Cross-cultural Preferences for Visual Aesthetics in Food Magazine Covers

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Abstract

Cultural differences in visual preference have been demonstrated in a variety of applications including advertising, social media, and web design. Our paper extends this investigation to food magazine covers, examining how magazines from varying geographic regions differ in the way they choose to depict images of food and arrange their text and graphics. We collect a dataset of 1,051 images of magazine covers from a geographically diverse set of 14 magazines. We then algorithmically extract image features that capture well-specified visual properties such as color, luminance, and complexity. These features, which capture elements of artistic style, are then used to quantify stylistic similarity between magazines. Finally, we validate previously discovered cultural preferences for visual properties against our regionally-based dataset. We find that the visual style of food magazine covers can be described by two properties, high/low colorfulness and high/low complexity, resulting in four distinct style types. Additionally, we find regions consistently differ in these preferences: e.g., colorfulness in France is low but in Malaysia is high, and visual complexity in Mexico is high. Lastly, we find that Western countries focus their covers more on salient foreground features, whereas Eastern countries present a more balanced background.

Index terms: cross-cultural analysis, computational aesthetics, magazines

1 Introduction

Visual appeal is a key aspect in many areas, including news consumption, advertisement, and user experience design. It has been shown that a product's visual aesthetic can significantly influence one's intention to purchase (Bloch 1995). In a user experience setting, studies have found that the initial impression of a website's graphical interface will greatly determine whether a user clicks off immediately or not (Kim and Fesenmaier 2008).

Therefore, it is imperative that companies, media corporations, and those designing products in general, are able to curate things in a way that is visually pleasing. However, such a task is complicated by the fact that although some visual preferences appear to be universal—for instance, the dislike of dark-yellow (olive) colors—others have shown to be culturally dependent (Ou et al. 2004; Yokosawa et al. 2015; Palmer and Schloss 2010).

Many attempts to study these differences employ survey-based methods by sampling participants from varying demographic groups, although these experiments are often limited in scale. More recent alternative approaches scrape data from content-sharing platforms such as YouTube and Instagram, and use engagement metrics (e.g. views, likes, and comments) as implicit measures of visual preference.

To study the cultural preferences for the visual depiction of food, we adopt a similar data-scraping methodology. We crawl online archives to automatically collect food magazine cover images from various geographic regions. We choose to study food magazines specifically, since food has been shown to be a strong indicator of culture, and thus images of food are likely to reflect cultural preferences in visual aesthetics (Cervellon and Dubé 2005).

From each of the images, 19 pre-defined statistical image properties ("SIPs") are extracted. We choose SIPs that have been extensively studied in the literature, which measure properties such as color, luminance, and complexity. We then use clustering and visualization techniques based on these extracted features, in order to identify culturally-dependent patterns in their depictions of food.

Our contributions in this paper are:

1. A dataset of 1,051 magazine cover images from 14 food magazines based in the Asia, Europe, and North America.
2. An analysis of the stylistic similarities and differences in visual properties across magazines and geographic regions.
3. The validation of several—but not all—published empirically-derived cultural preferences for visual aesthetics in the domain of food imagery.

2 Related Work

2.1 Cultural Differences (Survey-based)

Survey-based methods have been used to study cultural effect of visuals on aesthetic rating in a variety of contexts, including art, advertisements, and signage (Masuda and Nisbett 2001; Chiu et al. 2019; Iftikhar, Asghar, and Luximon

