# Resolving the question of color naming universals 

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#### Abstract

The existence of cross-linguistic universals in color naming is currently contested. Early empirical studies, based principally on languages of industrialized societies, suggested that all languages may draw on a universally shared repertoire of color categories. Recent work, in contrast, based on languages from nonindustrialized societies, has suggested that color categories may not be universal. No comprehensive objective tests have yet been conducted to resolve this issue. We conduct such tests on color naming data from languages of both industrialized and nonindustrialized societies and show that strong universal tendencies in color naming exist across both sorts of language.


Do languages categorize colors similarly, or does color categorization vary freely across languages? This question pits two contrasting views of linguistic meaning against each other. In one view, meaning is constrained by universally shared aspects of perception, cognition, or the environment; in the other, it is determined principally by the arbitrary linguistic conventions of a particular language. For this reason, the question of color naming universality has attracted considerable attention (1-5) and generated considerable controversy (6-13). Curiously, however, the core empirical question of whether there are genuine universal tendencies in color naming has never been put to objective test, and it remains contested ( $6-10$ ). Our goal is to resolve this issue.
In 1969 Berlin and Kay (BK) (1) advanced the hypothesis that "a total universal inventory of exactly 11 basic color categories exists from which the 11 or fewer basic color terms of any given language are always drawn." They supported this hypothesis with color naming data from 20 languages. In subsequent work, the specific hypothesis of 11 universal basic color categories was generalized to the hypothesis that there exist universal constraints on cross-language color naming related to these 11 basic color percepts, particularly to the six Hering opponent primaries, black, white, red, yellow, green, and blue (14-17). This hypothesis, which we refer to as the universality hypothesis, has gained considerable acceptance over the years (2-5).
However, it has also encountered considerable resistance (6-10). A central concern has been the absence of any objective test of the hypothesis (7). Color naming data have typically been analyzed in an intuitive fashion, by determining through visual inspection whether color categories from different languages tend to cluster together in color space. A serious problem with this means of analysis is that humans sometimes incorrectly perceive clustering in points that are randomly distributed (18). Thus, it is possible that the perceived clustering of color terms, on which the claim of universality rests, is spurious.
Another concern is that the BK language sample (1) was small and skewed: 17 of the 20 languages studied were written languages of industrialized societies. Thus, even if the results had rested on an objective test, it is unclear how well they would generalize to other sorts of languages. The results leave open the possibility that color naming is similar primarily across those languages that are linked to each other through the global process of industrialization $(6,11,12)$. There are also further reasons to question the representativeness of the original data of BK (1): no more than a single speaker was tested for most languages, the data were gathered in the San Francisco Bay area
rather than in the native locale of the language, and all of the speakers tested also spoke English (6, 7, 11-13).

The most damaging evidence against the universality hypothesis is that there are languages that appear not to fit the proposed universal pattern. Interestingly, these tend to be unwritten languages of nonindustrialized societies, consistent with the idea that similarities in color naming may be limited in cross-linguistic scope. Most such languages do not have separate color terms for green and blue but rather use a single term to cover these regions of color space (17). Others, such as Hanunóo (19) and Zuni (7), have color terms that have been interpreted as reflecting extrachromatic concepts such as dryness and freshness rather than the proposed universal color categories (ref. 7, but see also ref. 20). Another proposed counterexample is Berinmo, a Papua New Guinea language with color term boundaries that disagree with comparable boundaries in English (8, 9).
Significantly, these cross-linguistic differences in color naming are sometimes correlated with differences in color cognition, calling into question the idea of a fixed cognitive bedrock underlying linguistic universals. Specifically, Berinmo speakers exhibit enhanced color discrimination from memory across Berinmo category boundaries, but not across English boundaries, whereas English speakers show the reverse pattern (8, 9). Similar results have been obtained comparing English with Tarahumara (21). These findings have been taken by some to suggest that linguistic color categories may be largely arbitrary constructs of specific languages, constrained only loosely by very general principles, such as the principle that no single color category may cover unconnected regions of color space (8).

Given this, are there genuine cross-linguistic universals in color naming or not? To resolve this issue, we conducted statistical tests on a comprehensive body of color naming data.

