcomes and suggesting a weak colourimetric foundation for the system (Maki and Yamamoto 1998). For example, Takamatsu et al. (2015) specifically identified the issue of inconsistency in hues classified as personal colours by different colourists. This subjective variance is the core methodological problem that prevents the system from being fully evidence-based (Takamatsu et al. 2015).

1.2 Historical Foundations in Colour Theory and Image Politics

Although contemporary personal colour analysis appears as a late-20th-century lifestyle technology, its conceptual roots lie in early colour harmony theory and mid-century image politics. In the 1920s, American colourist Robert Dorr proposed a harmony system built on two basic undertones: blue-undertone and yellow-undertone colours (Knapp and Dorr 1985). His approach, combined with practical "colour key" programmes for fashion and interior design, offered one of the earliest systematisations of the warm–cool distinction that later became central to personal colour practice.

Around the same period, Johannes Itten's influential teaching at the Bauhaus linked colour harmony to observations of the natural environment. In his writings, he suggested that the sources of colour and harmony are to be found in the four seasons of nature, inviting designers to study seasonal atmospheres as archetypes of colour composition (Itten and Birren 1970). While Itten himself did not formalise a personal diagnostic system, later practitioners retrospectively read his seasonal metaphors as a conceptual bridge from Dorr's two-way warm/cool distinction to a four-season framework that divides colours into Spring, Summer, Autumn, and Winter palettes.

By the mid-20th century, colour expertise was institutionalised in the figure of the "colour consultant" in the United States. Consultants such as Faber Birren applied colour adjustment and harmony principles to factories, public facilities, and domestic interiors, treating colour as both a technical and psychological variable in the built environment (Birren 1969). In parallel, the emergence of television foregrounded the strategic management of visual impression in politics: the 1960 US presidential debates famously illustrated how carefully curated "on-screen" appearance could shape voter perception, and subsequent accounts often cite the Kennedy campaign as an early demonstration that appearance and media framing can decisively influence outcomes.

From the 1970s onwards, colour consulting expanded as a commercial service directed at individual clients. It is in this period that the term "personal colour" gained currency, and the practice was popularised for a mass audience through works such as Color Me Beautiful (Jackson 1985), which explicitly tied four-season palettes to everyday clothing and makeup choices. Contemporary personal colour analysis inherits this layered history: it translates early colour harmony theory and seasonal metaphors into a diagnostic service that promises to rationalise self-presentation in consumer societies.

1.3 Ambiguity, Quantitative Research, and Problem Foundation

The methodological instability of personal colour diagnosis is compounded by the ambiguous nature of the "suitability effect." Studies confirm a genuine psychological effect of suitability, demonstrating that subjects wearing professionally diagnosed "Best" colours are rated as significantly more attractive even by personal colour-unaware third parties (Nonaka et al. 2023). However, this effect is highly susceptible to external factors; the aesthetic impact of colour-matching makeup can be overshadowed by the model's social popularity (Omagari et al. 2024), suggesting that the concept may function as a "social illusion" derived from acceptance rather than pure chromatic truth. This debate is highly salient for lipstick, which is a primary determinant of facial impression (Kiritani, Ushikubo and Takano 2004).

To overcome the ambiguity of subjective visual judgment, research has responded by leveraging colour science and data-driven methods to establish objective standards. These efforts confirm that while subjective harmony is unstable, the underlying chromatic principles are quantifiable. Quantitative studies focusing on lipstick have used metrics such as Munsell, RGB, or CIE L*a*b* to establish rules for colour suitability (Hirayama et al. 1998; Sripian et al. 2020). More recently, technological approaches utilise CIE L*a*b* and clustering algorithms to establish objective skin tone clusters (Phan et al. 2025), and this objective data are vital for validating foundation colour classifications (Choi and Bae 2024) and creating reproducible technical standards in virtual applications (Park et al. 2018). While these advancements validate the theoretical basis of personal colour, they highlight a core tension: stability is found in objective metrics, but the subjective visual process remains volatile, as illustrated by the finding that the impressions conveyed by lipstick colours can be an unstable perceptual construct susceptible to context (Hsu and Lee 2024).

