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Feast for the Eyes: Effects of Food Perceptions and Computer Vision Features on Food Photo Popularity

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The widely circulated food photos online have become an important part of our visual culture. Combining human ratings of food characteristics and computational analysis of visual aesthetics, we examined what contributed to the aesthetic appeal of a diversity of food photographs (N = 300) and likes and comments they received in an artificial newsfeed from participants (N = 399). The results revealed that people tended to like and share images containing tasty foods. Both healthy and unhealthy foods were able to gain likes. Aesthetic appeal and specific visual features, such as the use of arousing colors and different components of visual complexity, also influenced the popularity of food images. This work demonstrates the potential of applying computer vision methods in visual analysis, offers insights into image virality, and provides practical guidelines for communicating healthy eating.

Keywords: food, virality, computer vision, visual aesthetics, health communication

With the rise of camera phones and photo-sharing networks, people are constantly sharing food images online (Hu, Manikonda, & Kambhampati, 2014). The hashtag #foodporn, which emphasizes the glamorized visual presentation of food, has spread across the globe (Mejova, Abbar, & Haddadi, 2016). What people say about food on social media has also been linked to health outcomes such as obesity and access to healthy food (Culotta, 2014).

Understanding what impacts food images' popularity should provide significant implications for health communication about dietary choices in today's digital media environment. Our diets are heavily affected by mediated representations of food, ranging from real-world television commercials to food pictures in functional MRI studies (Spence, Okajima, Cheok, Petit, & Michel, 2015). Studies frequently show that even exposure to appealing food imagery can evoke hunger and desire and can influence

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consumption choices (Jansen, Mulkens, & Jansen, 2010; Simmons, Martin, & Barsalou, 2005). Moreover, the impacts of messages in online social networks can be amplified by social contagion (Bond et al., 2012). The prevalence of food images on social media, accompanied by popularity indicators such as the number of likes, might further shape our perceptions of social norms about food choices.

In addition, visual content plays an increasingly important role in today's communication landscape. Camera phones and image-based social media, such as Instagram and Snapchat, have gained widespread popularity, particularly among the younger generation (Lenhart, 2015). Widely used in health communication (King, Jensen, Davis, & Carcioppolo, 2014; Lazard, Dudo, Dennis, Ewald, & Love, 2016; McWhirter & Hoffman-Goetz, 2014), visual content can provide concrete evidence; enhance attention, comprehension, and memory; and influence health behaviors (Houts, Doak, Doak, & Loscalzo, 2006). Scholars have also made successful attempts to use visually appealing pictures to encourage consumption of healthy food (Jansen et al., 2010). Despite the prevalence and effects of visual content, previous research on content virality has focused on textual materials (Berger & Milkman, 2012; Martin-Biggers, Beluska, Quick, Tursi, & Byrd-Bredbenner, 2015). Although studies have shown that the use of visuals, compared with plain text, can increase the diffusion of messages (Guerini, Staiano, & Albanese, 2013), the effects of specific visual features are relatively understudied. To design effective messages in today's networked, visually oriented media environment, we need a better understanding of what specific features make a piece of visual content popular.

At last, traditional methods of image analysis often require a significant amount of human labor and rely on coders' subjective interpretation (Hu et al., 2014; Lazard et al., 2016). Although communication research has benefited substantially from computational content analysis, it has mostly been limited to linguistic data (Kim, 2015). To advance our analysis of visual materials, we draw inspiration from an emerging field: computer vision. Computer vision aims to imitate the human vision's ability to perceive and understand visuals, and is being applied in a variety of contexts, such as medical imaging, facial recognition, and automated driving (Szeliski, 2010). Particularly, one line of computer vision research has used computationally coded visual features to predict a variety of outcomes, ranging from images' visual appeal (Ke, Tang, & Jing, 2006; Schifanella, Redi, & Aiello, 2015; Totti et al., 2014) to users' personality (Liu, Preotiuc-Pietro, Samani, Moghaddam, & Ungar, 2016). However, these studies often include dozens of predictors and focus on the accuracy of their prediction models, paying less attention to the theoretical links between visual features and outcomes. Therefore, although computer vision may provide researchers with efficient, convenient, and standardized tools for analyzing visual data, it is also important for us to contextualize this method in the field of communication research.

In summary, we brought together three lines of research: what features make messages viral (Berger & Milkman, 2012; Cappella, Kim, & Albarracín, 2015), how visual factors shape our perceptions of food (Michel, Velasco, Gatti, & Spence, 2014; Spence et al., 2015), and what computer vision features predict the aesthetic appeal of visual content (Ke et al., 2006; Schifanella et al., 2015). By analyzing the popularity of food images, this research contributes to communication studies by providing both theoretical insights of image popularity and practical recommendation for health communication regarding dietary choices, and demonstrating the potential of applying computational methods in visual analysis.

Conceptualizing and Defining Concepts Relevant to Virality

Despite the extensive research on virality, scholars divide on its definition (Alhabash & McAlister, 2015). In a straightforward form, virality can be defined as "the number of people who accessed a given content in a given time interval" (Guerini, Strapparava, & Özbal, 2011, p. 507). Yet, other scholars have proposed more expanded views on virality. For example, Alhabash and McAlister (2015) defined virality in terms of not only reach (e.g., views, shares), but also users' affective (e.g., likes, dislikes) and cognitive responses (e.g., comments) to messages. Guerini et al. (2011) also argued that virality is a complex phenomenon that incorporates different facets of audience reaction, such as spreading, appreciation, and positive and negative comments. In contrast, others have argued for a narrower definition that incorporates the spreading mechanisms of virality; resembling a biological virus, viral content should spread by a sequence of interpersonal contagions instead of a large broadcast from a single source (Goel, Anderson, Hofman, & Watts, 2015).

In this study, we designed a newsfeed with food pictures embedded and instructed respondents to interact with it. We looked at two prevailing metrics, likes and comments, which are two predominant ways of content engagement on popular photo-sharing platforms such as Instagram. In addition, participants' sharing intentions were also measured later. In response to the conflicting views and terminology on virality in previous research, we use *popularity* to broadly refer to the extent to which a piece of content can attract audience reactions such as views, likes, comments, and shares while limiting the use of *virality* only for sharing.

