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Visual Representations in Organizational Instagram Photos and the Public's Responses: Focusing on Nonprofit Organizations

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This study aimed to explore what were visually represented in nonprofit organizations' (NPOs') Instagram photos and how the features of the photos were related to the public's responses. The contents of the photos were examined using online artificial intelligence services. NPOs' Instagram photos and accounts were clustered discretely, and the resulting clusters were compared in terms of the photo features at content and pixel levels. The public's responses were correlated with and predicted from the photo features. The results showed that photos of people made up the largest share of NPOs' Instagram photos. Three photo clusters and three account clusters were detected and found to be different in terms of their content- and pixel-level characteristics. A part of photo features was significantly associated with the public's responses, and engagement was predicted from the photo features with an acceptable level of accuracy whereas comment sentiment was not.

Keywords: visual representation, Instagram, nonprofit organization, clustering, engagement, comment sentiment

Nonprofit organizations (NPOs) can take advantage of social media (SM) for their activities. Unlike for-profit organizations, NPOs usually lack enough financial and human resources for large-scale campaigns or mass media advertisements to deliver their messages to the public. They can overcome this barrier using the SM functions that enable them to communicate with many individuals quickly and cheaply, hence SM have become one of the major communication channels of NPOs.

Self-presentation can play a significant role in NPOs' SM communication. Self-presentation has been one of the theoretical perspectives through which individuals' SM use has been examined (Bullingham & Vasconcelos, 2013). This can be also the case in organizational SM accounts. Like individual users,

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organizational accounts present themselves in SM posts. These presented selves can be direct descriptions of the organizations' goals, activities, and achievements, or they can be representations of how the organizations want themselves to be seen. Since their online identities and relationships with other users may be based on what they have presented, analyzing the self-(re)presentations of organizations can reveal the central aspect of organizations' SM communication.

However, previous studies that analyzed NPOs' SM posts (Campbell & Lambright, 2020) have mainly focused on the strategy of communication or purpose of the posts and have not closely examined the self-(re)presentation of NPOs' SM accounts. Furthermore, most of the previous studies have analyzed the data in text form, such as tweets, and visual data, such as photos, have drawn insufficient attention. One photo can express richer information than one word, and photos can be easily taken, edited, and shared using personalized devices and photo-centric SM, such as Instagram. Although SM photos can provide much potential for NPOs' activities, scant attention has been paid to this communication via photos. Thus, the characteristics of the photos, which are used by NPOs in their visual self-presentation on SM, have not been identified.

In addition, there is a lack of focus on how the visual representations in NPOs' SM photos are related to the public's responses. Prior works have reported significant relationships between the message features of NPOs and the public's responses (Chung, Woo, & Lee, 2020; Wang & Yang, 2020), and some of them have examined the influence of multimedia posts on engagement (Smith, 2018). However, photos on NPOs' SM accounts have not been actively examined in terms of their relationships with the public's responses. Thus, little is known about the characteristics of photos that would generate more positive responses from the public.

Based on these considerations, this study aims to explore what are visually represented in NPOs' Instagram photos. The visual representations are examined in two aspects: the overall content and the characteristics of subgroups. The overall content of photos is examined using an online artificial intelligence (AI) service. Also, photos and accounts are clustered discretely, and the resulting subgroups are compared in terms of their content- and pixel-level characteristics. Another aim of this study is to investigate how the characteristics of NPOs' Instagram photos on the accounts are related to the public's responses to the accounts. In addition to engagement, the sentiment of comments made to the photos is used as the metric of the public's responses.

The remainder of this article is organized as follows: First, previous studies on visual self-presentation, clustering SM data, and the public's responses to NPOs' SM messages are reviewed. This is followed by a description of how the data were gathered, how the photos and accounts were clustered, and which photo features were used for analysis. Finally, the results of the analysis are presented, and their implications and limitations are discussed.

Theoretical Backgrounds and Related Works

Visual Self-(Re)presentation

Self-presentation refers to disclosing of an individual, done by oneself, to others in social contexts (Goffman, 1959). Individuals determine which information about themselves to disclose or hide to manage their impression because others perceive them based on the presented information. Goffman (1959) compared this process to actors performing roles: they design their appearances or behaviors to shape viewers' impressions about the actors and the contexts (Carpenter, Kanver, & Timmons, 2017). This self-presentation can be more easily performed online than in face-to-face settings because individuals can control more easily which information to disclose to others (Bullingham & Vasconcelos, 2013).