In summary, personal colour possesses immense social authority and a demonstrable psychological effect, but its traditional methodology is plagued by questions of consistency and subjective bias. While technological advancements have provided the necessary objective models, a critical ambiguity remains in the degree to which the subjective visual criteria currently popularised and employed by non-expert consumers and social media influencers are systematically linked to quantifiable colour space. Specifically, there is no uniform, reproducible standard to verify if the labels assigned online are truly based on colour dimensions like lightness, chroma, and hue. The lack of this foundational evidence prevents the field from fully establishing an evidence-based system for colour guidance. Therefore, this study aims to explicitly address this fundamental methodological gap by conducting a quantitative analysis of the consistency and objectivity of the subjective criteria used in personal colour diagnosis, specifically focusing on establishing the predictability of influencers' personal colour labels from objective lipstick colour data using CIE L*a*b* coordinates and machine learning classifiers.

2. Data and Methods

2.1 Overview of the analytic procedure

The analysis proceeded in four steps:

1. To compare differences in colour perception among influential users who explicitly rely on personal colour theory, we selected a set of Instagram accounts and collected all posts that classified cosmetic products into personal colour categories.
2. For each product mentioned in those posts, we obtained the corresponding product image from the official website of the manufacturer and extracted its representative colour as an sRGB hex code. This code was converted to CIE L*a*b* coordinates to analyse the distribution of colours in a perceptually uniform colour space.
3. We linked these L*a*b* values with the personal colour labels assigned by each influencer (yellow-base vs. blue-base; four seasonal types).
4. We trained gradient-boosted decision tree classifiers to predict the influencers' labels from the L*a*b* coordinates and evaluated how consistently the labels could be recovered from colour information alone.

2.2 Target accounts and dataset

To conduct a quantitative comparison of colour perception within the framework of personal colour diagnosis, it was necessary to choose accounts that are influential enough and that provide a sufficient number of labelled cosmetic items. Previous work suggests that accounts with larger numbers of followers tend to exert stronger influence on information receivers and to encourage further diffusion of their content (Matsui 2021). We therefore treated follower count as a proxy for influence. We selected Instagram accounts that satisfied all of the following criteria on 1 October 2022: (1) at least 1,000 followers; (2) posts that introduce cosmetic products grouped by brand or manufacturer; (3) posts in which the user explicitly assigns each product to one or more personal colour categories.

For each qualifying account, we collected all posts and all listed products published before 30 October 2022, together with the corresponding personal colour labels. Table 1 summarises the five accounts that met these criteria, showing anonymised user IDs (A–E), follower counts, number of posts, and the number of products for which a valid colour sample could be obtained. For each account, the table also reports how many products were labelled only as yellow-base or only as blue-base, how many received both yellow and blue labels, and how the same set of products was distributed across the four seasonal categories (spring, summer, autumn, winter) and multi-season labels. Across all accounts, the dataset comprises 1,600 product–account pairs; among these, 1,229 items have a single yellow/blue label and 673 have a single seasonal label, which form the basis of the classification analyses in Sections 3.3 and 3.4. For anonymisation, the original account names are replaced with the labels A-E throughout this paper. Products for which no colour sample was available on the official website were excluded from the dataset. Several of the selected users state in their profiles that they hold qualifications such as Test in Colour Coordination or Cosmetic Skill Certification, suggesting that they position themselves as knowledgeable about colour and cosmetics.

2.3 Colour measurement and transformation to CIE L*a*b*

For each product, we retrieved the official colour sample image from the manufacturer's website and recorded its representative colour as a hexadecimal sRGB triplet (e.g. #d8595b). The hexadecimal values for red, green, and blue were converted to decimal integers (0-255) and then normalised to the [0,1] range by division by 255.