Food Characteristics and Popularity

Previous research has examined a variety of message features that contribute to content popularity, to name a few, information utility, emotional valence and evocativeness, novelty, exemplification, and controversiality (Berger & Milkman, 2012; Cappella et al., 2015; Kim, 2015). Scholars have also identified several mechanisms underlying people's viral behaviors. For example, Berger (2014) summarized five psychological functions for sharing information—impression management, emotion regulation, information acquisition, social bonding, and persuasion—and linked each function to content features such as being entertaining, useful, or arousing.

This rich line of research on virality, however, has focused on content in textual or narrative forms such as news articles (Berger & Milkman, 2012; Kim, 2015). Some content features examined previously—for example, exemplification and information utility—cannot easily apply to the domain of food images. Therefore, this study starts with food characteristics that are of particular concern in public health—tastiness, fillingness, and healthiness (Carels, Konrad, & Harper, 2007; Oakes, 2006; Raghunathan, Naylor, & Hoyer, 2006; Schuldt, 2013)—and uses possible psychological mechanisms (Berger, 2014) to generate hypotheses. Specifically, two mechanisms—arousal and impression management—should contribute to the popularity of food images.

Tastiness and Fillingness

Previous research has frequently demonstrated that arousal, either physiological or psychological, can lead people to share content with others (Berger, 2014). For example, Berger and Milkman (2012) found that online news articles that evoked high-arousal emotions (e.g., awe and anger) were more likely to be e-mailed by viewers than articles that conveyed deactivating emotions (e.g., sadness). Studies on visual content also showed that images that elicited sexual arousal or arousing emotions such as amazement and ecstasy were more likely to go viral on photo-sharing platforms than images that evoked deactivating feelings such as serenity or fatigue (Deza & Parikh, 2015; Gelli, Uricchio, Bertini, Del Bimbo, & Chang, 2015).

Both tastiness and fillingness—the expected capability to satisfy hunger—are important dimensions of food perceptions (Oakes, 2006). As seeking food is an important function of our brain, energy-rich foods that are high in sugar or fat are usually linked to pleasure and reward (Spence et al., 2015). Hypothetically, this association may have served as an evolutionary advantage that drove our ancestors to maximize their caloric intake in the prehistoric world that lacked stable food resources (Spence et al., 2015). Empirical research has shown that tasty and high-calorie food evokes high arousal; even mere exposure to appetitive food images can increase the brain's metabolism and activate the reward system (Simmons et al., 2005; Wang et al., 2004). Therefore, we predicted the following:

H1: Photos of foods that are perceived as more tasty are more popular.

H2: Photos of foods that are perceived as more filling are more popular.

Healthiness

Public health practitioners are particularly concerned with the healthiness of food that people consume. On one hand, unhealthy food pictures should easily go viral, as healthiness and tastiness are usually negatively associated: Portraying a food item as healthier could lead people to expect it to be less tasty and less enjoyable (Raghunathan et al., 2006). On the other hand, people share things to show personal beliefs and values and to maintain a positive self-image (Berger, 2014). As health is widely viewed positively (Smith & Wallston, 1992), people might engage with healthy food photographs to affirm their values or enhance their self-image.

Analysis of social media data has so far found mixed effects of healthiness on the popularity of food images. Holmberg, Chaplin, Hillman, and Berg (2016) found that the majority of adolescents' Instagram food posts displayed high-calorie items such as cookies and pastry, outnumbering images of such healthy foods as fruits and vegetables. Sharma and De Choudhury (2015) showed that Instagram users tended to engage with photos of moderate-calorie foods instead of low- or high-calorie foods, which might suggest a curvilinear relationship between healthiness and food popularity. Mejova et al. (2016) found that the hashtag #foodporn on Instagram was dominated by unhealthy foods (e.g., cake and chocolate) but some healthy foods such as sushi and salad were also widely shared. Given the mixed evidence, we proposed a research question:

RQ1: How does perceived healthiness impact the popularity of food photos?

At last, novelty and expensiveness of foods could also increase popularity as novelty can attract attention and people tend to share novel and expensive things for positive self-presentation (Berger, 2014; Kim, 2015; Martin-Biggers et al., 2015). Given that the impacts of these two features have been frequently documented and are not directly linked to health communication, we included them as control variables.

Visual Features and Popularity

Our perceptions of food are impacted by not only food itself but also its visual presentation (Spence, Levitan, Shankar, & Zampini, 2010; Spence et al., 2015; Wadhera & Capaldi-Phillips, 2014). Therefore, visual features should additionally impact the popularity of food images.

Aesthetic Appeal

People often rate food with a visual display of higher aesthetic appeal—in other words, more beautiful and more visually pleasing—more favorably. For example, participants were willing to pay more for a dish and evaluated it more positively if its elements were artistically arranged like a Kandinsky abstract painting (Michel et al., 2014). In addition, restaurants across the globe are also making more "Instagrammable" dishes with enhanced composition and colors, so customers can take more eye-pleasing food pictures for social media (Whittle, 2017). Regarding general visual content, Schifanella et al. (2015) showed that subjective ratings of an image's aesthetic appeal from crowd workers could well predict the number of favorites an image received on Flickr. Therefore, we expected the following:

H3: Food photos with higher subjective aesthetic appeal are more likely to be popular.

In addition, visual features related to aesthetic appeal should also influence image popularity.

Colorfulness

As evolutionary biologists have hypothesized, primates developed the trichromatic color vision as an adaption to efficiently detect food in the environment, such as red fruits against green foliage (Spence et al., 2015). Colored images or highly saturated images also evoke stronger emotions, are perceived more favorably, and are shared more on social media than monochrome images or photos of low saturation (Bakhshi & Gilbert, 2015; Detenber, Simons, & Reiss, 2000; Guerini et al., 2013; Peng, 2017). Therefore, we made the following hypothesis:

H4: Colorful food photos are (a) more aesthetically appealing and (b) more popular.

