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VISUAL NORMALIZATION AND ALGORITHMS ON SOCIAL MEDIA
The Role of Chromatic Codes in Building Digital Positioning

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ABSTRACT

Using aggregated survey responses from Spanish university students (18-35), this study compares Instagram, TikTok, Facebook, LinkedIn and YouTube through self-reported color associations (not automatic color extraction from images). We quantify concentration and diversity with HHI and Shannon entropy, segment differences with Jensen-Shannon divergence, and map platform-color positioning via correspondence analysis with clustering. Results suggest segmented normalization: compact, low-entropy palettes compress segment differences, whereas higher diversity separates chromatic territories and often amplifies age effects. Dominant-color share generally relates inversely to entropy, varying by platform.

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1. Introduction

The ubiquity of visual posts has turned the image into a central resource for understanding communication on social media. This "visual turn" has become an analytical and methodological challenge: studying platforms centred on the visual requires attention both to production/curation practices and to the ways images circulate and are read in environments such as Instagram (Wiesenberg & Verčič, 2020; Rogers, 2021). Within this framework, chromatic codes acquire relevance because they operate as shortcuts for recognition and as signals of aesthetic belonging, reinforcing dynamics of visual homogenisation linked to recommendation and visibility logics.

The relevance of photography goes beyond the mere act of showing. Evidence suggests that the expansion of image-centred networks is accompanied by renewed interest in deciphering which visual attributes capture attention and define reputations. This shift aligns with the premise of Kim (2024), who warns that research on personality and social media still privileges text despite the vertiginous growth of graphic formats. This theoretical imbalance has left in the background the mechanisms of "visual normalization" that, by condensing into recurrent palettes, could act as implicit guides for behaviour and consumption.

From visual culture research, colour is not understood as an isolated attribute but as a socio-semiotic code that organises expectations of reading, belonging and reputation within visual circulation environments. On platforms where visibility is hierarchised and distributed, these recurrent palettes function as visual grammar that stabilise dominant styles and orient forms of self-presentation. Hence, concentration and chromatic diversity metrics operate here as operationalisation instruments: they do not pursue a mere quantitative description, but the identification of visual normalisation patterns linked to platform dynamics and segmentation. In this framework, the article is situated within digital visual culture by connecting aesthetics, circulation and visibility asymmetries.

In corporate communication, visual communication is articulated as a problem of image and identity: visual representations contribute to constructing meanings about attributes, values and differentiating elements in dialogue with stakeholders (Apolo Buenaño et al., 2018). In social media environments, the standardisation of visual repertoire through style guides can be understood as a practical response aimed at sustaining visual consistency and reinforcing brand identity in competitive contexts of visibility and recognition (Prasetyo & Revinzky, 2024).

The algorithmic component introduces another layer of complexity. The architecture of platforms such as Instagram remains largely opaque and inscrutable for most of their users, who are unaware of how the system prioritises or hides certain representations (Cotter, 2019). Moreover, the deployment of artificial intelligence in recommendation processes extends the discussion to how perceptions of beauty and desirability are modulated by automatic decision rules (Hussain et al., 2025). All indications are that any attempt to understand the circulation of chromatic codes must consider the interaction between cultural dynamics and technical logic.

Nevertheless, an underexplored issue remains: comparability among platforms whose identity is precisely built upon different visual formats. TikTok, for example, has captured dazzling media attention, but the academic literature on celebrity and influence on this platform remains relatively limited (Abidin, 2021). Considering this gap, the present study is articulated around the following thesis: segmented variations in chromatic concentration and diversity condition the relative magnitude of age and gender divergences on Instagram, TikTok, Facebook, LinkedIn and YouTube.

Preliminarily, the comparison suggests that each platform tends to stabilise chromatic codes with different degrees of concentration and diversity, and that these configurations are associated with divergences by age and gender of variable intensity. Section 4 develops this overview by platform and segment, together with a platform-colour correspondence map.

Methodologically, the study adopts a descriptive quantitative cartography based on aggregated chromatic distributions by platform and segment. The aggregate units allow the articulation of concentration/diversity measures (HHI and entropy), divergences between segments, and a factorial correspondence space in which colours and platforms share F1–F2 coordinates to explore neighbourhoods and digital positioning. The algorithmic reading remains contextual (not causal) and, given that the design is built on aggregated tables, the discussion of scope, traceability and data constraints is presented systematically in Section 5.1 (Limitations).

Against this backdrop, the study aims to broaden the theoretical debate on visual normalization and chromatic codes, while offering a replicable protocol for mapping these logics in different environments. The metrics employed, together with the focus on five widely used platforms, allow us to sketch a bridge between conceptual arguments about visual culture and the empirical evidence that sustains sociodemographic group divergence. Following the orientation proposed by Schreiber (2017a) about considering aesthetics as an intrinsic trait of the communicative process, the research seeks to elucidate the extent to which the chromatic grammar of a network delimits the margins of exposure and, by extension, of social recognition.

1.1. Objectives

O1: To examine the relationship between the chromatic concentration and diversity of each platform and the divergences in colour distributions by age and gender.

O2: To explore whether, within each platform and segment, the proportion of the dominant colour is differentially associated with entropy in the 18–25 and 26–35 age groups and in the male and female gender groups.

O3: To propose a positioning scheme that integrates factorial coordinates and platform-colour clusters to delineate visual normalization patterns replicable in future comparative analyses.