Since raw RGB coordinates do not correspond to perceptual distances, we transformed these sRGB values into CIE L*a*b* coordinates, which approximate perceptual uniformity. The conversion followed the standard pipeline: sRGB → linear RGB (gamma correction) → CIE XYZ (D65 white point) → CIE L*a*b*. For each product, we thus obtained three continuous variables: lightness (L*), red-green axis (a*), and yellow-blue axis (b*). These values were used as explanatory variables in the subsequent classification analyses. All transformations were implemented in Python. The resulting dataset combines, for each product, the anonymised influencer ID, the personal colour labels, and the corresponding L*a*b* coordinates.

2.4 Classification of personal colour labels from L*a*b* coordinates

We examined to what extent the influencers' personal colour labels can be predicted from L*a*b* coordinates alone. Two classification tasks were defined:

- Task 1 (Yellow vs. Blue base). The dependent variable was the higher-level personal colour category: yellow-base vs. blue-base. Products labelled as both categories (e.g. "yellow/blue") were excluded so that each training instance had a single nominal label.
- Task 2 (four seasonal types). The dependent variable was the seasonal category: spring, summer, autumn, or winter. Again, products assigned to multiple seasons (e.g. "spring/summer") were excluded from this analysis.

In both tasks, the predictors were the three L*a*b* components (L*, a*, b*). We employed gradient-boosted decision trees using the XGBoost library. For each task, the data were split into training and test sets using a 70/30 stratified split to preserve the class distribution. The models were trained with standard hyperparameters (maximum tree depth = 4,300 estimators, learning rate = .05, subsample and column-subsample rates = .9). Model performance was evaluated on the held-out test set using accuracy and macro-averaged F1-score, in addition to class-wise precision, recall, and F1-scores. Confusion matrices were also computed to identify typical misclassification patterns between categories. Finally, we examined the feature importance scores reported by XGBoost (gain-based importance) to assess the relative contribution of L*, a*, and b* to the prediction of each type of label. All analyses were conducted in Python (scikit-learn and XGBoost). The anonymised dataset and full analysis code are available in an open-access repository at Zenodo (DOI: 10.5281/zenodo.18646259, v1.0.0. Feb 15, 2026), which ensures long-term reproducibility and facilitates reuse.

To assess whether each classifier performed reliably above chance level, we conducted a permutation test. For each task, we repeatedly (1,000 times) shuffled the class labels in the training data, refitted the model with the same hyper-parameters, and evaluated its accuracy on the fixed test set. The proportion of permutations that yielded an accuracy equal to or higher than the empirical accuracy provides an approximate p-value for the null hypothesis that the model performs at chance.

As a supplementary analysis, we also examined the seasonal classification problem in CIE LCh* space. The Lab* coordinates were transformed to LCh*, and an additional XGBoost classifier was trained using L*, C* and h* as predictors. Model training, test-set evaluation and permutation testing followed the same procedure as for the Lab*-based seasonal model.

3. Results

3.1 Agreement of personal colour labels across influencers

Among the 1,600 product entries collected from the five accounts, 1,193 corresponded to unique lipstick products with valid colour samples. Of these, 298 products were mentioned by at least two influencers. For this subset, we compared the labels assigned by different influencers to assess the internal consistency of personal colour practice. The agreement rate was .93 for yellow/blue labels (272 out of 293 comparable cases) and .91 for seasonal labels (207 out of 228 comparable cases). Products for which influencers disagreed on the yellow/blue or seasonal label were excluded from the modelling dataset. The remaining products, together with items mentioned by a single influencer, formed the basis for the classification analyses. Table 2 summarises the successive filtering steps used to construct the modelling datasets for the yellow/blue and seasonal tasks.

3.2 Distribution of labelled colours in CIE L*a*b* space

Figure 1(a) plots all products with single yellow-base or blue-base labels in the a*-b* plane. Overall, products labelled as Yellow tend to occupy the upper part of the diagram, with predominantly positive b* values, whereas those labelled as Blue are more widely spread along the b* axis and extend further into the region with low or negative b*. At the same time, there is a substantial area of overlap around moderate a* and b* values, where both categories co-exist. This suggests that the influencers' yellow/blue assignments are not random with respect to the perceptual yellow-blue axis, but that they are far from being separable by a single linear boundary.