Organizations present themselves on SM accounts as individuals do. They shape their online identities and build relationships with other users through self-presentation (Djafarova & Trofimenko, 2019). In addition, they manage their online self-presentation so that it can contribute to achieving the organizational goals. Individuals also have goals that they want to achieve through self-presentation, but organizational goals are more measurable and whether they are achieved or not can be easily observed. The literature has demonstrated that the active online presence of organizational SM accounts is related to successful marketing (Jung & Jeong, 2020), fundraising (Gloor, Colladon, Grippa, Hadley, & Woerner, 2020), and even survival (Antretter, Blohm, & Grichnik, 2018) of organizations. This is especially the case for small organizations such as NPOs with few resources for other ways of communication.

Meanwhile, photos are effective media for online self-presentation. Visual information is much easier to express and understand than written information because writing must be learned, while visual processing is an innate ability (Joo & Steinert-Threlkeld, 2022). Thus, SM users can take and share photos to present themselves instead of writing about what they do and feel. In this regard, various kinds of SM users have been investigated in the literature to understand how they present themselves visually on SM: athletes (Sadeghi & Leng, 2021), politicians (Brands, Kruikemeier, & Trilling, 2021), journalists (Carpenter et al., 2017), and laypeople (Hong, Jahng, Lee, & Wise, 2020).

In this study, NPOs' Instagram accounts are investigated in terms of what they visually represent in their photos. Specifically, the overall content of photos is examined. Photos on SM can present and/or represent the uploaders, their settings, and their desires by means of various objects in the photos (Jurgenson, 2019). Thus, examining the content of the photos can be the principal strategy for investigating visual representations. The following research question is raised:

RQ1: What is the overall content of the Instagram photos uploaded to the NPOs' accounts?

Clustering as an Analytical Strategy for Examining Visual Representations

As another strategy for examining visual representations, this study employs a clustering method. Clustering is an unsupervised learning technique that splits a data set into subgroups. Similar data units are assigned to the same group, and the resulting subgroups can manifest the latent structures or patterns in the data set (Filho et al., 2014). Clustering can be a useful analytical strategy for examining the structure of visual representations. The structures of representations have been one of the key themes in social representations research (Lo Monaco, Piermattéo, Rateau, & Tavani, 2017), and the subgroups identified by clustering and the differences among them would show the central elements in visual representations. In this regard, clustering has been used in the literature for grouping SM users (Dietz, Sen, Roy, & Wörndl, 2020) or posts (Mostafa & Nebot, 2020). In particular, SM photo data have been analyzed using clustering methods to show the events represented in geo-tagged tweets (Kaneko & Yanai, 2016), the image of the

Tri-City region in Poland (Huang, Obracht-Prondzynska, Kamrowska-Zaluska, Sun, & Li, 2021), and vaping in Instagram photos (Ketonen & Malik, 2020).

This study applies the clustering method to analyze the visual representations in the Instagram photos of NPOs. For clustering, features extracted by a pretrained convolutional neural network (CNN) are used. Each photo is represented as a vector by using a pretrained CNN model, and each account is represented as a mean of photo vectors of the account. Features based on deep neural networks (DNNs) have been reported to show better performance for document clustering (Curiskis, Drake, Osborn, & Kennedy, 2020), so CNN-based features are used for clustering. However, CNN-based features are difficult for humans to understand and are of limited use for comparing subgroups. Thus, photo features, which lend themselves more easily to human interpretation, are also extracted to compare photos among clusters. Also, photos can be analyzed at the pixel level, as well as at the content level, where information can be conveyed and meaning can be created. Features at these two levels would reveal the differences in visual representations among clusters. The following research questions are pursued:

RQ2a: *How are the photos clustered, and how do the photo clusters differ in terms of their content- and pixel-level characteristics?*

RQ2b: *How are the accounts clustered, and how do the account clusters differ in terms of their content- and pixel-level characteristics?*

The Public's Responses to NPOs' SM Messages

One of the primary concerns of NPOs is the public's responses to their SM messages because they show how successful the organizations' SM activities are. Studies have mainly used engagement to measure the public's response. Engagement is concerned with what people feel about the SM messages from organizations and what they do in response to or as a consequence of the messages, and it is usually expressed by online behaviors such as searching, liking, commenting, and sharing (Smith & Gallicano, 2015).

Previous studies have shown the relationships between the characteristics of SM messages on NPOs' accounts and engagement. Regarding the purpose of messages, the information-community-action framework (Lovejoy & Saxton, 2012) has been widely used, but the results were contrasting: For example, one-way informational tweets were reported to be retweeted more than community- and action-based tweets in one study (Chung et al., 2020), while dialogic tweets were found to generate more public engagement in another study (Wang & Yang, 2020). Regarding the mode of messages, SM posts with visual or multimedia materials generally had more engagement than posts with only texts (Smith, 2018). In addition, the frequency of communication, such as the number of tweets, retweets, and mentions in NPOs' Twitter accounts, was found to be related to public engagement (Guo & Saxton, 2018).