2. Theoretical framework

Visual normalization has become a cardinal phenomenon for understanding the circulation of images on social media and, at the same time, for interrogating the way platforms and publics negotiate what is visible. If every mediated repertoire acquires specific vernacular features, this is because visual vernaculars are conditioned by multiple platform affordances (e.g., front-end and back-end structures, platform cultures and commercial interests), which combine with different social phenomena to produce specific platform vernaculars where the visual and the textual coexist (Pearce et al., 2018). In this intersection between technical conditions and social practices, the central problem of this work is outlined: how certain chromatic codes, once stabilised, come to function as filters of digital positioning, simultaneously delimiting opportunities and margins of exclusion.

The genealogy of the issue refers to the transition from writing cultures centred on text to communicative ecologies dominated by multimedia compilations. This turn, still expanding, has been described by noting that on social media there might be a shift from mainly text-based UGC towards curated collections that incorporate more complex multimedia sets, raising new questions about how they can be leveraged (Jalali & Papatla, 2016). This visual densification coincides with the observation that memory is no longer housed in stable repositories, for in the distributed and networked environment of digital photographs, visual memory ceases to be fixed in a single place and becomes shared (van Dijck, 2008). Fragmentation, ubiquity and remix therefore configure the backdrop against which metrics measuring chromatic concentration or diversity acquire meaning.

Some works have emphasised the mobile affordances that naturalise the instantaneous capture and dissemination of everyday images: the affordances of mobile devices, combined with social media applications such as Instagram, have caused people's daily lives to be remediated into new contexts of social visibility and connection (Zappavigna, 2016). To this reconfiguration of the everyday is added the argument that the technical developments of platforms suggest that the collaborative construction of meaning is a central practice of visual communication (Schreiber, 2017b). Both perspectives converge in situating image production as a distributed and co-interpreted social activity, a circumstance that enhances the weight of chromatic codes when they act as mechanisms of interpretative convergence.

The massive deployment of curation algorithms reorders that scenario by regulating the interdependence between users, platforms and commercial logic. An early reading of Facebook's News Feed showed how mediated and constructed visibility is configured within social networks (Bucher, 2012), while research on platform vernacular shows how publishing practices adapt to conventions and circulation rules that condition visibility; algorithms structure that environment without unilaterally determining it (Hu & Kidd, 2023). From this tension between human agency and automation emerge recurrent aesthetic patterns that, even without being normatively prescribed, normalise the valued chromatic palette and thereby stabilise attention hierarchies.

It is not enough, however, to recognise the existence of algorithmic filters; it is necessary to interrogate their articulation with the permanent personalisation of the feed. Sustained exposure to

certain visual patterns and usage dynamics on networks has been linked to indicators of affective state, which reinforces the ambivalent reading of the feed experience: it can be rewarding, but also associated with discomfort (Reece & Danforth, 2017), reinforcing the need to unravel the logics of visual saturation. The case of TikTok synthesises this operation by articulating visibility through recommendation logics that order exposure and force the negotiation of algorithmic visibility (Jaramillo-Dent, 2023). In such a context, chromatic codes act as relevance shortcuts: the more they conform to detected preferences, the higher the probability of being amplified.

The expansion of what is called algorithmic culture generates a contradictory scenario: what is at stake is the gradual abandonment of the public character of culture and the emergence of a new elite culture that purports to be its opposite (Striphas, 2015). From this perspective, chromatic standardisation can be read as a dual device: on the one hand, it pluralises repertoires by offering accessible templates; on the other, it consolidates a dominant aesthetic that reinforces cleavages of symbolic capital by distinguishing who knows and handles fashionable codes.

Algorithmic mediation can have normative effects on what is perceived as aesthetically "valuable": if the platform modulates reach and discovery, the aesthetics most compatible with that regime tend to stabilise and become a reference. In this sense, aesthetic normalization can be discussed as a result of visibility governance, even when the design does not allow direct observation of the recommendation system (Zeng & Kaye, 2022).

Online identity studies remind us that users simultaneously navigate between personal and group markers: on social networks, both signals of personal identity and social identity are evident (Barker, 2009). This ambivalence deepens when platforms encourage self-branding, because they impel aspiring entrepreneurs to practise self-branding, taking as a reference the codes, processes and market logics typical of dominant cultural industries (Duffy & Hund, 2015). In both cases, colours function as symbolic labels that communicate affinities and professional competencies without mediating explicit text.

The micro-curation of influencers illustrates the affective dimension of the matter: bloggers use images on Instagram to strengthen the connection with their audiences, articulating in professional profiles a series of more intimate and personal snapshots (Ramos-Serrano & Martínez-García, 2016). This strategy aligns with the widespread habit of sharing lifestyles, insofar as contents express lifestyles that, when they become widely shared preferences, contribute to shaping the culture of a society (You et al., 2017). By privileging certain colour ranges, creators not only care for the aesthetic coherence of their feed but also model collective expectations about what is desirable.

The emergence of imagined communities around specific visual signs shows the connotative power of colour. Digital photography on Instagram, as an application that allows amateurs and professionals to disseminate images globally, discursively contributes to creating archives and even imagined communities through the formation of sub-ummas (Demerdash, 2024). However, the overabundance of stimuli can overwhelm interpretative capacity, for if one lacks visual skills to encode that information, much of what is shared remains barely comprehensible and communicative effectiveness is reduced (Esparza Morales & Vences-Esparza, 2024). Therefore, measuring chromatic concentration and diversity acquires relevance by offering clues about symbolic accessibility and accidental exclusion.

On this framework, the constructs guiding the thesis of the present study are articulated: chromatic concentration indicates the extent to which few tones dominate the scene; diversity refers to the equitable distribution among ranges; and divergences by age or gender inform about mismatches in visual consumption between segments. The underlying assumption holds that variations in concentration or diversity condition the relative magnitude of these divergences, an operation that makes sense when comparing the ecosystems of Instagram, TikTok, Facebook, LinkedIn and YouTube. Instead of attending only to the prominence of each platform, the argument underscores the role of the platform-segment matrix to discover hidden regularities in social colorimetry.