Figure 1(b)(c) shows the corresponding distribution for the four seasonal categories. Spring and Autumn products, both associated with "warm" palettes in personal colour theory, are concentrated in regions with higher b* (i.e. more yellowish hues), while Summer and Winter products, considered "cool" seasons, are distributed towards lower b* values. However, the four seasons present extensive overlap in the central region of the colour space; no clearly separated clusters emerge that could be uniquely associated with each season.

3.3 Predicting yellow-base versus blue-base labels

To quantify the extent to which the yellow-base versus blue-base distinction can be recovered from L*a*b* coordinates alone, we trained an XGBoost classifier using L*, a*, and b* as predictors and the binary personal colour label as the target. The evaluation on the held-out test set (N = 370) yielded an overall accuracy of .82 and a macro-averaged F1-score of .82, compared with a chance level of .50 for this two-class problem. A permutation test with 1,000 random label shuffles confirmed that this performance was significantly above chance ($p < .001$). At the class level, the Yellow category achieved a precision of .85, recall of .83 and F1-score of .84 (support = 217), while the Blue category achieved a precision of .77, recall of .80 and F1-score of .78 (support = 153). The weighted average F1-score was .82. Thus, in spite of the visual overlap in Figure 1(a), the classifier can correctly recover most yellow/blue labels from L*a*b* coordinates.

The feature importance scores reported by XGBoost indicate that the b* component plays the dominant role, with an importance of .52, compared with .24 for L* and .24 for a*. In other words, the influencers' binary personal colour assignments rely primarily on the perceptual yellow-blue axis, with lightness and the red-green axis contributing to a lesser but non-negligible extent. The confusion matrix in Table 3(a) shows that most errors arose from blue-base products being misclassified as yellow-base, consistent with the slightly lower F1-score for the Blue category.

3.4 Predicting seasonal categories

We then trained a second classifier to predict the four seasonal categories (Spring, Summer, Autumn, Winter) from the same L*a*b* coordinates, again restricting the analysis to products with a single seasonal label. On the test set (N = 202), the model attained an overall accuracy of .65 and a macro-averaged F1-score of .65. Given the four-way choice (chance level .25), a permutation test again showed that the accuracy was significantly higher than chance ($p < .001$). Class-wise performance varied noticeably. Spring and Winter reached F1-scores of .69 and .70, respectively (supports = 62 and 42), whereas Autumn reached .64 (support = 56) and Summer only .53 (support = 42). The weighted average F1-score across all four classes was .65. These results indicate that, while some seasonal categories can be predicted moderately well from L*a*b* values, others (especially Summer) are much harder to distinguish.

In contrast to the yellow/blue task, the feature importance profile for the seasonal classifier assigns the largest weight to L* (importance .41), followed by b* (.35) and a* (.24). Seasonal labelling therefore appears to depend more strongly on lightness differences, in combination with the yellow-blue axis, rather than on hue alone. As visualised in the confusion matrix in Table 3(b), misclassifications were most frequent for Summer items, which were often confused with Spring or Autumn, whereas Spring and Winter showed relatively clearer separation.

3.5 Supplementary analysis of seasonal labels in L*C*h* space

To test whether the seasonal labels might align more clearly with lightness-chroma structure, we re-expressed the colour coordinates in CIE LCh* space and trained a seasonal classifier using L*, C*, and h* as predictors. On the held-out test set, this model achieved an accuracy of .62 and a macro-averaged F1-score of .62 (chance level .25), again significantly above chance in the permutation test ($p < .001$). Overall performance was slightly lower than that of the Lab*-based model, suggesting that access to the full a* and b* axes is not detrimental. Figure 1(b) plots the distribution of the four seasonal labels in the L*-C* plane. While Spring and Autumn tend to occupy somewhat higher chroma regions than Summer, and Winter tends to be darker, the four categories still form broad, overlapping clouds rather than distinct clusters.