However, there are relatively few studies on which characteristics of photos in NPOs' accounts draw more engagement from the public. Besides the general associations between multimedia materials and public engagement, little research has been conducted concerning which photo features are associated with the public's responses to organizational SM photos. In this study, we associate various photo features at the content and pixel levels with the public's responses to NPOs' Instagram accounts. Also, in addition to engagement, we use comment sentiment as another metric of the public's responses: The sentiment with which the public commented on organizational posts as well as how many likes and comments the posts received is also examined. The following research question is raised:

RQ3: How are the content- and pixel-level characteristics of NPOs' Instagram photos related to the public's responses?

Method

Research Sample

The lists of NPOs were obtained from the Top 100 Nonprofits on the Web (Nonprofit Times, n.d.), the Top 100 NGOs (The Global Journal, n.d.), and the UN-affiliated NGOs (n.d.). We visited the official website of each organization and acquired its Instagram account. Organizations without an Instagram account or whose number of posts on the account was fewer than 30 were excluded from the list. As a result, 175 Instagram accounts were selected as the research sample (see Table 1). All photos and metadata, including likes and comments, uploaded to the accounts were collected using Instagram-scraper (n.d.) on September 23, 2020, and 211,509 posts, 5,408,144 comments, and 524,848,625 likes were used for analysis.

Table 1. Instagram Accounts of NPOs in the Research Sample.

Account name
350org, aarp, actionagainsthunger, actionaidusa, acumenorg, aflatoun_international, stjude, alzassociation, aaasorg, americancancersociety, aclu_nationwide, amdiabetesassn, aei, american_heart, americanhumanist, americankidneyfund, amnh, americanredcross, aspca, americares, amnesty, amrefhealthafrica, antislaveryinternational, herorats, ashokachangemakers, barefootcollege, boyscoutsofamerica, bracworld, brothersbrotherfoundation, cambiahealth, careorg, catholicreliefservices, ccrjustice, centerconcern, charitywater, childrenssurgeryinternational, clevelandclinic, clintonfoundation, compassion, conservationorg, cfr_org, creativecommons, cf_foundation, danafarber, deliveringgood, directrelief, dosomething, doctorswithoutborders, earthcharterinternational, environmental_defense_fund, experimentabroad, fareshareuk, feedthechildrenorg, feedingamerica, focusonthefamily, friends_intl, geneva.call, girlscouts, globalfootprintnetwork, global_witness, globalgiving, gramvikasodisha, habitatforhumanity, harlemchildrenszone, humanrightscampaign, humanrightswatch, humanity_inclusion_us, injazalarab, international_alert, crisisgroup, internationalmedicalcorps, rescueorg, interpeace, ippnw_central, kickstart_international, kiva.org, landesaglobal, legacyintl, makeawishamerica, mapintl, mariestopes, mayoclinic, medicmobile, mentalhealthamerica, mercycorps, metmuseum, montereybayaquarium, movember, mfaboston, prochoiceamerica, audubonsociety, ul_ncfr, insidenatgeo, mssociety, nationalwildlife, nrdc_org, npr, napfofficial, oceana, one, oneacrefund, oneworldhealth, opensocietyfoundations, oregonzoo, oxfaminternational, panzifoundation, partnersinhealth, pathglobalhealth, pbs, philamuseum, planinternational, plannedparenthood, prathameducation, rainforestalliance, rare_org, rsfinternational, reprievehq, roomtoread, rooseveltntwrk, rootcapital, samaritanspurse, sandiegozoo, savethechildren, sfcg_, shrinershospitals, sierraclub, soroptimist, stepup4students, teachforamerica, ted, als, artinstitutechi, atlanticcouncil, thebigissuefoundation, thecartercenter, csis, christianbroadcastingnetwork, collegeboard, gatesfoundation, humanesociety, kennedycenter, leagueofwomenvoters, momaps1, nature_org, nypl, rotaryinternational, trevorproject, tostaninc, transparency_international, transparenthands, refugees, una.usa, unitednationshumanrights, unicefusa, unitedway, ushahidi, wainwrighthouseinc, waterforpeople, water, wemovement, wgbh, ngowgg, wikileaks, wikipedia, thewcs, witness_org, womensaction, wfwpi, worldbank, wfuna, wfpusa, worldvision, world_wildlife, worldymca, worldywca

Content Category, Content Tags, and Confidence Scores of Photos

Each photo in the research sample was categorized based on its content using Computer Vision application programming interface (API) in Microsoft Azure Cognitive Services (Microsoft, n.d.). The pretrained AI categorized a given photo into one of the 15 predetermined classes: *abstract*, *animal*, *building*, *dark*, *drink*, *food*, *indoor*, *others*, *outdoor*, *people*, *plant*, *object*, *sky*, *text*, or *transportation*.