Arousing and Relaxing Colors

Colors differ in their salience, emotion, and meanings (Elliot & Maier, 2014). According to the color-in-context theory, the effects and meanings of colors depend on the context in which colors are perceived (Elliot & Maier, 2014). For instance, the same color of red might provoke either positive mental associations (e.g., a flush that signals sexual interest) that lead to approach behaviors or negative associations (e.g., grading in red ink) that lead to avoidance (Elliot & Maier, 2014; Richards & Fink, 2017). In the context of food, as many fruits ripen and sweeten with their colors transitioning from green to red, some evolutionary psychologists have argued that we might still connect red to sweetness and green to sourness (Spence et al., 2010). Empirical studies have shown that red-colored solutions were perceived as sweeter than green or uncolored ones (Wadhera & Capaldi-Phillips, 2014), popcorn was rated as sweeter when served in red bowls than in white bowls (Harrar, Piqueras-Fiszman, & Spence, 2011), food products in red packages were judged sweeter than those in green and blue packages (Huang & Lu, 2015). As hypothesized before, perceived tastiness can increase popularity. Therefore, images with more red should outperform images with more green or blue.

In addition, research has shown that red and orange are often linked to arousal, warmth, and salience, whereas green and blue are associated with relaxation and coolness (Elliot & Maier, 2014). As psychological arousal drives attention and sharing (Berger, 2014), we should expect that the use of arousing colors (e.g., red, orange) instead of relaxing colors (e.g., blue, green) would increase popularity. Analysis of social media data found that on Pinterest, images that contained more red, pink, and purple were shared more than photos that featured predominantly black, green, blue, or yellow (Bakhshi & Gilbert, 2015), and on Flickr, warmer photo filters attracted more views and comments for photographs than cooler filters (Bakhshi, Shamma, Kennedy, & Gilbert, 2015). Combining these two lines of research, we proposed the following hypothesis:

H5: The use of arousing colors (e.g., red, orange), instead of relaxing colors (e.g., green, blue), increases (a) aesthetic appeal and (b) popularity of food images.

Rule of Thirds

In addition to color, composition also affects images' aesthetic appeal (Amirshahi, Hayn-Leichsenring, Denzler, & Redies, 2014). One common guideline in photography is the rule of thirds: With a picture divided into nine equal parts by two horizontal lines and two vertical lines, subjects of interest are best placed along these lines or in their intersections (Amirshahi et al., 2014; Ke et al., 2006). In one empirical study, participants' judgment of whether an image followed the rule of thirds could predict their aesthetic ratings of the image (Amirshahi et al., 2014). We thus hypothesized the following:

H6: Following the rule of thirds enhances a photograph's (a) aesthetic appeal and (b) popularity.

Visual Complexity

Visual complexity, which deals with the amount of visual variations, also influences our perception of images, but its impacts are often mixed (Lazard & Mackert, 2014). First, in photography, a good picture should focus on a central theme and clearly convey the message, eliminating other elements that may distract or overwhelm viewers (Langford & Bilissi, 2011). In an experiment, using white space in advertisements led viewers to evaluate a brand more positively (Pracejus, Olsen, & O'Guinn, 2006). However, too-simple stimuli may lack the sufficient information to stimulate and attract people, decreasing attention and engagement (Geissler, Zinkhan, & Watson, 2006). Therefore, a curvilinear relationship has often—although not consistently—surfaced in previous studies, as participants tend to respond more favorably to visual content of moderate complexity than too-simple and too-complicated stimuli (Berlyne, 1970; Geissler et al., 2006).

Visual complexity may also contain multiple dimensions. Some scholars have distinguished the quantity and the variety of elements from the complexity in elements' spatial organization and order (Deng & Poole, 2010). Others have differentiated between feature complexity—the density of perceptual features—and design complexity, which incorporates design principles such as the irregularity and dissimilarity of objects (Lazard et al., 2016; Lazard & Mackert, 2014; Pieters, Wedel, & Batra, 2010). Other factors have also been proposed, for example, the complexity in objects' surfaces and textures (Ramanarayanan, Bala, Ferwerda, & Walter, 2008) and the variety in images' color (Purchase, Freeman, & Hamer, 2012). In this study, food images differ in the amount of details and objects in the frame, the spatial arrange of these elements, and the variety in their color (Deng & Poole, 2010; Ke et al., 2006). We proposed the following research question:

RQ2: How do different types of visual complexity impact food photos' aesthetic appeal and popularity?

Method

Stimuli

To ensure that our stimuli covered a diversity of foods or drinks, we preselected a list of food items that differed in characteristics including tastiness (e.g., ice cream vs. water), fillingness (e.g., pizza vs. cocktail), healthiness (e.g., mixed vegetables vs. cheesecake), novelty (e.g., caviar vs. fries), and culture (e.g., kebab vs. taco). Next, to maximize the variance in images' aesthetic appeal, we retrieved photographs of those foods from multiple sources, including Flickr, an online photo-sharing platform, and Shutterstock, a professional stock photography website. For user-generated content on Flickr, we limited our search to photos released to the public domain or under Creative Commons licenses. We included only photos with a ratio size around 3:2 and cropped them to 600 × 400 pixels. The final stimuli image set contained 300 photos of 116 food or drink items.

Participants

We recruited 401 participants from the crowdsourcing platform Amazon Mechanical Turk. Research has shown that this platform can provide scholars with comparably good-quality data from participants who are more demographically diverse than traditional convenience samples (Buhrmester, Kwang, & Gosling, 2011). Furthermore, to enhance the quality of our data, we included only participants who (1) were located in the United States, (2) had at least 50 tasks approved, and (3) had a historical approval rate above 95%. Forced responses were used on key variables to ensure complete responses. Each participant received $0.52 for completing the study.

Two duplicate responses were removed. The sample (N = 399) included 60.7% female, with an average age of 38.9 years (SD = 12.9, range = 19–77 years). Participants also reported their educational level (10.5% some high school or high school graduate, 28.6% some college, 45.6% college degree, 15.3% postgraduate), race (9.8%, 6.8%, and 79.2% identified as African American, Asian/Pacific Islander, and White, respectively)[2], weight, height, and social media use. Body mass index (M = 27.04, SD = 7.22) was calculated based on participants' self-reported weight and height (3.5% underweight, 40.6% normal, 32.8% overweight, 23.1% obese; World Health Organization, n.d.). Regarding social media use, participants reported how frequently they used Facebook, Twitter, Instagram, and Flickr (α = .631, M = 2.84, SD = 1.03) on four 6-point scales (1 = *never*, 6 = *almost all the time*).