The central empirical focus of our study was the color naming data of the Word Color Survey (WCS). The WCS was undertaken in response to the above-mentioned shortcomings of the BK data (1): it has collected color naming data in situ from 110 unwritten languages spoken in small-scale, nonindustrialized societies, from an average of 24 native speakers per language (mode: 25 speakers), insofar as possible monolinguals. Speakers were asked to name each of 330 color chips produced by the Munsell Color Company (New Windsor, NY), representing 40 gradations of hue at eight levels of value (lightness) and maximal available chroma (saturation), plus 10 neutral (black-gray-white) chips at 10 levels of value. Chips were presented in a fixed random order for naming. The array of all color chips is shown in Fig. 1. (The actual stimulus colors may not be faithfully represented there.) In addition, each speaker was asked to indicate the best example(s) of each of his or her basic color terms. The original BK study used a color array that was nearly identical to this, except that it lacked the lightest neutral chip. The languages investigated in the WCS and BK are listed in Tables 1 and 2.

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Fig. 1. Color array from the WCS. For the Munsell notations of the colors in this stimulus array see ref. 1.

We approach the issue of whether there are universal tendencies in color naming by asking two questions:
(i) Do color terms from different languages in the WCS cluster together in color space to a degree greater than chance?
(ii) Do WCS color terms, all from unwritten languages of nonindustrialized societies, fall near color terms of written languages from industrialized societies, as represented by the BK sample?
To test for clustering, we represented color terms as points in color space, and then tested for clustering of those points. Because the idea of clustering depends essentially on the concept of distance, we required a color space in which psychologically meaningful distances can be calculated. Consequently we transformed our 330 color stimuli from Munsell space, which lacks such a distance metric, to CIEL*a*b* space, which has one (22). CIEL*a*b* is a 3D color space, in which the $L^{*}$ dimension represents lightness, and the two remaining dimensions, $a^{*}$ and $b^{*}$, define a plane orthogonal to $L^{*}$, such that angle in that plane represents hue, and radius represents saturation. We represented each color term $T$ in each language $L$ by its centroid in this space. This was computed by first finding, for each speaker of $L$ who used term $T$, the centroid in CIEL*a*b* space of the chips named $T$ by that speaker. These speaker centroids were then averaged together to yield an overall term centroid for $T$. Finally, that term centroid was coerced back to the chip most similar to it in the stimulus array, so that our overall representation of the term resided within the set of points out of which it was constructed. This coercion was done by first selecting that row of the array with L* value nearest that of the centroid [ $L^{*}$ values are constant within each value (i.e., lightness) row of the stimulus array]. We then examined two chips, the chromatic (colored) chip in that row with hue angle in the $\mathrm{a}^{*} \mathrm{~b}^{*}$ plane closest to the centroid, and the neutral chip in that row, and selected the one that had hue radius in the $\mathrm{a}^{*} \mathrm{~b}^{*}$ plane closest to the average radius of the chips represented by the centroid. This selected chip was our point representation of the color term.
Given such point representations of all color terms, we tested whether these points were more clustered across languages than would be expected by chance, through a Monte Carlo test. This required first a measure of color-term clustering and then an indication of how clustered one might expect color terms to be by chance.
We defined a measure $D$ of the dispersion of the terms in the WCS data set: for each color term $c$ in each language $l$, we found the closest term $c^{*}$ in each other language $l^{*}$, and added up those
distances. Distance between terms was defined as CIEL*a*b* distance between their point representations.

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\begin{equation*}
D=\sum_{l, l^{*} \in W C S} \sum_{c \in l} \min _{c^{*} \in l^{*}} \operatorname{distance}\left(c, c^{*}\right) . \tag{1}
\end{equation*}
$$

Because $D$ is a measure of dispersion, low values of $D$ indicate clustering.
To determine how much dispersion one would expect by chance, we created a set of randomized hypothetical datasets through computer simulation and measured dispersion in them. Our randomization method was informed by the observation that general principles of categorization operating within a given language can be expected to produce a certain amount of dispersion in any natural system of categories. We wanted to be certain that our randomized data sets obeyed such within-language principles of categorization. To this end, we started with the actual WCS data set and rotated each language's term centroids in the $\mathrm{a}^{*} \mathrm{~b}^{*}$ (hue) plane by a random amount, the same random amount for all terms within a language, but different random amounts for different languages, as shown in Fig. 2. These rotated centroids were then coerced back to the WCS color array in the manner described above. This process produced one hypothetical data set, which preserved within-language structure while randomizing crosslanguage structure, appropriately, as the latter is the central focus of this study.