Admittedly, the literature still leaves gaps that are difficult to bridge. There is a lack of consensual indicators that directly link chromatic palettes with demographic inequities, and methodological doubts persist associated with the global sample size or the absence of segmented heatmaps — gaps that the present study cannot fully remedy. Even so, the conceptual framework discussed here legitimises the pertinence of tracing how colour distribution is interwoven with algorithmic visibility policies and self-curation practices, granting the chromatic dimension a central place in the visual sociology of the platform.

In sum, the debate unfolds between two critical poles: one emphasises the democratising promise of access to standardised visual tools; the other warns about the danger of a uniform aestheticisation that

silences cultural heterogeneity. It will therefore be necessary to problematise the validity limits of any metric, recognise the relational nature of digital positioning, and attend to the fact that chromatic codes do not exist outside socio-technical devices and subjective repertoires in permanent negotiation.

In light of this review, an analytical turn is proposed that situates visual normalization at the crossroads between chromatic distribution metrics and digital positioning processes. In line with works linking visual features of posts with audience response on Instagram (Kim & Jang, 2022), we propose to move towards a scheme that integrates concentration/diversity indices and estimates of demographic divergence, so that the academic conversation transcends mere aesthetic description and contributes to critically mapping the colour economy in contemporary social media.

3. Methodology

3.1. Design and analytical approach

The work adopts an empirical quantitative design based on descriptive characterisation and non-inferential comparative reading. The guiding axis consists of investigating how the concentration and chromatic diversity of visual repertoires relate to age and gender divergences within five online social environments (Instagram, TikTok, Facebook, LinkedIn and YouTube). The strategy deliberately excludes any significance testing: the observed contrasts are of interest, not population inference. The thesis therefore rests on direct comparison of normalised metrics and on the visual inspection of a factorial space obtained through Correspondence Analysis (CA).

3.2. Data, sample and fieldwork procedure

The information comes from a single round of a self-administered survey of university students (18–35) residing in Spain. For each platform (Instagram, TikTok, Facebook, LinkedIn and YouTube), respondents were asked to select the colour primarily associated with the network from a closed list of 12 categories; responses were aggregated into proportions by platform and by segment, constituting the analysed distributions. Valid bases per platform in the analysed sample were: Instagram (n=399), TikTok (n=399), Facebook (n=400), LinkedIn (n=399) and YouTube (n=398). Recruitment combined an online panel and classroom recruitment, applying the same eligibility criteria. The questionnaire was administered between January and March 2025 through the Netquest (Bilendi) platform, with informed consent, automatic anonymisation and no incentives. General quality controls were applied before aggregation (cleaning of incomplete or low-quality records); overall, the aggregate dropout/exclusion rate was ≈10%. Given the aggregate nature of the corpus, exclusions are reported in general terms.

3.3. Construction of the analytical corpus and unit of analysis

After cleaning, individual records were aggregated into five output tables that constitute the quantitative corpus of the study. The first matrix collects the proportions of twelve colours (Yellow, Blue, White, Gold, Grey, Brown, Purple, Orange, Black, Red, Pink and Green) by platform in the total sample. A second table consolidates sample sizes by platform and segment; a third compiles, for each platform×segment combination, the Herfindahl–Hirschman Index (hhi_concentration), Shannon entropy (entropy), the dominant colour and its proportion (p_dominant), together with a closure control (sum_proportions). A fourth table stores the Jensen–Shannon divergences by age and by gender on each platform, while the fifth contains the F1 and F2 coordinates of the factorial space, the label (platform or colour) and the cluster identifier resulting from a k-means clustering applied to the labels (platforms and colours) on the F1-F2 plane of the total sample.

The analysis operates at two levels. The first corresponds to the platform considered globally; the second descends to the platform×segment intersection for the five defined analytical layers (Total sample, Age 18–25, Age 26–35, Men and Women). On the gender axis, all categories recorded in the questionnaire were retained (including “non-binary” and “other”). These responses are included in the total sample; however, due to the small size of those categories, the comparative analysis by gender is reported only for “men” and “women”, avoiding unstable estimates and non-robust readings. In the factorial plane, the unit changes: platforms and colours appear as labels in the same coordinate system, allowing symmetric associations to be read. This multilevel design makes it possible to contrast aggregate patterns with intra-platform variations without mixing scales.

3.4. Indicators and analytical instruments

The variables result from the aggregation described. As primary outcomes, hhi_concentration, entropy, js_divergence_age, js_divergence_gender, F1 and F2 are considered. The proportions of the twelve colours, the dominant_color, p_dominant and the cluster act as secondary outcomes. Platforms, demographic segments, type (platform or colour) and the nominal label function as predictors or classification factors. Additional control variables (base_n, sum_proportions and the counts of each segment) allow auditing the consistency of the information without intervening in the substantive explanation.

Five estimands guide the analytical phase: (1) chromatic distributions by platform in the total sample, (2) concentration and diversity by platform×segment, (3) chromatic dominance by platform, (4) divergences by age and by gender within each platform, and (5) joint positioning on the CA map. For the first estimand, the observed proportions are described, operationalising the dominant visual style as the distribution of chromatic associations (12 categories) per platform, within a digital methods approach to studying visual communication on social media (Highfield & Leaver, 2016). The second and third are based on hhi_concentration and entropy, metrics calculated on normalised distributions. Shannon entropy was computed with logarithm base 2, thus expressed in bits. The Herfindahl–Hirschman Index (HHI) is a measure of concentration calculated as the sum of the squares of the shares (s_i^2) of actors/categories in a finite space; higher values indicate greater concentration. Its calculation was implemented through standardised computational routines in the software literature (Waggoner, 2018).