Procedure

A newsfeed was designed to simulate the experience of browsing on social media, which mixed 15 food photos with 20 nonfood photos. The 15 food photos were randomly selected from the stimuli image set (N = 300). The nonfood photos served as distractions and remained the same for all the participants, including images of architecture, people, landscape, and so forth. In the newsfeed, each photo was accompanied by a like button, a comment button, and a blank bar for participants to write comments (see Figure 1). The images were displayed in a randomized order.

After answering questions about individual characteristics, participants were presented with the newsfeed and instructed to like and comment on the photos as if they were scrolling down a newsfeed on social media. After exiting the newsfeed, each participant rated another batch of 15 food photographs that were randomly selected from the stimuli set. Therefore, each food photo appeared in the newsfeed 19.95 times (SD = 5.56, range = 8–31) and was also rated 19.95 times (SD = 4.38, range = 9–34) on average.

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[2] Regarding race, participants were allowed to check all the options that applied.

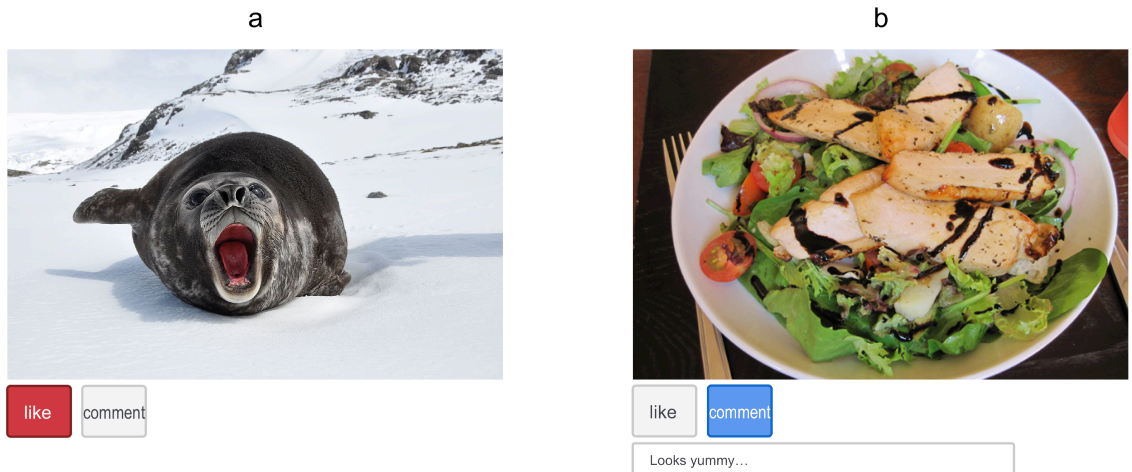

Figure 1. Illustration of the newsfeed posts and participants' potential interactions with the newsfeed: (a) like and (b) comment. Images by Serge Ouachée/Wikipedia (left); Carol/Flickr (right).

Measures

Participant ratings

Based on previous literature on food perceptions, we listed a series of 5-point semantic differential scales[3] for participants to rate the food or drink item in each photo, including tastiness (*untasty–tasty*, *not delicious–delicious*; α = .957, *M* = 3.73, *SD* = 0.62;[4] Werle, Trendel, & Ardito, 2013), fillingness (*unlikely to fill me up–likely to fill me up*, *unlikely to satisfy hunger–likely to satisfy hunger*; α = .987, *M* = 3.28, *SD* = 0.84; Carels et al., 2007; Oakes, 2006), and healthiness (*unhealthy–healthy*; *M* = 2.99, *SD* = 0.93; Carels et al., 2007; Schuldt, 2013). Participants rated the photograph's aesthetic appeal on *bad quality–good quality* and *ugly–beautiful* (α = .897, *M* = 3.25, *SD* = 0.49). Regarding control variables, participants also rated the food's novelty (*conventional–novel* and *ordinary–unique*; α = .958, *M* = 2.98, *SD* = 0.75; White, Shen, & Smith, 2002) and estimated its price ("How much do you expect to pay for this food/drink in U.S. dollars?"; *M* = \$7.37, *SD* = \$3.57). We averaged respondents' ratings for each photo (Milkman & Berger, 2014).[5] A confirmatory factor analysis (CFA) showed that these measures were indeed loaded on separate factors.[6]

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[3] Participants were shown a list of paired words/phrases, with 1 representing the term on the left and 5 representing the term on the right.

[4] Summary statistics of image features (e.g., α, *M*, *SD*) were based on image-level analysis (*N* = 300).

[5] Median was used for price estimation, as participants were free to write any amount and might give extreme values.

[6] The CFA model (*N* = 300) achieved acceptable fit, $\chi^2(22) = 80.07$, $p < .001$; comparative fit index = .982; root mean square error of approximation = .094; standardized root mean residual = .036.

Popularity

We used whether participant liked and commented on the photo in the newsfeed as two behavioral indicators of popularity. On average, each food image had a 43.3% (*SD* = 16.5) chance of getting likes and a 9.76% (*SD* = 6.94) chance of getting comments, which were calculated as the number of likes and comments it received from the participants, divided by the number of times it appeared in the newsfeed. In addition, participants also indicated their intention to share a food photo on a 5-point scale (1 = *very unlikely*, 5 = *very likely*): "If I have the same food/drink in the photo, I will take a photo and share it on my social media accounts" (*M* = 2.35, *SD* = 0.44). Previous research measuring sharing intention often has asked about people's willingness to retransmit a message to their acquaintances or share it on social media accounts (Alhabash & McAlister, 2015; Berger, 2014). However, given that photo-taking is a popular way of sharing food images (Hu et al., 2014; Mejova et al., 2016), we instead specifically measured participants' intention to take and share photos.

Computer vision features

Colorfulness was measured using the formula in Hasler and Süsstrunk (2003). This method calculated an image's colorfulness based on each pixel's values in the RGB color model—a system that uses combinations of red, green, and blue to represent different colors—and achieved a correlation of .953 with human ratings of colorfulness in their study.