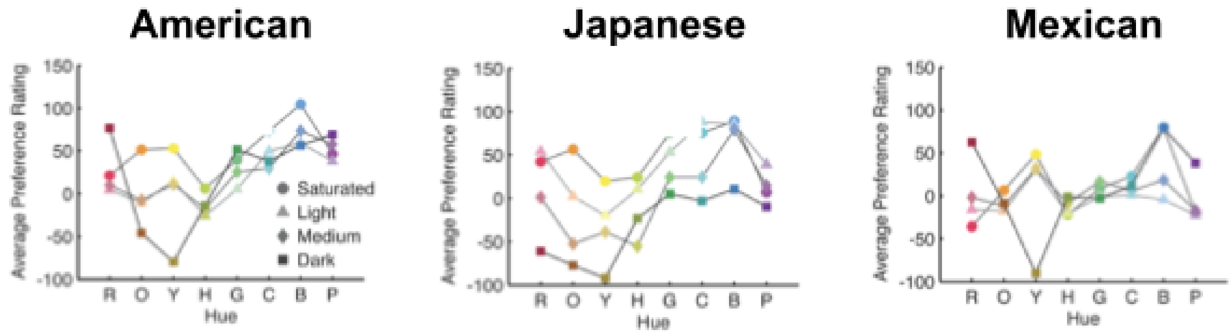


Figure 1: Color preferences for different hues and lightness by American, Japanese, and Mexican individuals (Palmer, Schloss, and Sammartino 2013). Dark yellow is universally disliked; saturated blue is universally preferred.

2021). Both universal and culture-specific behavioral patterns regarding aesthetic preference have been discovered as a result.

For example, people tend to prefer curved-contours as opposed to sharp angles (Gómez-Puerto et al. 2018), and prefer only a medium textual complexity (Street et al. 2016). A liking for bluish colors and the dislike for dark-yellow (olive) colors also appears to be universal (Palmer, Schloss, and Sammartino 2013); see Figure 1. East Asian countries (Japan, Korea, and Taiwan) show a stronger preference of whitish colors relative to other countries (Saito 1996). Similarly, Japanese people seem to favor light colors (pastels) over dark colors more, when compared to Americans (Yokosawa et al. 2015). Chinese individuals find red colors more appealing than British people (Ling and Hurlbert 2007). Additionally, those from different cultural backgrounds may have different associations between visual features (e.g. colors, shapes) and specific *flavors* (Wan et al. 2014).

These differences are frequently attributed to cultural values. For instance, white often symbolizes cleanliness and purity, which are highly valued in East Asian cultures, and this may explain their preference for whiter or lighter colors.

Colors may also have culture-specific meanings. In the case of Chinese culture, red is considered to be an auspicious color. Palmer and Schloss (2010) suggested the ecological valence theory of human color preference in which cultural preferences for color are attributed to "people's average affective responses to color-associated objects". The authors propose that a culture group's affective rating of objects, weighted by how similar they associated that object with a color, may partially explain the variance in color preference across cultures.

2.2 Cultural Differences (Online Data-based)

With the increasing amount of data being made available online, the analysis of metrics such as the views, likes, and comments that are associated with imagery have allowed researchers to study culture-specific visual preferences at scale. Using 2.4 million ratings of the visuals of websites from nearly 40,000 participants, Reinecke and Gajos (2014)

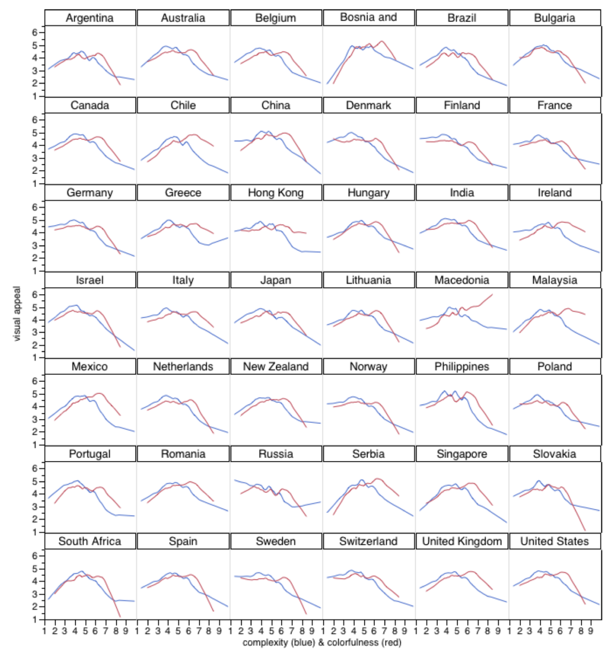


Figure 2: Color (red) and complexity (blue) preferences across different countries (Reinecke and Gajos 2014). Extreme preferences for complexity: Russia low, Mexico high; for color: Germany low, Macedonia high.