The content tags and accompanying confidence scores suggested by the Computer Vision API were also used. For a given photo sent to the server through API, the pretrained AI suggested tags, which correspond to the photo content, with confidence scores that show the degree of correspondence.[2] For example, the following content tags and confidence scores were returned for the sample photo in Figure 1: valley (0.9831775426864624), ground (0.9821665287017822), mountain (0.9721373915672302), nature (0.9638031721115112), canyon (0.943977952003479), carnivore (0.9233812093734741), and animal (0.9041041135787964). These content tags and confidence scores can display the content of the photo.

Figure 1. A sample photo (American Museum of Natural History, 2013).

Clustering Photos and Accounts

The photos and the accounts were clustered respectively using k-means clustering. First, the photos in the research sample were transformed into vectors using the ResNet50 model (He, Zhang, Ren, & Sun, 2016), which was trained on the ImageNet (Deng et al., 2009) data set. Each photo was infused into the pretrained model, and the parameter values in the penultimate layer of the model were used as a photo vector with 2,048 dimensions. The transformation was performed using the img2vec-keras (n.d.) library. Then, the optimal number of photo clusters was determined using the elbow and the silhouette score methods (Yuan & Yang, 2019). As shown in Figure 2, the elbow (a) and the highest silhouette score (b) were observed when the number of clusters was three, which can be considered the optimal number of photo clusters. Thus, all photos in the research sample, regardless of their accounts, were clustered into three subgroups.

[2] For a given photo, a classification model can produce one of the two kinds of results: (a) a single class to which the photo can be assigned, or (b) probabilities that classes can be assigned to the photo. Generally, the number of predetermined classes is much larger in (b) than in (a) (e.g., 1,000 classes in ImageNet data set). In Computer Vision API, the classes and their probabilities are called content tags and confidence scores.

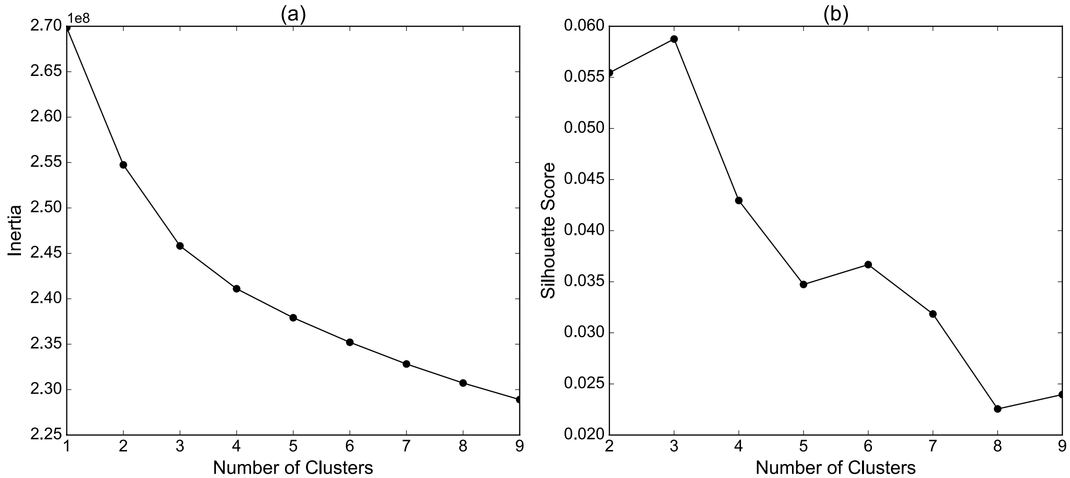

Figure 2. Finding the optimal number of photo clusters by (a) the elbow method and (b) the silhouette score method.

The accounts were also transformed into vectors. All photo vectors of an account were averaged in each dimension to generate the account vector. As in photo clusters, the optimal number of account clusters was determined. As shown in Figure 3, the elbow (a) and the highest silhouette score (b) were observed when the number of clusters was three, which can be considered the optimal number of account clusters. Thus, the accounts in the research sample were clustered into three subgroups.