To measure the percentages of arousing and relaxing colors in each image, we categorized each pixel's value into different basic colors (see Figure 2b) following the work of van de Weijer, Schmid, and Verbeek (2007). This work provided a data set that associated each RGB value with one of the 11 basic colors in the English language (e.g., red, green) based on color-related online images. We created an arousing–relaxing color index by subtracting the percentages of two relaxing colors (green and blue) from two arousing colors (red and orange).

Regarding the rule of third, we first detected the edges in photographs (van der Walt et al., 2014). Edges are where color or texture markedly changes in a picture, usually representing the textures or boundaries of objects (Szeliski, 2010; see Figure 2d). When a photo is divided into nine parts by two equally spaced horizontal lines and two equally spaced vertical lines, edges should be located close to these lines or their intersections if a photo follows the rule of thirds. We thus calculated the minimal distance from edge points' centroid to the four intersection points (reversed) to capture this feature.

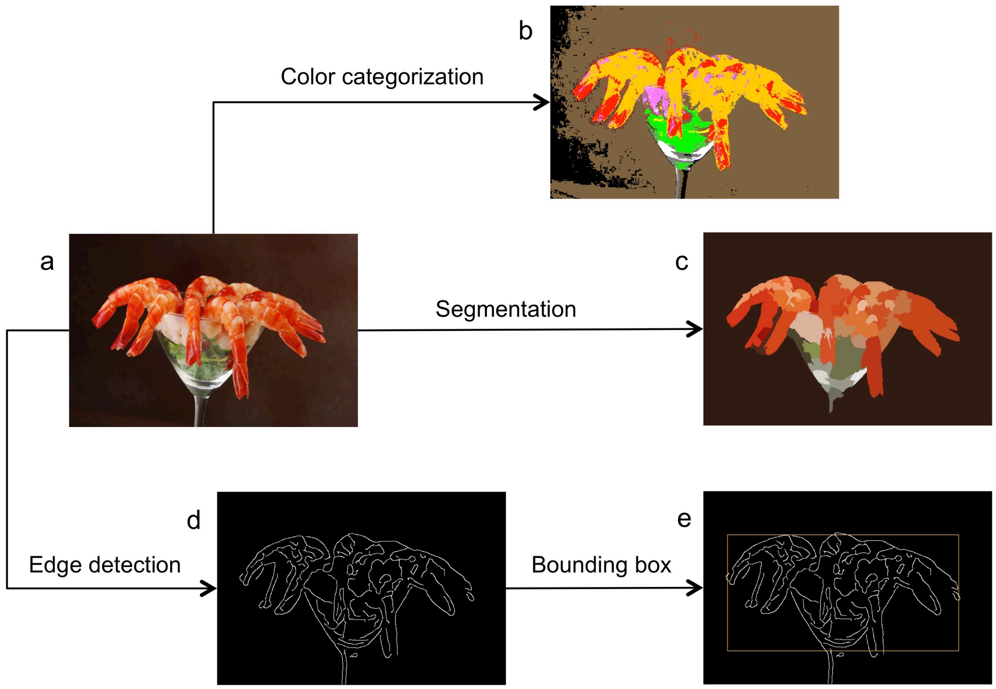

Figure 2. Illustration of (a) original photo, (b) color categorization, (c) segmentation, (d) edge detection, and (e) bounding box.

Six measures were used in total for visual complexity. First, we included a conventionally used measure of visual complexity: the JPEG file size of the image (Pieters et al., 2010). We also segmented the image by grouping pixels of similar color (van der Walt et al., 2014; see Figure 2c).[7] A complicated photo with more objects and elements should have more edges and segments, and its edges should be more evenly distributed in the image, compared with a simple image that has only a few elements located in a clean background (Ke et al., 2006). Therefore, we also included the number of segments (Totti et al., 2014); edge density, measured as the area occupied by edges (Purchase et al., 2012); edge distribution, measured as the mean of Euclidean distances among edge points; and the minimum size of a bounding box that contained 95% of the edges (see Figure 2e). At last, we measured color variety by sorting each pixel's hue value (H in the HSV color space) into different color bins and summing the number of unique hues in an image (Ke et al., 2006).

As visual complexity may be multidimensional (Deng & Poole, 2010; Pieters et al., 2010), we conducted a factor analysis on the six measures. Results suggested that the JPEG size, edge density, and the number of segments were loaded on the same factor (α = .918), which seemed to correspond to the

[7] We applied Canny edge detection and normalized-cut image segmentation using scikit-image, an image-processing Python package (van der Walt et al., 2014).

quantity of different elements and details in images; edge distribution and bounding box size loaded on another factor (α = .937) that seemed to reflect the spatial arrangement of elements—whether they were filling the whole frame or situated within a clean background. These two dimensions were named *feature complexity* (Pieters et al., 2010) and *compositional complexity*, respectively.[8] Color variety did not load on these two dimensions well (r = .352, p < .001; r = .108, p = .061) and was treated separately in future analysis. A CFA confirmed this three-dimensional structure of visual complexity.[9]

Two commonly used computer vision features were also included as control variables (Liu et al., 2016): Brightness was measured as the average perceived luminance value (Y in the XYZ color space) of all pixels; contrast was measured as the standard deviation of all pixels' luminance values.

Results

Similar to prior research that had participants rate a variety of messages and used a combination of message and participant characteristics to predict certain outcomes (Milkman & Berger, 2014), we conducted multiple multilevel regressions (see Table 1). In the regression models, one like, comment, rating of sharing intention, or aesthetic appeal per participant served as one observation. Quadratic terms of healthiness and visual complexity were included as predictors as they might curvilinearly correlate with images' popularity (Geissler et al., 2006; Sharma & De Choudhury, 2015). Aesthetic appeal as the outcome in Model 1 refers to each participant's rating of a specific photo, and aesthetic appeal as a predictor in Models 3, 5, and 7 refers to averaged ratings of each photo. Participants' age, gender, race, education level, social media use, and body mass index were also included as covariates. All models controlled for participant characteristics as fixed effects, with images (N = 300) and participants (N = 399) entered as random effects. Analyses were weighted on how many times a photo was rated (Models 1–3) or appeared in the newsfeed (Models 4–7; Milkman & Berger, 2014).