The fourth estimand quantifies differences between segments within each platform using Jensen–Shannon divergence on normalised distributions, consistent with recent applications of this metric in comparative palette/distribution analysis (Shagyrov & Shamoi, 2024). Logarithm base 2 was used, so divergence is expressed in bits and bounded between 0 and 1. Values close to 0 indicate very similar distributions; for example, magnitudes such as 0.044 represent small dissimilarities. In all cases it is verified that $0 \leq p_i \leq 1$ and that the sum of proportions approaches unity — explicit checks in the aggregated tables. Finally, the CA map translates the platform×colour matrix into a two-dimensional space; interpretation relies on the fact that closeness between a colour and a platform is interpreted as relative association (Greenacre, 2010). The k-means clustering on F1 and F2 introduces an additional level of territorial reading without inferential pretension, in line with the methodological note of Nenadic & Greenacre (2007). k=3 was set for parsimony and interpretability, aiming to segment the factorial plane into a reduced number of proximity areas. The partition is used solely as a descriptive aid for reading the map and its composition is reported in Table 4. The algorithm was run with multiple initialisations and a fixed seed to ensure partition stability.

3.5. Controls, missing data, robustness, reproducibility and ethics

Correspondence Analysis requires non-negative inputs and row/column closure; these assumptions are reviewed through the variable sum_proportions and the absence of negative values. The clustering algorithm starts from factorial coordinates (F1-F2) obtained from CA, so no additional standard errors are estimated. In concentration and diversity metrics, the absence of out-of-range proportions and the internal consistency of demographic segments are verified. Such checks are documented in an accessible control log for review, although they are not reported numerically in the article.

No imputation is applied. Any missing cell in the proportion or metric tables remains null value and is identified with an explicit symbol in the reporting outputs. Zeros are interpreted as real observations, not as missing values. On the gender axis, minority categories (non-binary and others) are included in the total sample, but are not reported as analytical subgroups due to insufficient size. If any discrepancy between the sum of segmentations and the total base is detected, it is noted as an incident and the data are neither substituted nor adjusted.

Since the study renounces inference and does not propose hypothesis tests, no corrections for multiple comparisons are implemented. Nor are models that would require robust standard errors or clustering corrections estimated: the data are already aggregated and interest is circumscribed to descriptive comparison. The cluster identifier reflects only a heuristic partition on the factorial plane, not a sampling design.

The data custody chain begins with the original questionnaire, proceeds through case cleaning, and culminates in the five analytical tables, all generated via scripts with version control. Each

transformation incorporates metadata on date, responsible person and summary of operations. Column names are kept in lower case with underscores, respecting the original header to facilitate linking between tables and code. Proportions are expressed as decimals with commas, as stored in the CSVs, avoiding automatic reformatting upon export. The visualisations and tables accompanying the text are reproduced from these same structures, so that a third party with access to the scripts and tables can fully replicate the analytical path.

The report adheres to aggregated values, avoiding any trace that would allow individual reidentification. No personal data is retained outside the secure environment provided by the collection platform. The publication deliberately omits microdata and complies with Spanish data protection regulations and the GDPR.

It could be argued that the absence of significance tests reduces the ability to rule out random fluctuations. However, the aim of the study is not to infer to a population, but to map the observable articulation between colour codes and digital positioning — an approach closer to exploration than confirmation. Another possible criticism concerns the age cut-off of the participants, which excludes users over 35; this decision responds to the intention to analyse platforms with a youth predominance, even at the risk of sacrificing generality. Finally, the fixed number of colours and the decision to work with twelve shades may be considered a cultural simplification; nevertheless, the chosen repertoire covers the predominant chromatic categories in the literature on digital branding and facilitates cross-sectional comparison.

In summary, the methodology articulates a careful combination of survey aggregation, concentration and diversity metrics, dissimilarity measures and factorial representation. The absence of statistical inference is compensated by rigorous consistency controls and exhaustive traceability that allows each figure and table to be reproduced without ambiguity. This establishes a replicable framework for examining segmented visual normalization on social media and its possible link with digital positioning processes.

4. Resultados

Overall, the results show segmented visual normalization: (i) platforms are organised into chromatic regimes with varying degrees of concentration, (ii) age divergence tends to exceed gender divergence, although not uniformly across networks, and (iii) the platform-colour factorial scheme delimits chromatic territories consistent with the observed dominances. Furthermore, at the platform×segment level, the relationship between the proportion of the dominant colour and entropy is generally inverse, with clear differences in its intensity according to platform.

To consistently interpret the contrasts between platforms and between segments (age and gender), base sizes by platform are reported. These bases contextualise the comparative reading of divergences and intra-platform chromatic metrics, avoiding interpretations disconnected from the effective volume of each analytical cross.

Table 1. Base sizes by platform and segment

Platform	Total sample	Age 18–25	Age 26–35	Men	Women
Instagram	399	241	158	161	233
TikTok	399	241	158	160	234
Facebook	400	242	158	161	234
LinkedIn	399	241	158	160	234
YouTube	398	240	158	159	234

Note. The total sample also includes minority gender categories (non-binary and other) that are not disaggregated in this table; they are presented integrated in the total for comparability and clarity of exposition.