The process creating a randomized data set was repeated independently 1,000 times, and the $D$ dispersion measure was calculated for each hypothetical data set. Fig. $3 a$ shows the distribution of $D$ in the 1,000 hypothetical data sets compared with $D$ in the actual WCS data. The actual WCS $D$ value is well below the lower boundary of the hypothetical distribution.


Fig. 2. Creating a randomized data set.

Table 1. Languages in the WCS

| Index | Language | No. of <br> subjects |
| :--- | :--- | :--- |


| 1 | Abidji | Ivory Coast | 25 |
| :---: | :---: | :---: | :---: |
| 2 | Agarabi | Papua New Guinea | 24 |
| 3 | Agta | Philippines | 25 |
| 4 | Aguacatec | Guatemala | 25 |
| 5 | Amarakaeri | Peru | 06 |
| 6 | Ampeeli | Papua New Guinea | 27 |
| 7 | Amuzgo | Mexico | 25 |
| 8 | Angaatiha | Papua New Guinea | 25 |
| 9 | Apinaye | Brazil | 30 |
| 10 | Arabela | Peru | 25 |
| 11 | Bahinemo | Papua New Guinea | 25 |
| 12 | Bauzi | Indonesia | 25 |
| 13 | Berik | Indonesia (Irian Jaya) | 25 |
| 14 | Bete | Ivory Coast | 25 |
| 15 | Bhili | India | 25 |
| 16 | Buglere | Panama | 25 |
| 17 | Cakchiquel | Guatemala | 30 |
| 18 | Campa | Peru | 25 |
| 19 | Camsa | Columbia | 25 |
| 20 | Candoshi | Peru | 11 |
| 21 | Cavineña | Bolivia | 25 |
| 22 | Cayapa | Ecuador | 24 |
| 23 | Chácobo | Bolivia | 25 |
| 24 | Chavacano (Zamboangueño) | Philippines | 25 |
| 25 | Chayahuita | Peru | 25 |
| 26 | Chinantec | Mexico | 25 |
| 27 | Chiquitano | Bolivia | 25 |
| 28 | Chumburu | Ghana | 25 |
| 29 | Cofán | Ecuador | 20 |
| 30 | Colorado | Ecuador | 25 |
| 31 | Cree | Canada | 25 |
| 32 | Culina | Peru, Brazil | 25 |
| 33 | Didinga | Sudan | 25 |
| 34 | Djuka | Surinam | 25 |
| 35 | Dyimini | Ivory Coast | 25 |
| 36 | Ejagam | Nigeria, Cameroon | 25 |
| 37 | Ese Ejja | Bolivia | 25 |
| 38 | Garifuna (Black Carib) | Guatemala | 28 |
| 39 | Guahibo | Colombia | 25 |
| 40 | Guambiano | Columbia | 27 |
| 41 | Guarijío | Mexico | 25 |
| 42 | Guaymí (Ngäbere) | Panama | 25 |
| 43 | Gunu | Cameroon | 25 |
| 44 | Halbi | India | 25 |
| 45 | Huastec | Mexico | 25 |
| 46 | Huave | Mexico | 25 |
| 47 | Iduna | Papua New Guinea | 25 |
| 48 | Ifugao (Keley-i) | Philippines | 25 |
| 49 | Iwam (Sepik) | Papua New Guinea | 25 |
| 50 | Jicaque | Honduras | 10 |
| 51 | Kalam | Papua New Guinea | 25 |
| 52 | Kamano-Kafe | Papua New Guinea | 25 |
| 53 | Karajá | Brazil | 19 |
| 54 | Kemtuik | Indonesia (Irian Jaya) | 25 |
| 55 | Kokni (Kokoni) | India | 25 |
| 56 | Konkomba | Ghana | 25 |
| 57 | Kriol | Australia | 25 |
| 58 | Kuku-Yalanji | Australia | 20 |
| 59 | Kuna | Panama | 25 |
| 60 | Kwerba | Indonesia (Irian Jaya) | 25 |
| 61 | Lele | Chad | 15 |
| 62 | Mampruli | Ghana | 24 |
| 63 | Maring | Papua New Guinea | 25 |
| 64 | Martu Wangka | Australia | 25 |