Food Characteristics and Popularity

In accord with H1, people intended to share (β = .067, p < .001) and liked more (β = .122, p < .001) tasty foods in the newsfeed. However, people did not comment more on tasty foods, contradicting H1. In terms of H2, fillingness increased people's sharing intention (β = .037, p = .013), but not likes and comments in the newsfeed, offering partial support for H2.

[8] As composition is frequently used to describe the spatial arrangement of elements in photography (Langford & Bilissi, 2011), we labeled the second dimension *compositional complexity*. We did not choose another commonly used term, *design complexity*, as this concept did not entirely overlap with our measurement (Pieters et al., 2010).

[9] The CFA model (N = 300) had acceptable fit, $\chi^2(7)$ = 27.041, p < .001; comparative fit index = .984; root mean square error of approximation = .098; standardized root mean residual = .034.

Table 1. Multilevel Regression Results.

	Aesthetic appeal	Intention to Share		Like		Comment	
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Participant characteristics							
Male	−.050†	.039	.040	.090**	.092**	.052†	.053†
Age	.016	−.108**	−.108**	−.088*	−.084*	−.007	−.008
African American	−.016	.062†	.060†	.041	.041	.034	.033
Asian	.034	.064†	.065†	.047	.046	.071*	.071*
Education	−.046†	−.025	−.027	−.066*	−.067*	−.019	−.020
Body mass index	.009	−.043	−.041	−.022	−.020	.003	.003
Social media use	−.005	.251***	.251***	.136***	.138***	.022	.022
Computer vision features							
Colorfulness	−.001	−.037*	−.013	−.021	.002	−.008	.002
Arousing–relaxing color	.091**	.057**	.000	.075***	.012	−.009	−.016
Rule of thirds	.079**	.022	−.003	.035*	.009	−.010	−.006
Feature complexity	.091*	.043*	−.011	.047*	.014	−.003	.001
Feature complexity^{2}	.016	.015	.008	.002	−.023	.010	.008
Compositional complexity	−.136***	−.033*	.001	−.003	.019	−.014	−.006
Compositional complexity^{2}	−.019	−.024	−.011	−.026	−.020	−.017	−.007
Color variety	.187***	.076***	−.007	.069**	−.003	−.005	−.003
Color variety^{2}	−.053†	−.034*	−.004	−.034	−.002	.010	.007
Brightness	.056*	.008	−.015	−.007	−.014	.023†	.021
Contrast	.021	.029†	.014	.010	−.008	.048**	.041**
Image ratings							
Tastiness			.067***		.122***		−.036
Fillingness			.037*		−.016		−.017
Healthiness			−.026*		−.031*		−.049**
Healthiness^{2}			.021*		.042**		.020
Aesthetic appeal			.128***		.091***		.014
Novelty			.087***		.023		.019
Estimated price			.009		.036*		.018
Estimates of covariance							
Residual	12.083	9.136	9.106	12.174	12.154	14.133	14.142
Image (*N* = 300)	.168	.032	.000	.040	.007	.008	.006
Participant (*N* = 399)	.209	.422	.419	.344	.352	.339	.337

Note. $N_{\text{observation}}$ = 5,985. Regression coefficients were standardized. Quadratic terms were labeled with a superscript 2.
$^{†}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

In terms of RQ1, participants intended to share (β = −.026, *p* = .031), liked (β = −.031, *p* = .040), and commented on (β = −.049, *p* = .002) unhealthy foods more. Furthermore, the positive quadratic term of healthiness in predicting likability (β = .042, *p* = .001) and people's sharing intention (β = .021, *p* = .044) suggested that both healthy and unhealthy foods got more likes or were perceived as more sharable than foods in the middle.

Figure 3 illustrates the curvilinear relationship between perceived healthiness and each image's likelihood of getting likes. Unhealthy foods such as ice cream, milkshakes, and various kinds of cake indeed got more likes. However, some healthy foods also attracted more likes, such as chicken salad and mixed fruit.

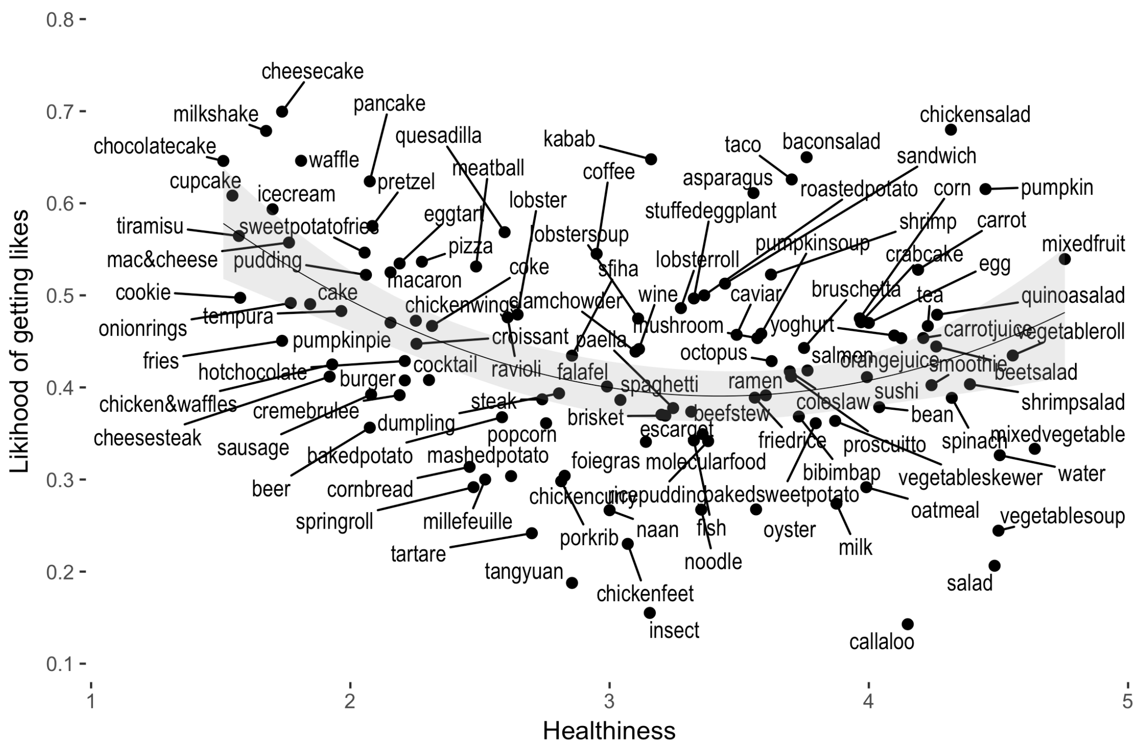

Figure 3. Curvilinear relationship between perceived healthiness and likelihood of getting likes (photos of the same food/drink item were aggregated into 1 point).