found that the level of visual complexity and colorfulness at which visual appeal peaks varies significantly across countries; see Figure 2. Complexity and colorfulness scores, ranging from 1 to 10 and 1 to 9 respectively, are computed based on the models presented in Reinecke et al. (2013) and displayed against participant ratings on a 1 to 9 scale. For example, Russians favored less complex websites and Macedonians displayed a strong preference for designs with lots of colorful elements. Likewise, in an analysis of Facebook profile pictures, Huang and Park (2013) found that East Asian users were more likely to de-emphasize their faces,

Group	Feature	Description
1: Color	*a: Hue*	mean of hue channel in HSV space
	b: Saturation	mean of saturation channel in HSV space
	c: Lab(a)	mean of a* channel in L*a*b* space
	d: Lab(b)	mean of b* channel in L*a*b* space
	e: Color Entropy	Shannon entropy of hue channel in HSV space
2: Lightness	*a: Contrast*	standard deviation of L* channel in L*a*b* space
	b: Luminance	mean of L* channel in L*a*b* space
	c: Luminance Entropy	Shannon entropy of L* channel in L*a*b* space
3: Complexity	*a: Self-Similarity*	similarity of HOG features
	b: Complexity	mean gradient strength
	c: Anisotropy	standard deviation of HOG features
	d: Fractal Dimension	density of edges
	e: Birkoff Measure	ratio of order and complexity
4: Symmetry	*a: Symmetry-LR*	left-right symmetry based on first layer activations on pre-trained AlexNet
	b: Symmetry-UD	up-down symmetry based on first layer activations on pre-trained AlexNet
5: CNN	*a: Sparseness*	median variance of each max-pooled response map from the first layer of pre-trained AlexNet
	b: Variability	variance over all max-pooled response maps from the first layer of pre-trained AlexNet
6: Fourier	*a: Fourier Slope*	slope of line of best fit on the log-log plot of the Fourier power spectrum
7: Other	*a: Shot Scale*	close, medium, or long shot, from fine-tuned CNN

Table 1: Seven groups of 19 Statistical Image Properties (SIPs) extractable from cover images. The first six groups are scalar; the last group is discrete (Bartho, Thoemmes, and Redies 2023; Braun et al. 2013; Savardi et al. 2018).

whereas American users tended to prioritize their faces over backgrounds.

Cultural differences in the visual content that users are interested in have also been found. The above study concluded that East Asians expressed less emotion in their profile pictures compared to Americans. Another study of YouTube thumbnails showed that the objects that appear in trending video thumbnails differ across countries. For instance, Indian users displayed a great interest in train videos, whereas U.S. users preferred car videos (Zhang, Aktas, and Luo 2021). Advertisements from Japan, Korea, and China tended to use symbolic visuals, celebrity ambassadors, and indirect portrayals of products; whereas U.S., U.K., and German advertisements demonstrated the opposite behavior (An 2007).

2.3 Statistical Image Properties

Statistical image properties are algorithmically-defined numerical image features that capture visual aspects such as color, lightness, and texture (Bartho, Thoemmes, and Redies 2023). As opposed to the features dynamically learned in deep neural networks, these SIPs are easily interpretable.

More importantly, SIPs have been shown to be useful in a variety of downstream tasks. For instance, the SIPs from "favorited" images can used to infer a Flickr users' personality traits (Segalin et al. 2016). In assessing image aesthetics, SIPs are reliable predictors of aesthetic ratings for abstract paintings (Redies and Bartho 2023) and for website and app interfaces (Miniukovich and De Angeli 2015). Further, images taken from different domains, such as print advertisements, visual artworks, natural scenes, and others, contain specific patterns in their SIPs that can distinguish them from one another (Braun et al. 2013).