4. Discussion

4.1 Regularities and limits in influencers' personal colour labelling

The analyses above show that the influencers' personal colour labels are neither purely arbitrary nor fully determined by objective colour measurements. On the one hand, the binary yellow-base versus blue-base contrast is highly predictable from L*a*b* coordinates: an accuracy of about .82 is substantially higher than the 50% that would be expected from random guessing, and the dominance of the b* component aligns well with the theoretical interpretation of this axis as representing the yellow-blue contrast. This suggests that, taken as a group, the influencers are tracking a perceptually meaningful dimension of colour and deploying it in a relatively consistent way.

On the other hand, the substantial overlap between yellow and blue labels in the a*-b* plane (Figure 1(a)) and the non-trivial error rate indicate that this practice is not reducible to a simple threshold on the b* axis. Products near the centre of the colour space, or those with intermediate b* values, tend to be labelled in both ways. In practical terms, this means that for many cosmetics, the same colour could plausibly be described as yellow-base or blue-base depending on context, the influencer's judgement, or the surrounding palette. The yellow/blue dichotomy thus appears as a probabilistic tendency rather than a strict partition of colour space.

4.2 Ambiguity of the four seasonal categories

As shown in Table 1, nearly three-fifths of all products received multi-season labels, indicating that even at the level of everyday practice influencers frequently treat seasonal categories as overlapping rather than mutually exclusive. The four seasonal categories show an even more ambiguous picture. Although Spring and Autumn products tend to cluster in more yellowish regions (high b*), and Summer and Winter in comparatively cooler regions, the four groups form broad, overlapping clouds rather than distinct clusters (Figure 1(b)). This visual impression is borne out by the classification results.

The seasonal classifier's accuracy of .65 is clearly above the random baseline of .25 and, for Spring and Winter, F1-scores around .70 are quite high given the four-way choice. At the same time, the lower performance for Summer and the overall macro F1-score indicate that the seasonal boundaries are less sharply defined than the binary yellow/blue split. It is noteworthy that the most informative feature here is L*, rather than b*: lightness differences, in combination with hue, seem to drive many of the seasonal assignments.

One way to interpret these findings is that the seasonal system adds an additional narrative layer on top of the coarse yellow/blue split. While the latter aligns fairly directly with a single perceptual dimension, the seasons appear to encode more complex combinations of lightness, chroma, and hue, and possibly also associations with imagery such as “soft” versus “vivid” or “muted” palettes. Such composite, partly metaphorical constructs are harder to capture through simple geometric regions in colour space, which may explain both the overlap in Figure 1(b) and the limited performance of the classifier.

4.3 Implications for the discourse on “personal colour”

From the perspective of colour science, these results position contemporary personal colour practice in a nuanced way. The reasonably high predictability of yellow/blue labels from L*a*b* coordinates suggests that influencers are not assigning categories at random; their judgements reflect systematic attention to established perceptual dimensions, especially the yellow-blue opponency encoded in b*. At the same time, the only moderate predictability of the seasonal labels, together with the extensive overlap of all four seasons in colour space, shows that the familiar discourse of “seasonal types” should not be taken as carving nature at its joints. For consumers, this means that personal colour diagnosis may offer useful heuristics about broad regions of colour space that tend to harmonise with particular complexions or stylistic preferences, but that the categories themselves should not be treated as rigid scientific facts. For researchers and practitioners in colour design, the findings underline the importance of distinguishing between perceptually grounded dimensions (such as L*, a*, b*) and culturally elaborated labelling schemes that build on, but also transform, those dimensions to create easily communicable stories about appearance and identity.

4.4 Limitations and directions for future research

Several limitations of the present study should be acknowledged, primarily stemming from data constraints and methodological focus.