Visual Features and Popularity

Consistent with H3, people liked more (β = .091, *p* < .001) and indicated higher sharing intention for (β = .128, *p* < .001) photographs of higher aesthetic appeal; however, respondents did not comment more on these pictures, partially rejecting H3.

We then looked at Models 1, 2, 4, and 6 to examine the effects of computer vision features. It is worth noting that once participants' ratings were controlled, computer vision features generally had negligible effects on the three popularity indicators (Models 3, 5, and 7). This pattern suggests that participant ratings might have mediated the effects of computer vision features.

Contradicting H4a and H4b, colorfulness did not increase an image's aesthetic appeal and likelihood of getting likes or comments; it even decreased people's sharing intention ($\beta = -.037$, $p = .043$), which was in the opposite direction of our hypothesis.[10]

Consistent with H5a and H5b, people found photos using more arousing colors more aesthetically attractive ($\beta = .091$, $p = .007$), reported higher sharing intention for them ($\beta = .057$, $p = .002$), and liked them more in the newsfeed ($\beta = .075$, $p < .001$), although this feature did not affect comments, partially rejecting H5b.

Consistent with H6a and H6b, adherence to the rule of thirds increased a photo's aesthetic appeal ($\beta = .079$, $p = .006$) and likability ($\beta = .035$, $p = .046$). However, it did not impact the other two popularity measures, partially rejecting H6b.

Regarding RQ2, the three dimensions of visual complexity showed different patterns. Participants were more likely to rate a photo with high feature complexity as aesthetically appealing ($\beta = .091$, $p = .013$), intended to share it ($\beta = .043$, $p = .030$), and liked it in the newsfeed ($\beta = .047$, $p = .042$), although this feature showed no effects on comments. In contrast, compositional complexity negatively impacted aesthetic appeal ($\beta = -.136$, $p < .001$) and sharing intention ($\beta = -.033$, $p = .047$), without influencing a photo's likelihood of garnering likes and comments in the newsfeed. Color variety increased aesthetic appeal ($\beta = .187$, $p < .001$), sharing intention ($\beta = .076$, $p < .001$), and likability ($\beta = .069$, $p = .003$), but showed no impacts on images' likelihood of getting comments. The negative squared term of color variety in predicting aesthetic appeal ($\beta = -.053$, $p = .091$) and sharing intention ($\beta = -.034$, $p = .042$) suggested that photos with extremely varied color did not outperform fairly varied ones.

Discussion

Our study reveals that the popularity of food images is driven by a combination of food characteristics and visual aesthetics. First, based on the results, tasty and unhealthy foods were more likely to go viral, in congruence with today's prevalence of #foodporn pictures on social media (Mejova et al., 2016). This poses a serious challenge to promoting healthy eating online: Unhealthy foods, mainly

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[10] Further inspection revealed that colorfulness strongly correlated with arousing–relaxing color (ARC; $r = .500$, $p < .001$, $N = 300$). Colorfulness had nonsignificant impacts on sharing intention when ARC was excluded ($\beta = -.006$, *ns*), but ARC still significantly predicted sharing intention ($\beta = .037$, $p = .015$) in the absence of colorfulness. This pattern seems to indicate suppression effects: Colorfulness captured something in ARC that was irrelevant to the outcome; so, including it in the regression enhanced the predictive power of ARC.

desserts, are shared and liked more, which may subsequently shape our perceptions of norms and in turn strengthen the popularity of unhealthy foods. Nevertheless, certain healthy foods were also able to gain popularity, reversing the association between unhealthiness and likability of foods (see Figure 3).

In addition, visual aesthetics are critical in determining the popularity of food images. First, compared with the intensity of color (colorfulness), the choices and variety of color mattered more. Containing more arousing colors (e.g., red and orange) and using a variety of colors enhanced a food image's aesthetic appeal and likeability as well as viewers' sharing intention for it. These results echo previous findings that arousing colors such as red can lead to more favorable perceptions of food (Spence et al., 2010) and increase an image's chance to become popular online (Bakhshi & Gilbert, 2015). Yet, the impacts of color may depend on specific contexts (Elliot & Maier, 2014). For example, red color in food images might provoke attention and favorable reactions among the audience, but it may also signal danger and alarm (e.g., blood, angry face) that have negative connotations in other contexts.

Similar to prior work (Deng & Poole, 2010; Pieters et al., 2010), this study shows that it is necessary to distinguish among different types of visual complexity. In our results, compositional complexity decreased a photo's aesthetic appeal. Indeed, consistent with the conventional wisdom in photography (Ke et al., 2006; Langford & Bilissi, 2011), photos following compositional simplicity or the rule of thirds were indeed rated as more aesthetically appealing than those with messy backgrounds or having a dish of food filling the whole frame (see Figure 4). Furthermore, feature complexity and color variety increased a photo's aesthetic appeal and likability. Participants favored photos with a diversity of elements, textures, and colors, for example, a bowl of mixed fruits of various colors or a plate of chicken salad of varied indigents (see Figure 4, panels 1c and 1d). These findings are in line with some previous studies showing that visual complexity is linked to arousal (Geissler et al., 2006)—which in turn could lead to virality (Berger, 2011)—and people have a variety-seeking tendency for food (Lähteenmäki & Van Trijp, 1995). In contrast, some minimalist photos featuring a prominent object placed in a simple background (usually black and white) were rated as aesthetically appealing, but might seem less evoking or impressive, lacking the visual impacts to stand out in a newsfeed (see Figure 4, panel 2). This seems to echo some previous research suggesting that beautiful images can be less viral if they evoke deactivating emotions such as serenity and calmness (Deza & Parikh, 2015), indicating a divide between "eye-pleasing" and "eye-catching" aesthetics. Future research could further investigate how different aspects of visual complexity and other visual features contribute to images' pleasantness, arousing potential, and, consequently, virality.