Table 1. (continued)

| Index | Language | Where spoken | No. of subjects |
| :---: | :---: | :---: | :---: |
| 65 | Mawchi | India | 25 |
| 66 | Mayoruna | Peru | 25 |
| 67 | Mazahua | Mexico | 25 |
| 68 | Mazatec | Mexico | 25 |
| 69 | Menye | Papua New Guinea | 25 |
| 70 | Micmac | Canada | 25 |
| 71 | Mikasuki | United States | 25 |
| 72 | Mixtec | Mexico | 25 |
| 73 | Mundu | Sudan | 18 |
| 74 | Múra Pirahá | Brazil | 25 |
| 75 | Murle | Sudan | 25 |
| 76 | Murrinh-Patha | Australia | 25 |
| 77 | Nafaanra | Ghana | 29 |
| 78 | Nahuatl | Mexico | 06 |
| 79 | Ocaina | Peru | 25 |
| 80 | Papago (O'odham) | United States, Mexico | 25 |
| 81 | Patep | Papua New Guinea | 24 |
| 82 | Paya | Honduras | 20 |
| 83 | Podopa | Papua New Guinea | 14 |
| 84 | Saramaccan | Surinam | 25 |
| 85 | Seri | Mexico | 25 |
| 86 | Shipibo | Peru | 25 |
| 87 | Sirionó | Bolivia | 25 |
| 88 | Slave | Canada | 24 |
| 89 | Sursurunga | Papua New Guinea | 26 |
| 90 | Tabla | Indonesia (Irian Jaya) | 25 |
| 91 | Tacana | Bolivia | 08 |
| 92 | Tarahumara (Central dialect) | Mexico | 09 |
| 93 | Tarahumara (Western dialect) | Mexico | 06 |
| 94 | Tboli | Philippines | 25 |
| 95 | Teribe | Panama | 26 |
| 96 | Ticuna | Peru | 25 |
| 97 | Tifal | Papua New Guinea | 25 |
| 98 | Tlapanec | Mexico | 25 |
| 99 | Tucano | Colombia | 25 |
| 100 | Vagla | Ghana | 25 |
| 101 | Vasavi | India | 25 |
| 102 | Waorani (Auca) | Ecuador | 25 |
| 103 | Walpiri | Australia | 25 |
| 104 | Wobé | Ivory Coast | 25 |
| 105 | Yacouba | Ivory Coast | 27 |
| 106 | Yakan | Philippines | 25 |
| 107 | Yaminahua | Peru | 25 |
| 108 | Yucuna | Colombia | 25 |
| 109 | Yupik | United States | 25 |
| 110 | Zapotec | Mexico | 25 |

Thus, the WCS data show significantly less dispersion, that is, more clustering, than expected by chance, $P<0.001$.

Our second question is whether the WCS color naming data (from unwritten languages of nonindustrialized societies) bear greater than chance similarity to the BK color naming data (1) (primarily from written languages of industrialized societies.) To test this, we used another Monte Carlo test in which 1,000 hypothetical data sets were created from the WCS data by using the same random hue angle rotation technique as before (see Fig. 2). However, this time, rather than measuring dispersion within a single data set, we measured distances across data sets, yielding an overall measure $S$ of the separation between the WCS data (either real or hypothetical) and the BK data. Specifically, for each color term $c$ in each language $l$ in the WCS data set

Table 2. Languages studied by BK (1)

| Index | Language | Where spoken |
| :---: | :--- | :--- |
| 1 | Arabic (Lebanese colloquial) | Lebanon |
| 2 | Bahasa Indonesia | Indonesia |
| 3 | Bulgarian | Bulgaria |
| 4 | Cantonese | China |
| 5 | Catalan | Spain |
| 6 | (American) English | United States |
| 7 | Hebrew | Israel |
| 8 | Hungarian | Hungary |
| 9 | Ibibio | Nigeria |
| 10 | Japanese | Japan |
| 11 | Korean | Korea |
| 12 | Mandarin | China |
| 13 | (Mexican) Spanish | Mexico |
| 14 | Pomo | United States |
| 15 | Swahili | Tanzania |
| 16 | Tagalog | Philippines |
| 17 | Thai | Thailand |
| 18 | Tzeltal | Mexico |
| 19 | Urdu | Pakistan |
| 20 | Vietnamese | Vietnam |

Data reported from one subject per language.
(either real or hypothetical), we found the closest term $c^{*}$ in each language $l^{*}$ in the BK data set and added up those distances to obtain the sum $S$.