First, the dataset is restricted in both demographic and geographic scope, limited to five Japanese Instagram influencers and the specific cosmetic products they chose to feature. In addition, all items in the present study are lipsticks. As can be seen in Figure 1(a), this results in a concentration of colour samples in the reddish-yellowish region of the a*-b* plane, reflecting the limited gamut of commercially available lipstick shades. The patterns we observe may therefore reflect not only the structure of personal colour practice but also the constrained portion of colour space occupied by lip products. Future studies should test whether similar regularities and ambiguities arise for less restricted media such as clothing or hair colour, which span a wider range of hues and lightness levels.

Secondly, the analysis relies heavily on digital colour samples obtained from manufacturers' websites and recorded as sRGB hex codes. This method has inherent limitations as it does not account for differences in display devices, ambient lighting conditions, or the actual optical properties (e.g., gloss, texture, opaqueness) of the cosmetic product applied on the skin. This reliance on lower-fidelity digital data limits the precision of our L*a*b* coordinates. Thirdly, due to methodological constraints, we focused strictly on the mapping from objective colour coordinates to subjective labels and necessarily excluded products assigned to multiple, nuanced categories (e.g., "yellow/blue"). Furthermore, we did not investigate the subjective layer of the phenomenon, such as how consumers perceive these labels, how they personally experience the diagnosis process, or how they integrate this information into their self-presentation.

The limitations above provide essential directions for future work to solidify the scientific foundation of personal colour. Future research must prioritise expanding the scope of data collection by comparing influencers from different cultural contexts to test the generalisability of these chromatic regularities. Methodologically, future studies must address the issue of colour fidelity by complementing web-based colour samples with controlled, physical colour measurements of the actual cosmetic products using a spectrophotometer. This is necessary to move beyond the digital ideal and analyse the true physical properties of the colour. Furthermore, researchers should integrate qualitative or survey-based studies of how personal colour categories are understood and used by clients, thereby investigating the subjective layer of this phenomenon. Finally, extending the present approach to other colour spaces or to more sophisticated models may also help to clarify how far the seasonal system can be reconciled with perceptual structure, and where its success reflects primarily cultural conventions rather than rigid physical boundaries.

5. Conclusion

This study quantitatively examined how far contemporary personal colour practice, as performed by Japanese beauty influencers, can be modelled within a perceptually uniform colour space. By linking influencers' yellow/blue and seasonal labels for 1,193 unique lipsticks to CIE L*a*b* coordinates and training gradient-boosted decision tree classifiers, we showed that both label systems are recoverable from colour information alone at levels substantially above chance. The binary distinction between yellow-base and blue-base is particularly tightly coupled to the b* (yellow–blue) axis, suggesting that influencers collectively track a core perceptual dimension when assigning these broad categories.

At the same time, the four seasonal labels form broad, overlapping regions in colour space and are only moderately predictable from L*a*b* or L*C*h* coordinates. Personal colour should therefore be understood as a hybrid formation: it is grounded in colour-scientific regularities, yet elaborated into narrative seasonal types that provide consumers with memorable, culturally meaningful heuristics rather than rigid scientific partitions of colour space.

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References

1. Ashar, Tahira Andi. 2025. "Personal Color and Its Role in Enhancing Professional Branding and Self-Presentation in Makassar City, Indonesia." Public Resource Innovation Manager and Excellence, 23–26.

2. Birren, Faber. 1969. Principles of Color: A Review of Past Traditions and Modern Theories of Color Harmony. New York: Van Nostrand Reinhold Co.

3. Choi, Young-Mee, and Seunghee Bae. 2024. "A Study on Foundation Color Classification with the Application of Personal Colors." Asian Journal of Beauty and Cosmetology 22 (2): 323–34.

4. Hirayama, Kenya, Mieko Yamamoto, Kazuhiro Yamazaki, and Satoshi Kimura. 1998. "Hada iro to niau rippu kara no shikisai chowa ni kansuru kenkyu" [A Study of Color Harmony of Face Color and Suitable Lipstick on the Individual]. Journal of the Japan Society of Cosmetic Chemists 32 (2): 170–77. (In Japanese.)