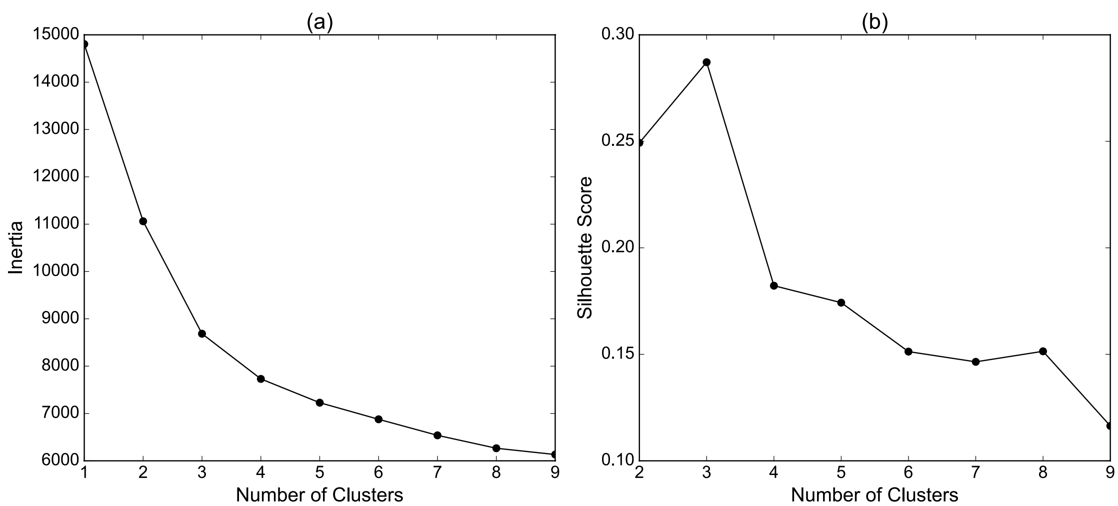

Figure 3. Finding the optimal number of account clusters by (a) the elbow method and (b) the silhouette score method.

Instagram Photo Features

Content Category Features

For a given account, the share of photos in each content class categorized in the above by Computer Vision API was measured. In addition, for the non-diversity in terms of the content of each account, the Gini coefficient[3] was also measured.

Facial Features

Features of human faces on each photo were extracted using Face API in Microsoft Azure Cognitive Services (Microsoft, n.d.). The pretrained AI detected human faces on a given photo and returned various kinds of information about the faces. Features extracted for analysis based on the information are as follows. *Number of faces* was counted on a given photo. *Close-up* was the ratio of the size of the biggest face on a given photo to the size of the photo, and *face ratio* was the ratio of the sum of all face sizes to the size of the photo. *Age* was the average age, and *gender* was the number of female faces estimated by Face API from the detected faces on a given photo. In addition, the relative strengths of eight classes of emotion were determined, by the values between 0 and 1, from each detected face so that the sum of all emotions on a given face became 1. The classes were *anger*, *contempt*, *disgust*, *fear*, *happiness*, *neutral*, *sadness*, and *surprise*, and the averages for each class on all faces in a given photo were used as analytic features.

Pixel Color Features

The information contained in pixels of a given photo was used to extract pixel-level features. The information can be expressed as RGB (red, green, and blue), HSV (hue, saturation, and value), or other color space models. In this study, the following color features of a given photo were extracted using Python programming language and OpenCV library.

First, respectively for RGB, all pixels in a given photo were averaged and their variances were also measured: The resulting features were *red mean*, *red variance*, *green mean*, *green variance*, *blue mean*, and *blue variance*. The same was performed for saturation and value (i.e., luminance): The resulting features were *saturation mean*, *saturation variance*, *value mean*, and *value variance*. Hue is a nominal feature unlike saturation and value, so its mean and variance were not used. Instead, a histogram was generated from hues in a given photo, and the number of peaks in the hue histogram (*hue peaks*) was counted: The number of local maximums of hue histogram, which was smoothed by Kernel density estimation, was counted. This metric is known to represent a given photo's being considered monotonous or mussy (Mao, Chen, & Muta, 2003).

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[3] Gini coefficient was originally developed for quantifying income inequality, and it has been used to quantify inequality in various domains. It can be calculated by the ratio between two areas in a triangle of cumulative shares: (a) the area under the imagined line of equality (45-degree line), (b) the area between the equality line and the distribution curve, and Gini coefficient is (b) divided by (a). See "Gini coefficient" (2022) for more information.

Visual Features

Measurement of how much a given photo looked visually attractive was carried out using the following features (San Pedro & Siersdorfer, 2009). First, *brightness* represents how bright a given photo is and was measured by the average of luminance (Y values in the YUV (luminance, blue projection, and red projection) color space) in the photos' pixels. *Colorfulness* stands for how colorful a given photo is and was measured using the metrics composed of relative amounts of RGB values in the pixels (Hasler & Süsstrunk, 2003). *Naturalness* denotes how much a given photo corresponds to the human perception of reality (Huang, Wang, & Wu, 2006), and it was measured using the proportion of pixels whose saturation and luminance fell within a certain range. *Contrast* is a metric of how local luminance is related to the surrounding luminance and was measured by the standard deviation of luminance in pixels divided by the number of pixels and *RGB contrast*, which extends contrast into the three-dimensional RGB color space, was measured as well. *Sharpness* is about a photo's clarity and level of detail, and it was measured by the Laplacian of each pixel's luminance normalized by the mean of local luminance in the surrounding pixels (Savakis, Etz, & Loui, 2000). Two visual features concerning color were also extracted. *Color diversity*, a metric of the diversity in colors of a given photo, was measured by the fractal dimension using the box-counting method (Feng, Lin, & Chen, 1996); it has been used for color diversity in previous studies (Kim, Son, & Jeong, 2014). And *color harmony*, a metric of how harmonious the dominant colors in a given photo are, was measured using the hue histogram mentioned above; the highest and the second-highest peaks were identified as the top two dominant colors, and the internal angle between the two colors on the color wheel is color harmony (Datta, Joshi, Li, & Wang, 2006).