In line with previous work (Peng, 2017), this study also highlights the role of individual characteristics in influencing images' aesthetic appeal and popularity. Similar to previous research (Milkman & Berger, 2014), our results also demonstrated that individual characteristics such as gender and race could impact viral behaviors (see Table 1), suggesting areas for future research. In addition, scholars could further examine the potential interaction between individual and message characteristics in influencing the popularity of food images. For example, individuals differing in body mass index might perceive the same food differently (Carels et al., 2007), which could lead to different patterns of liking and sharing food online.

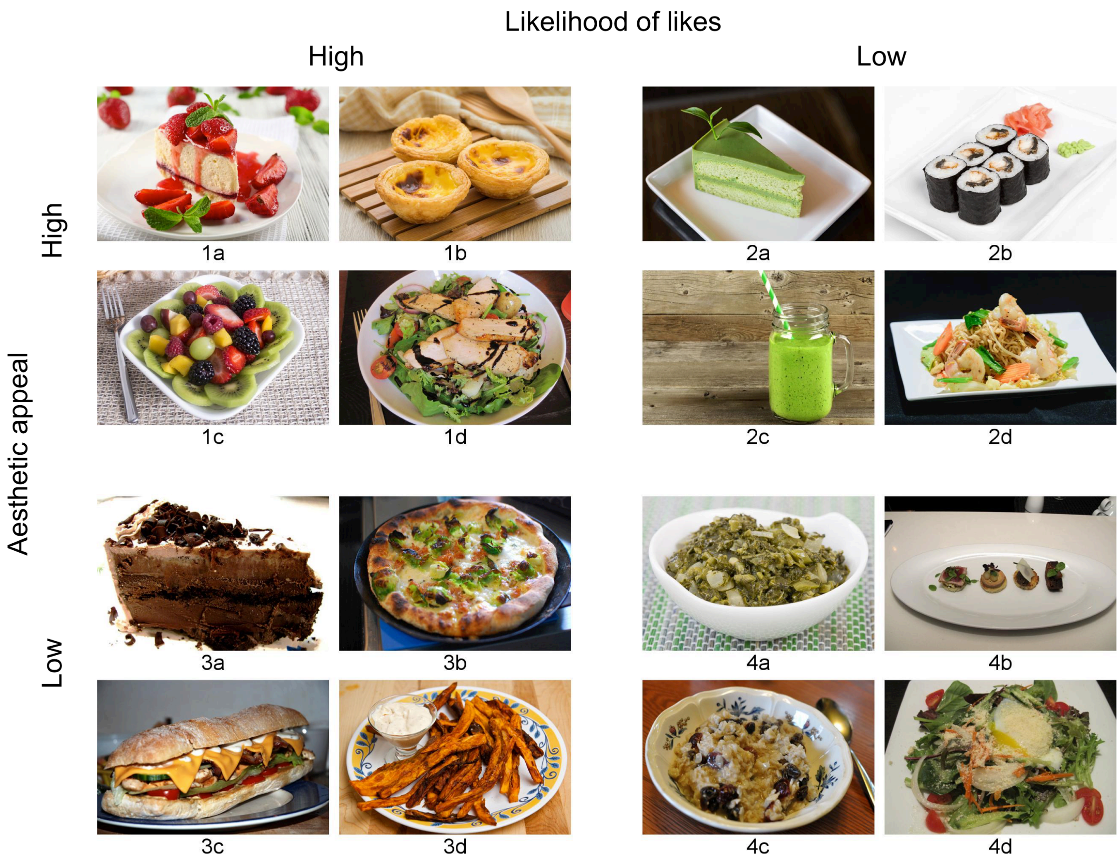

Figure 4. Examples of photos scoring high (top 30%) and low (bottom 30%) on aesthetic appeal and likelihood of getting likes in the newsfeed. Image credits (panel): Carol (1d); Melinda Bardon (3a); Neven Mrgan (3b); Jonas Lönborg (3c); KyleWiTh (3d); Raj Taneja (4b); Mark H. Anbinder (4c); Joel Abroad (4d).

One limitation of our study is that we put participants in a designed environment without presenting social cues. As people's online behaviors are often driven by social influences (Bond et al., 2012), social media users' real-world behaviors might differ from our results. First, behavioral data from online sources often incorporate effects of social and contextual factors (e.g., editorial cues, sources), which might obscure or override the effects of content features (Kim, 2015; Totti et al., 2014). Previous studies examining the effects of content features on real-world popularity measures often have relied on large sample sizes (e.g., N = 6,956 in Berger & Milkman, 2012; 187,796 in Totti et al., 2014). Therefore, the effects in our study might become smaller in the online environment where social and contextual factors are added. In addition, people might also adjust their liking and commenting behaviors if they realize that their behaviors are publicly visible. Therefore, future studies using other data sources are needed.

Like some previous studies (Alhabash & McAlister, 2015; Berger, 2011), this study also used people's intention of performing viral behaviors as indicators of their actual behaviors. One recent study showed medium-to-large correlations (r = .337 and r = .372) between participants' self-reported viral behavioral intention and actual online virality metrics (Scholz et al., 2017). However, more studies are needed to confirm the link between viral behavioral intention measures and online virality metrics.

This study also offers some insight into the potential bias in using social media data to infer people's dietary patterns (Culotta, 2014; Holmberg et al., 2016; Sharma & De Choudhury, 2015). According to our results, individuals constantly make decisions about what kinds of foods to upload to social media, and this mental process has already been shaped by the same factors that influence online popularity. Sampling on social media, therefore, might be heavily biased toward certain kinds of foods and does not offer a full spectrum of people's dietary consumption.

Last, this study also demonstrates the promise of using computational methods in analyzing visual content. In this study, the use of computer vision was able to objectively and efficiently retrieve a diversity of message features that might otherwise require a substantial amount of human labor to measure. In addition, this method also allowed us to examine features that were not easy to code, but still meaningfully influenced the outcome, such as the percentages of different colors. Communication researchers might add computer vision to their toolkits and further explore its possibilities in visual analysis.

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