5. Hsu, Ting-Yu, and Wen-Yuan Lee. 2024. "Examining the Consistency of Lip Color Impression Between Actual Face and Virtual Avatar." In Proceedings of the 8th Asia Color Association Conference, 87–92.

6. Ippan Shadan Hojin Nihon Kara Kodineta Kyokai [Japan Color Coordinator Association (J-color)]. 2022. Shikisai katsuyo pasonaru kara kentei koshiki tekisuto 3-kyu [Official Textbook for the Personal Colour Proficiency Test, Level 3]. Tokyo: Nihon Kogyo Shinbunsha.

7. Itten, Johannes, and Faber Birren. 1970. The Elements of Color: A Treatise on the Color System of Johannes Itten Based on His Book The Art of Color. New York: Van Nostrand Reinhold.

8. Jackson, Carole. 1985. Color Me Beautiful: Discover Your Natural Beauty Through the Colors That Make You Look Great and Feel Fabulous. New York: Ballantine Books.

9. Kamiyama, Yoko, and Nobuko Nagasaka. 2004. Pasonaru kara no kyokasho [Textbook of Personal Colour]. Tokyo: Shinkigensha. (In Japanese.)

10. Kiritani, Yoshie, Mae Ushikubo, and Ruriko Takano. 2004. "Keshohin haishoku no insho hyoka to hyogen media no kankei" [Impressions of Color Combination of Make-up Cosmetics in Different Media]. Journal of Japan Society of Kansei Engineering 5 (4): 27–32. (In Japanese.)

11. Knapp, Renae, and Dorr Dee. 1985. Beyond the Color Explosion: The Color Key Program. Rainy Day.

12. Maki, Kiwamu, and Sari Yamamoto. 1998. "Pasonaru kara no insho hyoka" [Impression Judgement of Personal Color]. Journal of the Color Science Association of Japan 22 (3): 127–39. (In Japanese.)

13. Matsui, Ayako. 2021. "SNS ni okeru daitasu no tasha no eikyoryoku no jissho: 'Tine' ya 'etsuransu' wa yuza kodo ni eikyo o oyobosu no ka?" [Does the Number of Likes and Views Matter?: An Experimental Study of the Influence of SNS Majority Users]. Marketing Review 2 (1): 30–37. (In Japanese.)

14. Nonaka, Yuto, Mami Ogino, Aki Kondo, and Katsumi Watanabe. 2023. "Pasonaru kara ga jinbutsu no miryoku hyoka ni ataeru kouka" [Effects of Personal Color

on Attractiveness Ratings]. In The 87th Annual Convention of the Japanese Psychological Association, 503. (In Japanese.)

15. NPO Hojin Nihon Pasonaru Kara Kyokai [Japan Personal Color Association]. 2001. "Pasonaru kara" [Personal Colour]. Accessed October 31, 2025. https://www.p-color.jp/about/.

16. Omagari, Miu, Naho Kuramochi, Naomi Sugawara, Natsuha Yamazaki, and Yusuke Hoshino. 2024. "Pasonaru kara no icchi fuicchi no insho" [Impressions of Personal Color Match or Mismatch: Case Study of a Makeup-Oriented Instagrammer]. In Proceedings of the 19th Spring Annual Meeting of Japan Society of Kansei Engineering. (In Japanese.)

17. Park, Jisoo, Hyungjoon Kim, Seonmi Ji, and Eenjun Hwang. 2018. "An Automatic Virtual Makeup Scheme Based on Personal Color Analysis." In Proceedings of the 12th International Conference on Ubiquitous Information Management and Communication.

18. Phan Van Song, Théo, Yue Qiao, Marco Vicic, and Anke Hadasch. 2025. "A New Method for Skin Color Classification Based on Global CIELAB Data and k-Mean Clustering." Color Research & Application, 1–15.

19. Sripian, Peeraya, Michiko Ohkura, Kejkaew Thanasuan, and Keiko Miyatake. 2020. "Shikisai tokucho no tokei kaiseki ni yoru kuchibeni no burando no tokuchozuke: Iro gazo no RGB chi wo mochite" [Characterization of Lipstick Brands by the Color Feature Analysis: Using RGB Values of Color Images]. Journal of Japan Society of Kansei Engineering 19 (4): 389–93. (In Japanese.)