The Public's Responses

The first measure of the public's response was engagement. It was measured by the number of likes and comments on a given photo, as in the previous study by Park, Reber, and Chon (2015). Another measure of the public's response was the sentiment expressed in the comments posted under a given photo. It was measured using the flair module (Akbik et al., 2019), which returned a score between −1 and 1, indicating the most negative and the most positive, respectively. Engagement and comment sentiment were averaged by accounts.

Results

The Overall Content in Instagram Photos (RQ1)

First, the overall content in the Instagram photos of NPOs was examined. Figure 4 shows the number of photos in each content category and the content tags with the highest confidence scores. It indicates that photos of people made up the largest share of NPOs' Instagram photos. Also, the content tags suggest that the persons in the photos were in clothing, showing their faces, smiling, and located mainly outdoors. Text was another major content of the photos. It made up the second-largest share and the third-highest confidence score; *abstract* in content category and *screenshot* and *design* in content tag might be related to the ways in which texts were presented in photos.

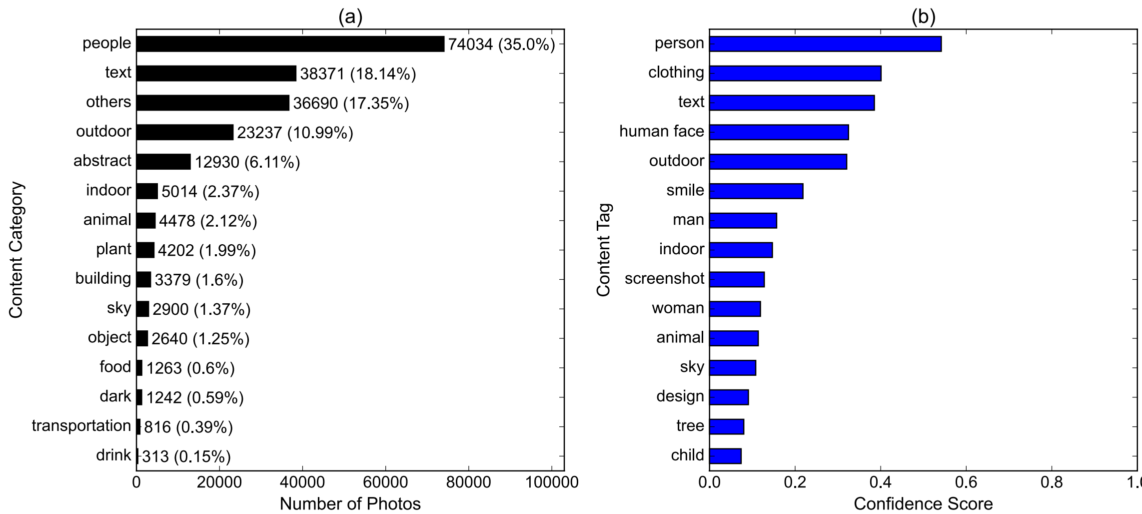


Figure 4. The content of NPOs' Instagram photos: (a) the frequency (and share) of photos by content category, and (b) content tags with the top 15 mean confidence scores.

Comparison Among Photo Clusters (RQ2a)

Three photo clusters were compared in terms of their content. Figure 5 presents content tags with the top 10 mean confidence scores and a sample photo closest to the centroid of each cluster. In the first cluster (68,147 photos), *outdoor*, *person*, *text*, and *animal* were included in the content tags with high confidence scores. This result indicates that the photos in the first cluster were mainly of persons and animals in outdoor settings. And the photos might contain texts in them. In the second cluster (103,188 photos), content tags such as *person*, *clothing*, *human face*, and *text* had high confidence scores. This illustrates that the photos in the second cluster were mostly of humans, especially human faces. The photos might also have texts in them. In the third cluster (40,174 photos), *text* was the content tag with the highest confidence score: It suggests that the photos in the third cluster were largely of texts, which probably manifest key messages. Content tags such as *person*, *clothing*, and *human face* followed: This indicates that humans also featured in the text-centric photos of the third cluster.