3 Methods

3.1 Data Collection

To source our magazine covers, we use the website www.magzter.com, an online repository of magazines. Food-related magaziness from a variety of countries are manually considered, using the website's built-in filters for topic and language. For each considered magazine, we obtained the URL to the magazine's Magzter page, which displays cover images of all of the archived editions of that magazine.

The final choice of magazines followed the dual criteria of having a geographically diverse set of magazines, and a sufficient number of available cover images (more than 20 editions per magazine).

Then, a program automatically parses each page's HTML structure, locates those elements that contain magazine cover images, and downloads the images locally. The final dataset consists of 1,051 images from 14 magaziness based across 10 different countries; see Table 2.

3.2 Image Feature Extraction

A total of 19 SIPs across 7 groups of features are extracted per image. They are displayed and described in Table 1. Together, these features capture aspects such as color, lightness, and complexity (basically edges), as well as other fea-

Region	Country	Magazine
Asia	China (CN)	*Oriental Cuisine*
	China (CN)	*Tasting Kitchen*
	Japan (JP)	*Food Commerce*
	Korea (KR)	*CookAnd*
	Malaysia (MY)	*Rasa*
	Singapore (SG)	*Epicure*
Europe	France (FR)	*ELLE à Table*
	France (FR)	*Gourmand*
	Portugal (PT)	*TeleCulinária*
	Sweden (SE)	*Gourmet*
North America	Mexico (MX)	*Cocina Fácil*
	United States (US)	*Bon Appétit*
	United States (US)	*Food*
	United States (US)	*Yummy*

Table 2: List of all 14 magazines with geographic origin.

tures used in understanding both human and machine perception.

Choice of features. As noted in the table, each image feature has been extensively studied in the literature. These have been shown to align with qualitative observation, accurately reflecting their intended visual properties (Limpijankit and Kender 2024). Finally, each are sufficiently different from one another and efficiently computable, making them suitable for our analysis.

3.3 Data Analysis

The analysis proceeds in three steps: first, dimensionality reduction leading to visualization; then, clusterization; and finally, validation of results with respect to some known empirical observations of cultures' visual styles.

Visualizing the stylistic space of magazine covers. The feature extraction process converts each image to a 19-dimensional representation, where each dimension corresponds to some visual property. Since these raw features vary in scale, they are first normalized to their z-scores. Dimensionality reduction is then performed via principal component analysis (PCA), in order to reduce this feature space into its two most significant dimensions; this two-dimensional PCA reduction resulted in 39% preserved variance. Plotting these two-dimensional vectors then visualizes most of differences between the covers' visual styles.

We then examine qualitatively the visualization of this space for any emergent groups of styles, and lastly cluster analytically the reduced data to find groups of magazines with similar styles.

Clustering magazines based on style. To compare magazine styles with one another, first, we obtain a single 19-dimensional embedding to represent each magazine. This is calculated by averaging across all editions for a given magazine. Then, we apply hierarchical clustering on these representations and visualize the result in a circular dendrogram, highlighting which magazines are most similar to one another. Additionally, we also display the origin region of each magazine to assess any potential geographic patterns.

Cross-validating previously discovered cultural patterns. Finally, we test culture-specific patterns presented in the existing literature against our dataset. For example, consider the claim *Japanese like light colors (pastels) more and dark colors less than Americans.*. First, we identify the relevant feature(s) from our dataset; in this case, it is luminance, as it describes the lightness of the color. Then, we collect the luminance values for the magazine cover images based in the countries/cultures mentioned (i.e. from Japanese and U.S. magazines). Finally, we perform a two-sample t-test to find whether there is a statistically significant difference in luminance between the two groups, and in what direction.

4 Results

4.1 Stylistic Space of Magazine Covers

The visualization of magazine covers onto the 2D stylistic space is given in Figure 3. Magazine covers can largely be described by two main eigen axes, color variety (horizontal) and average luminance (vertical). However, their overall perceptive differences are best seen along the principal diagonal, from the origin in the lower left, to the extreme corner in the upper right.