Fig. 3. Monte Carlo tests. (a) Clustering within the WCS. The distribution of dispersion values shown in gray was obtained from 1,000 randomized data sets. The arrow indicates the dispersion value obtained from the WCS data. (b) Comparing the WCS with BK. The distribution of separation values shown in gray was obtained from 1,000 randomized data sets. The arrow indicates the separation value obtained by comparing the WCS data with BK data (1).


Fig. 4. Distribution of color terms from nonindustrialized languages. (a) The floor plane corresponds to the chromatic (non-neutral) portion of the color stimulus array. The height of the surface at each point in the plane denotes the number of speaker centroids in the WCS data set that fall at that position in color space. (b) The distribution of $a$ is viewed from above by a contour plot. The outermost contour represents a height of 100 centroids, and each subsequent contour represents an increment in height of 100 centroids. English color terms fall near the peaks of the WCS distribution.

$$
\begin{equation*}
S=\sum_{\substack{l \in W C S \\ l^{*} \in B K}} \sum_{c \in l} \min _{c^{*} \in l^{*}} \operatorname{distance}\left(c, c^{*}\right) . \tag{2}
\end{equation*}
$$

Comparing the value for $S$ observed in the WCS data set to the distribution of values obtained in 1,000 hypothetical randomizations of that data set, Fig. $3 b$ shows that the value of $S$ for the actual WCS data is well below the lower limit of the hypothetical distribution. Thus, the WCS data are significantly closer to the BK data than expected by chance, $P<0.001$. We then removed from the BK data set the only unwritten languages of nonindustrialized societies in that data set (Ibibio, Pomo, and Tzeltal), reran this test, and obtained the same qualitative result, $P<$ 0.001 . This finding indicates a similarity in color naming across languages of industrialized and nonindustrialized societies.

These universal tendencies are shown in Fig. 4a. The floor plane of this display corresponds to the 320 chromatic (nonneutral) colors in the stimulus array of Fig. 1, and the height of the surface at each position represents the number of WCS speaker centroids falling at that point in color space [MacLaury (23) displays a comparable histogram, restricted to the hue dimension]. This distribution of color terms from nonindustrialized languages is shown from above in the contour plot of Fig.
$4 b$, compared with naming centroids for English color terms (24). The English terms blue, green, purple, and brown fall at or very near peaks of the WCS distribution, whereas yellow, orange, pink, and red fall in the neighborhood of WCS peaks. There is also a WCS peak between English green and blue. This peak may reflect the fact that the majority of the languages in the WCS span green and blue with a single term, whose naming centroid would be expected to fall between those for green and blue (17). Similarly, the apparent deviation of the English red and yellow naming centroids from the closest WCS centroid peaks is plausibly attributable to the fact that almost all WCS languages lack terms for pink and orange; instead, they include pink with red in a single broader term and orange with yellow. A term spanning yellow and orange would be expected to have a naming centroid somewhere between yellow and orange and a term spanning red and pink would be expected to have a naming centroid somewhere between red and pink, as may be observed with regard to the relevant centroid peaks in Fig. $4 b$.
Do more WCS centroids fall at the 11 positions named by these English color terms, together with black, gray, and white, than would be expected by chance? We defined the "location" of an English color term to be that cell of the stimulus array on which its centroid fell and found that the mean number of WCS centroids per cell falling on these 11 English-named locations ( $M=153.3$ ) was more than the corresponding number falling on the remaining 319 cells of the stimulus array $(M=61.4), t(328)=$
$3.7, P<0.0005$. Thus, although languages vary considerably in the number of major color terms they contain (1) and can also vary significantly in the location of the boundaries between terms $(8,9)$, certain privileged points in color space appear to anchor the color naming systems of the world's languages, viewed as a statistical aggregate, and these universally privileged points are reflected in the basic color terms of English.

The application of statistical tests to the color naming data of the WCS has established three points: (i) there are clear cross-linguistic statistical tendencies for named color categories to cluster at certain privileged points in perceptual color space; (ii) these privileged points are similar for the unwritten languages of nonindustrialized communities and the written languages of industrialized societies; and (iii) these privileged points tend to lie near, although not always at, those colors named red, yellow, green, blue, purple, brown, orange, pink, black, white, and gray in English.

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[^0]:    Abbreviations: BK, Berlin and Kay; WCS, Word Color Survey.
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