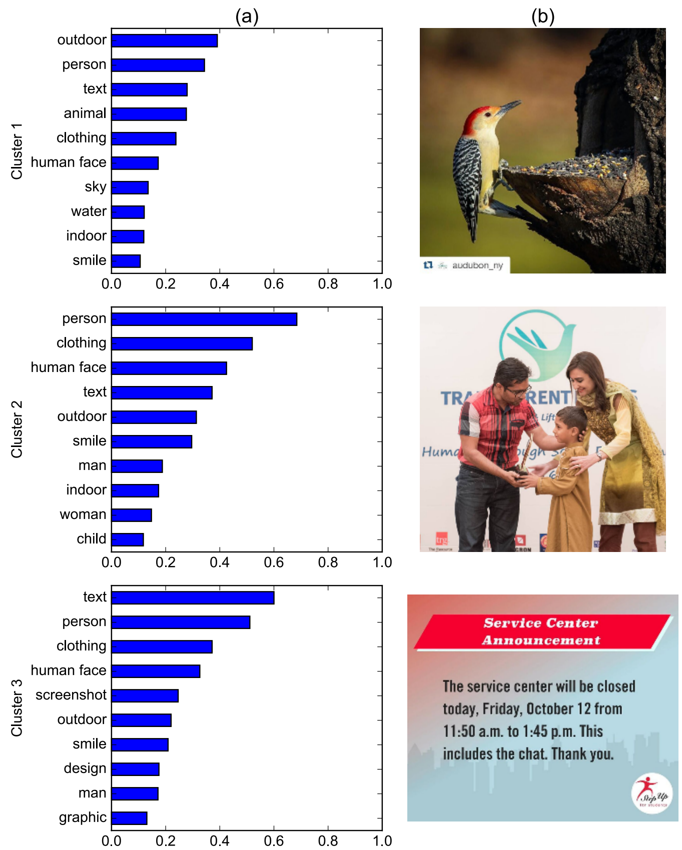


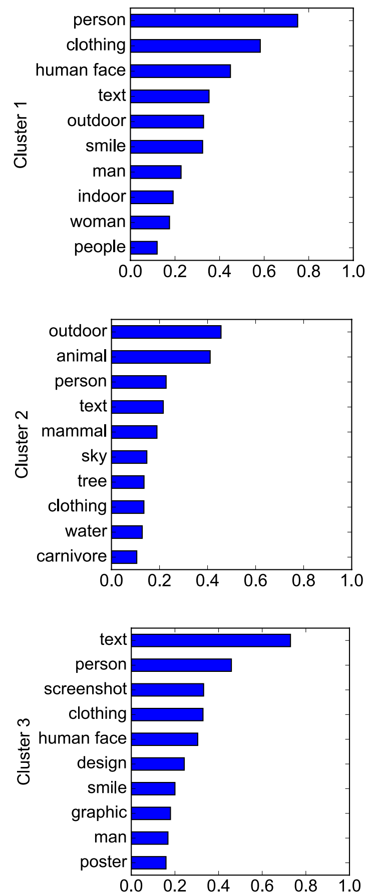
Figure 5. The content of photo clusters: (a) content tags with the top 10 mean confidence scores, and (b) a sample photo closest to the centroid of each cluster (National Audubon Society, 2015; Step Up For Students, 2018; Transparent Hands, 2016).

The photo clusters were compared in terms of photo features (see Table A.1 in Appendix for the full comparison table). Except for green and violet shares, all photo features differed by clusters. And the comparison exhibited characteristics of the photos in each cluster. Photos in cluster 1 contained younger human faces (less *age*) and fewer female faces (less *gender*) than those in other clusters. However, the faces were smaller (less *close-up*) and occupied less area in the photos (less *face ratio*). These results suggest that, in general, small faces of young boys were represented with animals in outdoor settings in the photos in cluster 1. Also, the photos in cluster 1 had smaller variances of red, green, blue, saturation, and value than those in other clusters. These smaller variances indicate that the photos in cluster 1 were relatively calm in color. The photos in cluster 2 included the most human faces on average (largest *number of faces*), and the *happiness* expressed on the faces was the strongest among the clusters. These results reveal that photos in cluster 2 were mainly of human faces, which manifested a happy emotion on them. In the photos in cluster 3, the means of red, green, blue, and value were significantly larger than those in other clusters, and *brightness* was the largest among clusters. These results suggest that photos in cluster 3 were brighter and more luminous than those in other clusters. This might have been due to the light background on which the texts were presented.