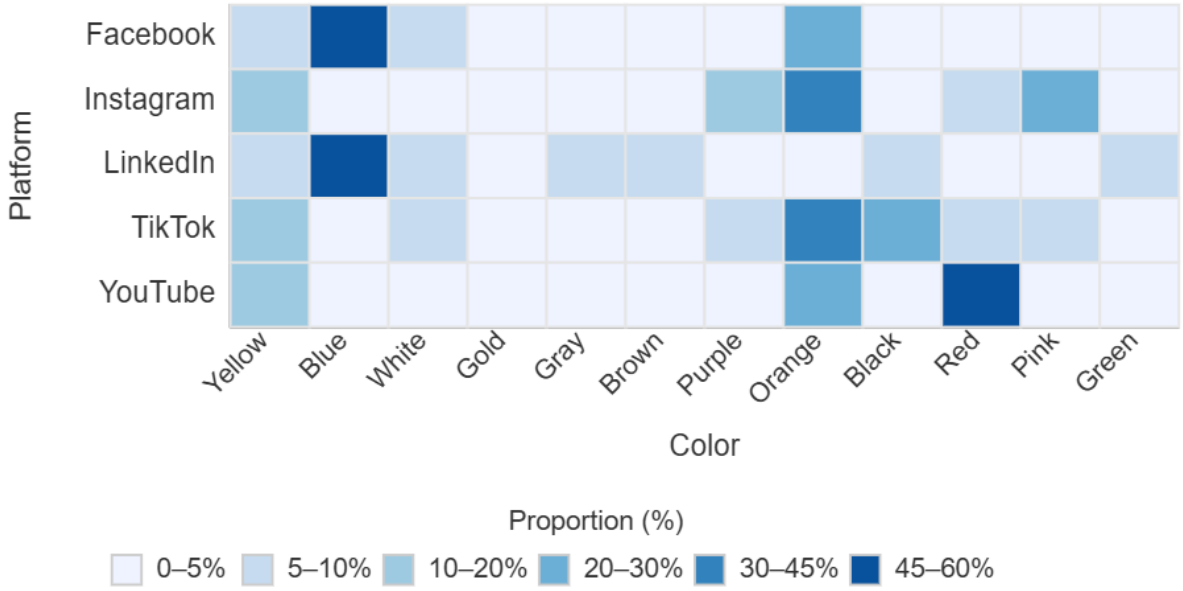
Source(s): Own elaboration.

4.1. Chromatic distribution by platform in the total sample and divergences by age and gender (O1)

Figure 1 shows a contrast between platforms with highly concentrated palettes and platforms with a more distributed palette. Facebook and LinkedIn activate the upper segment of the scale (45-60%), consistent with their dominance of Blue; the maximum observed in the matrix reaches 0.565 (56.5%).

YouTube also presents a high concentration around Red. In contrast, Instagram and TikTok show more cells in intermediate ranges, suggesting a more diversified chromatic repertoire in the total sample.

Figure 1. Color×platform heatmap (total sample)



Note. Each cell represents the proportion of participants (%) who associate a colour with each platform. The gradient is interpreted according to the range legend (0–5% ... 45–60%).

Source(s): Own elaboration.

Table 2 summarises the Jensen–Shannon (JS) divergence by platform, comparing the distance between colour distributions by age and by gender. In general terms, age divergence exceeds gender divergence on all platforms, with two relevant patterns: (a) YouTube (0.044) and LinkedIn (0.042) present the largest age divergences, while Facebook (0.029) shows the smallest; and (b) gender divergence is particularly low on YouTube (0.008) and Facebook (0.009), which is consistent with the reading of Figure 1 for platforms with more compact palettes in the total sample. In contrast, LinkedIn concentrates the largest gender divergence (0.040), approaching the magnitude of its age divergence, suggesting that on this platform both axes segment more evenly.

Table 2. JS divergence values by platform

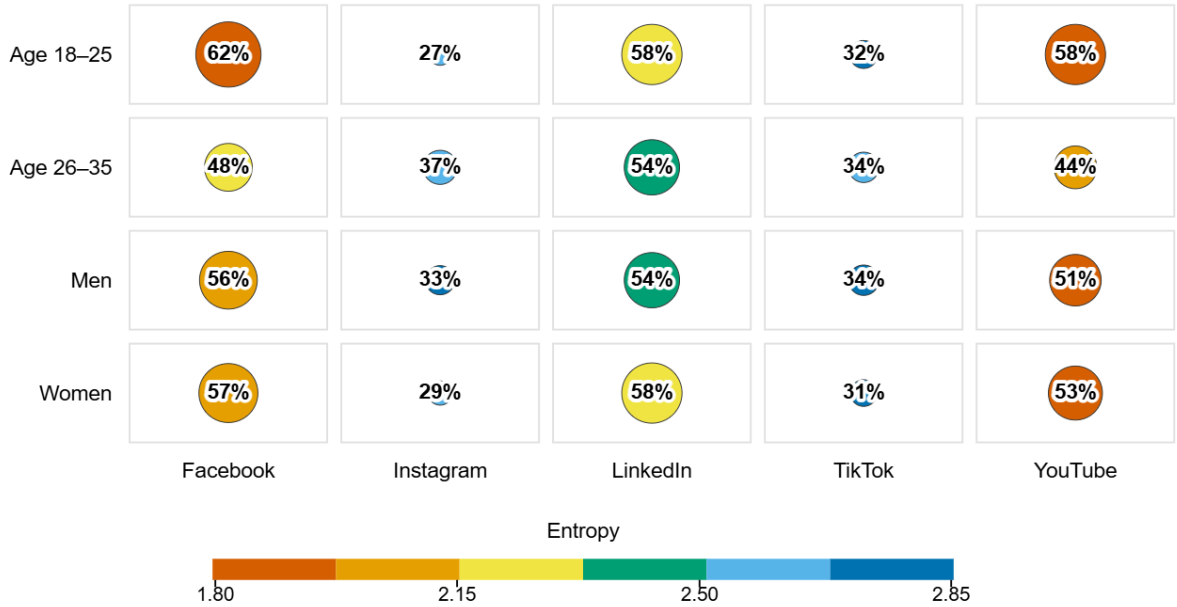
Platform	JS divergence (age, bits)	JS divergence (gender, bits)
Instagram	0.035	0.027
TikTok	0.037	0.030
Facebook	0.029	0.009
LinkedIn	0.042	0.040
YouTube	0.044	0.008

Source(s): Own elaboration.