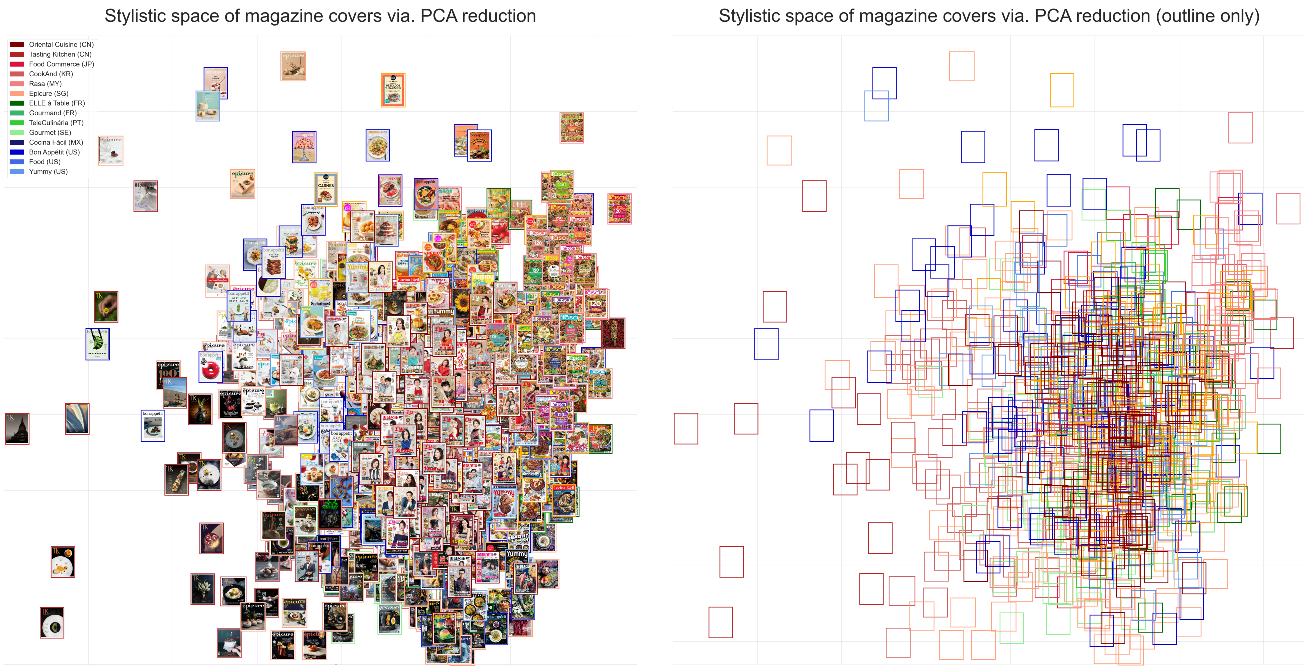
PCA-defined color. Magazine covers in the upper right quadrant make strong use of vibrant colors. Western magazine covers, such as those from *Cocina Fácil* (Mexico), *TeleCulinária* (Portugal), and *Bon Appétit* (U.S.) tend to fall into this category, using lots of warm hues (reds, yellows, and greens). The geographic outlier here is *Rasa* (Malaysia), whose covers also adhere to this style.

In contrast, in the lower left quadrant, magazines use a more limited palette and darker, often black, backgrounds. Magazines that occupy this section are often Asian, including *Epicure* (Singapore), *Tasting Kitchen* (China), and *CookAnd* (Korea). These feature images of dishes prepared by acclaimed fine-dining venues, with the black background further accentuating the up-scale feel.

Along the middle of this diagonal are covers from a mix of geographies (U.S., France, Sweden, Japan, China), which are neither particularly vibrant nor bright, often using white or single-color pastels as the background.

PCA-defined complexity. The opposing diagonal, from upper left to lower right, appears to correspond to increasing visual complexity, namely in texture and edge properties. Complex images (lower right) contain sharp detail, lots of overlaid text, complicated texture patterns, and occasionally many sub-images. Simpler images (upper left) tend to contain few objects, and use a more homogeneous color palette that produces softer edges, and use a more minimalist style with little text.