20. Takamatsu, Misao, Keiko Ishigami, Hiroko Inui, Masumi Maruyama, Takenori Ichiba, and Shinya Takahashi. 2015. "NCS irokukan zentai no pasonaru kara foshizun bunrui to sono tokucho" [Classifications and Characteristics of Four-Season Colors in NCS Color Space]. Journal of the Color Science Association of Japan 39 (5): 164–67. (In Japanese.)

21. Tani, Shoko, Saki Watanabe, and Chinagi Okawa. 2024. "Jyoshi daigakusei no kokkaku shindan, pasonaru kara shindan no ninchido to shohi kodo ni oyobosu eikyo" [Awareness of Skeletal Diagnosis and Personal Color Diagnosis Among Female University Students and Their Influence on Consumption Behavior]. In Abstract of Annual Congress of The Japan Society of Home Economics 76, P-91. (In Japanese.)

List of all figures and tables:

Table 1: Summary of Instagram influencer accounts included in the study.

User ID	Products with valid colour samples	Yellow/Blue			Four Seasonal				
		Yellow only	Blue only	Multi labels	Spring only	Summer only	Autumn only	Winter only	Multi labels
A	250	114	73	62	33	22	29	19	147
B	98	49	33	15	18	13	15	13	39
C	130	63	49	18	21	18	21	17	53
D	451	246	130	74	59	33	79	38	242
E	671	249	223	199	76	53	43	53	446
Total	1,600	721	508	368	207	139	187	140	927

Table 2: Data-flow from the initial collection to the final modelling datasets.

Stage	Description	Number of rows
0	Initial product entries	1,600
1	Rows with valid colour sample	1,600
2	Rows with single yellow/blue label (PColor)	1,229
3	Rows with single seasonal label (SColor)	673

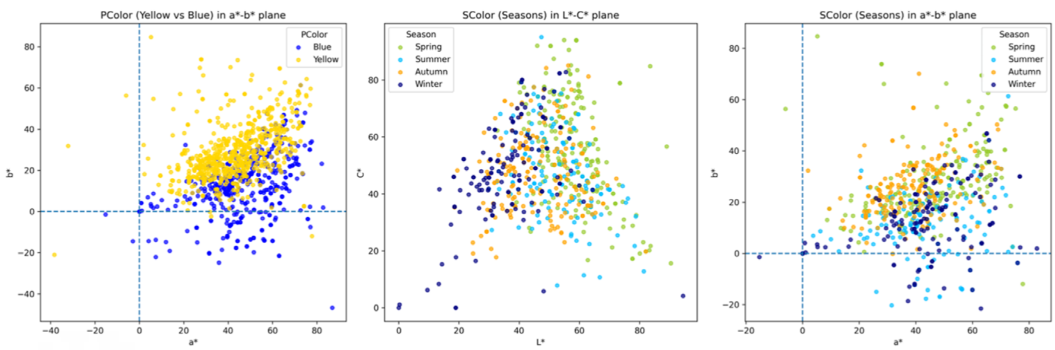
Table3: Confusion matrices for the XGBoost classifiers. (a) Yellow/blue model. (b) Seasonal model.

(a)

True \ Predicted	Yellow	Blue
Yellow	181	35
Blue	30	123

(b)

True \ Predicted	Spring	Summer	Autumn	Winter
Spring	43	8	10	1
Summer	8	25	4	5
Autumn	9	5	36	6
Winter	3	4	7	28



(a) (b) (c)

Figure 1: Distributions of influencer-assigned personal colour labels in CIE colour space. (a) Yellow-base versus blue-base labels in the a*-b* plane. (b) Four seasonal labels (Spring, Summer, Autumn, Winter) in the L*-C* plane. (c) Four seasonal labels in the a*-b* plane.