4.2. Relationship between proportion of the dominant colour and entropy by platform×segment (O2)

Figure 2 synthesises, for each platform×segment combination, the proportion of the dominant colour (marker size) and entropy (chromatic gradient). The overall pattern is consistent with an inverse relationship: where the dominant colour gains weight, entropy tends to decrease (more compact palettes), while more moderate dominances are associated with higher entropies (more diverse repertoires). This contrast is especially marked on Facebook and YouTube when comparing age groups: the 18-25 segments concentrate higher dominances and lower entropies than 26-35, suggesting greater chromatic compaction in the younger group within those platforms. In contrast, Instagram and TikTok predominantly show medium-sized markers and high entropies, indicating more distributed patterns and less extreme dominance.

Figure 2. Platform×segment matrix showing p_dominant and entropy in a single view



Note. Marker colour encodes entropy (according to the lower bar): high = greater chromatic diversity; low = more compact palettes. Marker size is proportional to p_dominant and the percentage printed in each cell corresponds to p_dominant (%).

Source(s): Own elaboration.

Table 3 reports the exact values of dominant colour, p_dominant, HHI and entropy by platform×segment, confirming the most informative contrasts. On Facebook, the 18-25 group shows the highest dominance (p_dominant=0.62) together with an increase in concentration (HHI=0.421) and the lowest entropy on the platform (1.938), while 26-35 reduces dominance (0.48), lowers concentration (0.309) and increases entropy (2.300). On YouTube the same age gradient is reproduced: 18-25 increases dominance (0.58) and concentration (0.409) with lower entropy (1.799), compared to 26-35 (0.44, 0.316, 2.007). Conversely, on TikTok the age variation is expressed more in diversity than in dominance: 18-25 maintains a moderate p_dominant (0.32) but reaches a very high entropy (2.854) and a low HHI (0.179), while 26-35 increases concentration (0.224) and reduces entropy (2.519). On the gender axis, platforms such as Facebook present very close values between men and women (p_dominant≈0.56-0.57; entropy≈2.069-2.132), which converges with the low JS gender divergence observed in 4.1.

In closing, these results connect O2 with O1: when dominance intensifies and entropy falls (more compact palettes), segment differences — particularly by gender — tend to compress; conversely, when the chromatic repertoire is more distributed, conditions open for more visible segmentary distances, especially by age.

Table 3. Chromatic metrics by platform and segment (numerical support for Figure 2)

Platform	Segment	n	Dominant color	p_dominant	HHI	Entropy (bits)
Instagram	Total sample	399	Orange	0.31	0.197	2.683
Instagram	Age 18–25	241	Pink	0.27	0.203	2.610
Instagram	Age 26–35	158	Orange	0.37	0.208	2.677
Instagram	Men	161	Orange	0.33	0.198	2.684
Instagram	Women	233	Orange	0.29	0.200	2.616
TikTok	Total sample	399	Orange	0.32	0.193	2.760
TikTok	Age 18–25	241	Orange	0.32	0.179	2.854
TikTok	Age 26–35	158	Orange	0.34	0.224	2.519
TikTok	Men	160	Orange	0.34	0.205	2.723
TikTok	Women	234	Orange	0.31	0.192	2.718
Facebook	Total sample	400	Blue	0.57	0.370	2.115
Facebook	Age 18–25	242	Blue	0.62	0.421	1.938
Facebook	Age 26–35	158	Blue	0.48	0.309	2.300
Facebook	Men	161	Blue	0.56	0.362	2.132
Facebook	Women	234	Blue	0.57	0.380	2.069

Platform	Segment	n	Dominant color	p_dominant	HHI	Entropy (bits)
LinkedIn	Total sample	399	Blue	0.56	0.342	2.362
LinkedIn	Age 18–25	241	Blue	0.58	0.359	2.315
LinkedIn	Age 26–35	158	Blue	0.54	0.322	2.332
LinkedIn	Men	160	Blue	0.54	0.320	2.471
LinkedIn	Women	234	Blue	0.58	0.364	2.201
YouTube	Total sample	398	Red	0.53	0.362	1.936
YouTube	Age 18–25	240	Red	0.58	0.409	1.799
YouTube	Age 26–35	158	Red	0.44	0.316	2.007
YouTube	Men	159	Red	0.51	0.349	1.961
YouTube	Women	234	Red	0.53	0.374	1.885

Source(s): Own elaboration.

4.3. Platform-colour positioning scheme using factorial coordinates and clustering (O3)

Table 4 integrates platforms and colours in the same factorial space (F1-F2) and adds a clustering (cluster) that delineates interpretable chromatic territories for the total sample. This solution is not imposed from prior categories but emerges from the relative proximity of the labels in F1-F2: two pairs appear particularly close, and one platform remains more isolated, making a three-area partition parsimonious. The first territory (cluster 1) brings together Facebook and LinkedIn in nearby coordinates and aligns with Blue (and associated colours in the same zone, such as Gold/Grey), reinforcing the reading of blue dominance observed in 4.1 and the greater relative compaction of these platforms. The second territory (cluster 2) groups Instagram and TikTok together with colours such as Orange, Pink and Purple, consistent with a more diversified repertoire and less extreme dominances. Finally, the third territory (cluster 3) places YouTube in the vicinity of Red, in line with its concentration around that hue. Overall, this scheme offers a replicable cartography of platform-colour positioning: it does not replace the distribution metrics but facilitates a territorial reading of relative associations between networks and palettes.