Some examples of high complexity (lower right) are notable. *Rasa* (Malaysia) heavily uses sub-images, and *Yummy* (U.S.) and *Cocina Fácil* (Mexico) use a lot of text. *Oriental Cuisine*, a Chinese magazine, often has high complexity since their covers showcase celebrities, which contain complex elements in their clothing, along with sub-images of food added. This is consistent with previous findings that



(a) (b)

Figure 3: PCA-reduced visualization of magazine styles. Horizontal axis is the first eigen-direction, which approximately measures amount of color variety. Vertical axis is the second eigen-direction, which approximately measures average luminance. (a) Cover images with borders. The legend indicates that the color of the image border signifies the magazine's region: reds are Asia; greens are Europe; blues are North America. (b) Border colors in isolation.

"high context" nations, such as China, prefer indirect portrayals (An 2007). Finally, the Korean upscale magazine, *Tasting Kitchen* (upper left), is something of an exception. It uses a minimalist style, photographing a single dish or sometimes even a single abstract object.

Cluster-based styles. A second approach to analysis is based on clustering theory, and gives similar results.

After manually experimenting with different similarity measures and numbers of clusters, the optimal result, according to some measures of cluster purity, produced three separated groups. Examples of Group 1 of low color and low complexity, Group 2 of medium color or medium complexity, and Group 3 of high color and high complexity are shown in Figure 5.

Group 1 ("plain and simple") consisted of less colorful, minimalist, and upscale magazine covers, most of which were from *Epicure* (Singapore), *Tasting Kitchen* (China), and *CookAnd* (Korea). Group 2 ("mixed") contained a wide range of covers that were neither minimal nor notably complex. And finally, Group 3 ("colorful and complicated") was composed mainly from *Rasa* (Malaysia) and *Cocina Fácil* (Mexico), and had vibrant, visually complex covers.

4.2 Stylistic Similarities Across Magazine Covers

A circular dendrogram visualizing the results of the hierarchical clustering is shown in Figure 4.

In terms of style, *Rasa* is especially unique, further suggesting the distinctly strong use of colorfulness and complexity described previously. *Tasting Kitchen* and *CookAnd* also exhibit a unique style, one that is common to each other, but not shared with any other magazine. This may be related to their minimalist cover design, though it is notable that *Epicure* is not included in this cluster. This is possibly because *Epicure* uses a mix of light/dark covers, affecting their average embedding representation, whereas *Tasting Kitchen* and *CookAnd* adhere more strongly to dark covers only. Finally, the remaining 11 magazines are distributed roughly evenly into two separate clusters, very roughly, Asian versus European (and not U.S.)

Regarding the geography of the magazines, there are two apparent patterns that arise in our dataset.

First, magazines with a unique, distinct style (concentrated in the top-right of the dendrogram) tend to be Asian. This may suggest that Asian magazines are more likely to deviate from a typical cover style and/or target specific niches within food. It may also indicate that the dataset is imbalanced, a potential limitation.

Second, of the two large clusters, one appears to be dominated by European magazines whereas the other contains mostly Asian magaziness. The U.S. magazines are split between both. This could indicate that European and Asian magaziness employ distinct visual styles, while U.S. magazines are more varied and can exhibit both.