Table 4. F1–F2 coordinates and cluster assignment (k-means, k = 3) by label

Tipo	Etiqueta	F1	F2	Clúster
Plataform	Instagram	-0.476	0.758	2
Plataform	TikTok	-0.344	0.457	2
Plataform	Facebook	0.721	-0.153	1
Plataform	LinkedIn	0.967	-0.162	1
Plataform	YouTube	-0.872	-0.903	3
Color	Yellow	-0.273	0.212	2
Color	Blue	1.053	-0.240	1
Color	White	0.205	0.038	1
Color	Gold	0.911	-0.254	1
Color	Gray	0.748	-0.261	1
Color	Brown	0.660	0.077	1
Color	Purple	-0.406	0.990	2
Color	Orange	-0.402	0.152	2
Color	Black	-0.147	0.430	2
Color	Red	-1.013	-1.113	3
Color	Pink	-0.531	1.104	2
Color	Green	0.461	0.055	1

Source(s): Own elaboration.

The objective provides a descriptive cartography of the joint positioning of colours and platforms in a factorial space with explicit clusters, designed for reuse in future comparative exercises.

5. Discussion

The findings invite us to treat visual normalization less as a monolithic “dominant style” and more as an ecology of constraints and opportunities assembled in the friction between platform identity, production habits and segmentation. This reading does not intend to attribute technical causality: what is observed are regular circulation, chromatic regimes, degrees of compaction/diversity and relational

neighbourhoods, which appear to stabilise with varying intensity depending on the environment. A reasonable objection may be raised: by relying on self-reported colour associations, the pattern could partly reflect perceived branding or cultural imaginaries rather than the "colorimetry" of content. Even so, that perception functions as a symbolic infrastructure of positioning: it delimits what is legible, recognisable and "proper" to each network.

Contribution 1 (O1). Figure 1 and Table 2 show that each platform configures a chromatic regime with a different degree of compaction. The interest is not "which colour wins", but how compaction modulates the visibility of differences between segments: more stabilised repertoires tend to flatten contrasts in the aggregate, while more open repertoires facilitate distinguishable segmentary profiles. In this framework, Jensen–Shannon divergence summarises dissimilarity between normalised distributions: higher values imply greater structural difference between segments (Nielsen, 2020).

This pattern fits an ecological view of the platform: design decisions, affordances and recommendation influence which styles circulate and are replicated. On TikTok, for example, it has been described that its affordances and deep-learning systems shape trends and content distribution (Rejeb et al., 2024; Dekker et al., 2025). Thus, chromatic normalization can be read as an emergent regularity: palettes perceived as compatible with the visibility logic tend to be reiterated, without assuming that the algorithm "imposes" a specific colour.

Contribution 2: p_dominant-entropy as a compaction/diversity mechanism (O2). Figure 2 and Table 3 allow moving from description to an interpretive mechanism: the relationship between the proportion of the dominant colour and entropy functions as a signature of repertoire narrowness. When the weight of the dominant colour increases, effective diversity tends to fall; when dominance moderates, the repertoire opens up. The theoretical importance of this relationship is that it explains how a recognisable aesthetic can coexist with internal variations: the platform may maintain a stable dominant colour while allowing (or restricting) the redistribution of the remaining colours. In terms of normalization, this is equivalent to distinguishing between an "anchoring" aesthetic (dominant) and a "modulating" aesthetic (diversity around the dominant). This distinction is central to avoid the criticism of "they only describe colours" and to turn the analysis into a discussion about margins of variation and aesthetic stabilisation.

This mechanism is better understood when connected to literature on perceived aesthetics and the effectiveness of visual signals. A multiple regression model reported that visual elements explain about 60% of the variance in perceived aesthetics and that colour is the most powerful predictor, followed by light and line (Hauser et al., 2022). Moreover, it has been argued that a coherent and pertinent chromatic palette acts as a brand trait, increases attraction and interaction time, and makes colour codes weigh in the competition for attention among platforms (Borysenko et al., 2024). Under this lens, compaction is not necessarily aesthetic "impoverishment", but a form of semiotic optimisation: it reduces perceptual uncertainty and facilitates recognition, which may benefit circulation in overloaded environments.

The link with engagement can be understood without repeating metrics. On Twitter, an effect of visual features of images on UGC engagement has been observed (Li & Xie, 2020), making it plausible that creators and brands converge on winning configurations through practical learning. Consistently, qualitative studies show a knowing-doing gap: even with critical awareness, social pressure and what the algorithm favours sustain the use of filters (Hussain et al., 2025). Applied to colour, codes consolidate by imitation and performance anticipation; therefore, the p_dominant-entropy relationship can be read as an indicator of how narrow the effective variation space is by platform and segment.

Contribution 3: aesthetic territories and symbolic positioning (O3). Table 4 adds a key interpretative level by integrating platforms and colours in a common space through Correspondence Analysis. In this framework, proximity between a platform and a colour should be understood as relative association within the compared set (not causal), and F1 and F2 as latent dimensions that organise these associations (Casales-García et al., 2025). This cartography facilitates talking about symbolic positioning: it is not that "colour X belongs" to platform Y, but that certain platforms are situated in chromatic neighbourhoods that function as territories of meaning. Along these lines, the cluster can be used to describe aesthetic territories: groupings of platforms and nearby colours that sustain a reading of positioning; clustering acts as a descriptive resource to read the map, not as an inferential result (Gretzel, 2017).