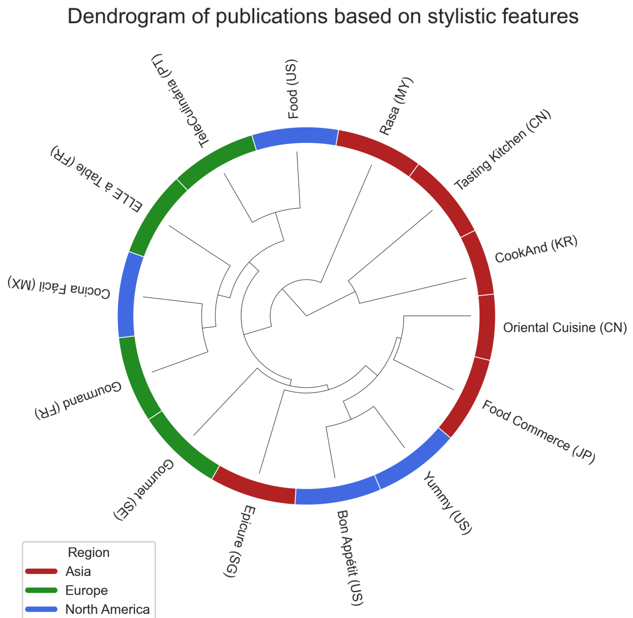


Figure 4: Magazines clustered based on visual similarity. Each section of the circumference is a magazine.

Figure 5: Example cover images for three different styles. Group 1 ("plain and simple") is more characteristic of Asian cultures. Group 2 ("mixed") is generic in most features. Group 3 ("colorful and complicated") is more characteristic of Western cultures.

4.3 Culture-specific Visual Preferences

Our features in Table 1 can be used to evaluate a number of empirically observed cultural preferences disclosed previously in the literature.

Colorfulness. Reinecke and Gajos (2014) found that *visual appeal peaks at a lower colorfulness for France compared to most other countries*. We measured colorfulness by using saturation mean, Feature 1b, which quantifies the vibrancy of the colors, and color entropy, Feature 1e, which quantifies the prevalence of many different colors. We did not find evidence for the claim, as color entropy and saturation for *Gourmand (France)* were, on average, larger compared to magazines from all other sources; this relationship was statistically significant ($p < 0.05$).

But the authors also found that *Malaysia has one of the highest preferences for colorful websites*. Our dataset did support this claim, finding that covers from *Rasa*, the only Malaysian magazine in our dataset, having significantly larger color feature (Feature 1b, 1e) values.

Complexity. Previously, it had been shown that *Mexico preferred websites with substantially higher complexity* Reinecke and Gajos (2014). To measure 'complexity', we used a broad range of metrics, including our color entropy, Feature 1e; luminance entropy, Feature 2b; complexity, Feature 3b; fractal dimension, Feature 3d; and variability, Feature 5b. Covers from the Mexican magazine *Cocina Facil* demonstrated larger values for all of these features, and with these being statistically significant in all cases except for variability. Thus, our features support this claim.

Lightness. Palmer, Schloss, and Sammartino (2013) disclosed that *Japanese like light colors (pastels) more and dark colors less than Americans*. We used our luminance feature, Feature 2b, as a metric for lightness, with larger values corresponding to brighter images and vice versa. Comparing Japanese and U.S. magazine covers, our findings supported this claim, with luminance being significantly greater for Japanese covers than U.S.

Similarly, Saito (1996) noted that a *stronger preference for white and whitish colors in Japan and Korea than other countries*. However, our findings do not support this, as luminance values for Korean magazines were low, likely due to those magazines specifically making use of dark backgrounds.

Other. Finally, we also noted that according to An (2007), *Asian countries focus more on the entire image whereas Western countries focus more on salient features*. To approximate this, we used Fourier slope, Feature 6a, which measures the presence of fine, detailed, high frequency image features. We assume that a predominant focus on salient features would lead to greater focus on the foreground object(s), with more blur of the background; whereas the opposite focus would include more background detail overall, resulting in a larger (less negative) Fourier slope. We did find this to be the case.

5 Discussion

Our paper presents a culturally-specific analysis of the visual aspects of food magazine covers. We find that ∼39% of the variance in styles can be attributed to the use of color and visual complexity. Three groups of styles appear from our data. The first style is mainly comprised of images from Asian magazines, which were minimalist in style, used little text, had darker backgrounds, and contained fewer objects. Contrastingly, high color with high complexity magazines were more crowded visually, had greater color usage, and tended to come from Western magazines, with the exception of one Malaysian magazine. The final category seemed to contain a wide mix of covers. Although the analysis is conducted on a limited dataset, it also suggests that visual properties are partially but not fully generalizable to geographic regions. Finally, we provide some analytic support for some manually observed findings previously discussed in the literature regarding culturally specific preferences.

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