Theoretically, territories help explain why normalization produces both convergence and differentiation. Convergence, because within a territory recognisable codes stabilise, facilitating legibility and consistency; differentiation, because territories delimit borders: transferring an aesthetic

from one territory to another may lose contextual fit and therefore affect reception. In this way, the factorial space functions as a relational translation of positioning: it complements distribution metrics (O1 and O2) with a structural view of how associations are ordered in the compared ecosystem.

At an applied level, chromatic territories suggest caution when transferring visual strategies between networks: a coherent palette on one platform may lose contrast or legitimacy on another. Moreover, age dissimilarity tends to exceed gender dissimilarity on several platforms, supporting consideration of age cohorts in style decisions, especially where personalisation sustains returns (Dekker et al., 2025).

Taken together, the results support platform-dependent chromatic normalization: compaction/diversity modulates the visibility of segment differences, and the CA map provides a relational reading of platform-colour positioning. The three goals (O1-O3) are covered by the evidence integrated in Figures 1-2 and Tables 2-4.

5.1. Limitations

The study is deliberately descriptive: it compares patterns without significance tests or causal models. Therefore, associations between concentration (HHI), diversity (entropy) and divergences (Jensen–Shannon) should not be read as generalisable mechanisms. The design does not incorporate exposure measures, rankings or feed traces; hence, any algorithmic reading must be understood as contextual, not causal (Abokhodair et al., 2024).

External validity is bounded by the population and temporal cut-off (one round; university students 18-35 in Spain). It is not certain that the same chromatic profiles or age/gender divergences would be replicated in other contexts or after interface changes. Moreover, the bases are heterogeneous by platform and subgroup (including a contingent without gender), which forces sober interpretation of small magnitudes, potentially sensitive to base asymmetries.

The aggregated level of analysis (platform and platform×segment) facilitates cartography but prevents observation of intragroup variation, composition by content types or cross-effects between variables. Divergences are calculated within each platform and their comparison between platforms is exploratory. Non-imputation preserves documentary coherence, but if absence is not random it could affect comparability without the design diagnosing it.

Chromatic measurement simplifies: discretising into twelve categories stabilises analysis but sacrifices perceptual and cultural resolution (close tones are collapsed and potentially relevant nuances are lost).

The factorial map and clustering demand additional caution: proximity on the F1-F2 plane is relational and exploratory. The "territories" organise and contrast associations, but should not be treated as natural typologies nor assumed to be stable structures. Other choices of k would produce different partitions (finer or coarser) without altering the descriptive character of the map or its function as interpretative support.

6. Conclusions and future research

This study delineated visual normalization and colour codes as observable mechanisms of digital positioning mediated by platform and segment, from an explicitly descriptive and comparative approach. The findings converge on a central idea: chromatic concentration and diversity regulate the distance between colour distributions of age and gender groups, and they do so in a manner dependent on the socio-technical grammar of each network.

Regarding the first objective, the evidence suggests that when a platform's aggregate palette is compact and exhibits low diversity, internal variations tend to be contained and divergences between age and gender remain close in magnitude. Where chromatic dispersion predominates, segments occupy more differentiated territories and distances grow, often with a greater weight of age. This is interpreted in light of Jensen–Shannon divergence as dissimilarity between normalised distributions: fluctuations in entropy at the segment level translate into larger or smaller distances according to the chromatic order of the reference pattern. The second objective reveals an, in general terms, inverse association between the proportion of the dominant colour and entropy, although with disparate gradients. In more visually oriented or accelerated consumption environments, the predominance of the main colour becomes established as a robust aesthetic indicator, while in stable sociability or professional networks this ascendancy is more attenuated. The third objective provides a relational scheme of platform-colour positioning: the CA map, supported by descriptive clusters, delimits

chromatic territories consistent with the observed dominances and offers a replicable cartography for future comparisons.

The three questions are answered conditionally: when the aggregate palette is more compact, divergences between segments tend to compress; when diversity increases, more visible segmentary distances emerge, with a greater relative weight of age. The evidence is descriptive and does not allow discrimination between rival explanations nor establish causality.

These patterns open high-level implications. Chromatic codes operate as devices of symbolic order that, coupled with specific visibility regimes, contribute to the organisation of publics and aesthetic territories within each platform. A coherent palette can function as a brand anchor and an interaction catalyst, while diversity, far from being mere noise, delimits alternative positions competing for attention. In accelerated discovery grammars, the combination of palette coherence and algorithmic micro-segmentation seems especially sensitive for differential performance, without this being read as an operational recipe or as proof of causality.

The contribution of the work is twofold. Conceptually, it offers a framework to observe visual normalization as an articulation between concentration, diversity and chromatic dominance, connected to processes of digital positioning mediated by platform and segment. Methodologically, it shows that the joint reading of these indicators through descriptive distances between segments provides a parsimonious and replicable device for mapping visual normalization patterns. The scope remains deliberately non-inferential and circumscribed to the platform level and its cross by segment.

Future research should explore whether this detected chromatic homogenisation is accentuated with the integration of content generated by Generative Artificial Intelligence, analysing whether recommendation algorithms tend to privilege synthetic aesthetics over traditional photographic captures.

From here, realistic future lines emerge. It is pertinent to delve into comparable maps of chromatic distribution by groups within each network and into divergence estimates weighted by effective sizes. It is also relevant to standardise definitions of concentration, diversity and dominant colour, together with colour space discretisation schemes that facilitate replication. A longitudinal design would allow observation of whether segmental colour codes stabilise or rotate and how this dynamic accompanies interface or recommendation modifications. Articulation with performance measures, such as exposure or interaction patterns, would enable more demanding tests of the visual positioning hypothesis. Finally, it would be useful to refine the treatment of subgroups with partial information and adopt consistent numerical conventions, to sharpen comparability between cuts and platforms.

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