Comparison Among Account Clusters (RQ2b)

Three account clusters were compared in terms of their content. Figure 6 shows content tags with the top 10 mean confidence scores and 20 sample accounts closest to the centroid of each cluster. In the first cluster (101 accounts), content tags such as *person*, *clothing*, and *human face* had high confidence scores, and the sample accounts included the World Bank, the Rotary Foundation, Action Aid, and One World Health. It can be inferred that the accounts in the first cluster were mainly of human rights and relief/aid organizations, and their photos largely expressed persons and human faces. In the second cluster (26 accounts), content tags such as *outdoor* and *animal* had high confidence scores, and the sample accounts included the American Museum of Natural History, World Wildlife Fund, Rainforest Alliance, and Conservation International. These illustrate that the accounts in the second cluster were mainly of ecological and environmental organizations, and their photos were mostly of animals and persons in outdoor settings. In the third cluster (48 accounts), content tags such as *text*, *person*, and *screenshot* had high confidence scores. The sample accounts in this cluster look more diverse than others; organizations such as Transparency International, Mental Health America, Global Footprint Network, and the League of Women Voters were included. These suggest that the accounts in the third cluster were mainly of social movement organizations concerning various issues, and they uploaded photos containing text materials that could manifest their key messages.

(a)



(b)

World Bank, Legacy International, The Rotary Foundation of Rotary International, ActionAid USA, Water for people, Partners in Health, American Red Cross, Acumen Fund, The Carter Center, OneWorld Health, MAP International, GlobalGiving, United Way, Kiva, Americares foundation, International Rescue Committee, Mercy Corps, United Nations Human Rights, Human Rights Watch, Brother's Brother Foundation, Oxfam International

American Museum of Natural History, World Wildlife Fund, Environmental Defense Fund, Wikimedia Foundation, Rainforest Alliance, National Geographic Society, TED, Conservation International, National Wildlife Federation, Wildlife Conservation Society, Sierra Club, Natural Resources Defense Council, The Humane Society of the United States, Monterey Bay Aquarium, Philadelphia Museum of Art, Boy Scouts of America, Museum of Fine Arts, Boston, The Art Institute of Chicago, The Nature Conservancy

Transparency International, ONE, Mental Health America, Do Something, American Heart Association, NARAL Pro-Choice America Foundation, Global Footprint Network, American Kidney Fund, The League of Women Voters, Marie Stopes International, Nuclear Age Peace Foundation, American Civil Liberties Union Foundation, Earth Charter, World Young Women's Christian Association, Women's Action for New Directions, American Diabetes Association, The College Board, The ALS Association, WITNESS, Soroptimist International of the Americas

Figure 6. The content of account clusters: (a) content tags with the top 10 mean confidence scores, and (b) 20 sample accounts (organizations) closest to the centroid of each cluster.

Account clusters were compared in terms of their photo features (see Table A.2 in Appendix for the full comparison table). Other than a small number of exceptions, most of the photo features differed by clusters. And the comparison exhibited the characteristics of the accounts in each cluster. Accounts in cluster 1 had a higher share of photos of people and stronger *happiness* than those in other clusters. These results suggest that accounts in cluster 1 uploaded photos mainly of people who manifested happy emotions on their faces.

Accounts in cluster 2 had the highest share of photos of *animal*, *outdoor*, *plant*, and *sky* among the three clusters. These results indicate that photos uploaded to the accounts in this cluster were mostly of animals in outdoor and natural settings. And the least values of the *number of faces*, *close-up*, and *face ratio* among clusters suggest that the accounts in cluster 2 had fewer photos of human faces than those in other clusters. *Age* and *gender* were also the least among clusters; young boys seem to appear with animals in outdoor settings in the photos. Concerning pixel-level characteristics, the variances of red, green, blue, saturation, and value were the least in cluster 2. These small variances indicate that the photos in the cluster were relatively calm in color than those in other clusters.

Accounts in cluster 3 had the highest share of photos of text among clusters. It corresponds to the above result that *text* was the content tag with the highest confidence score in this cluster. Because texts are usually imprinted on a bright background, the photos in this cluster were brighter than those in other clusters: The means of red, green, blue, and value were the largest, and *brightness* was also the largest among clusters. At the same time, the texts and backgrounds might have made the photos in this cluster less saturated than others: *Saturation mean* was the least in cluster 3 among clusters.

Photo Features of Accounts and the Public's Responses (RQ3)

A correlation analysis was conducted between photo features of accounts and the public's responses. Table 2 presents the correlations between the content category features and the public's responses. As presented in the table, accounts with higher shares of photos of natural settings, such as *animal*, *outdoor*, *plant*, and *sky*, had higher engagement, but those with higher shares of photos of *people* and *text* had lower engagement. Also, the negative correlation between the *Gini coefficient* and engagement suggests that accounts whose photos were less diverse in content had less engagement. Concerning comment sentiment, the account with more photos of *indoor* and *people* had more positive comments, but those with more photos of *text* had more negative comments.

Table 2. Correlations Between the Content Category Features of Accounts and the Public's Responses.

	Engagement	Comment Sentiment
Abstract	.240*	−.167*
Animal	.328*	−.065
Building	.062	−.072
Dark	.137	−.063
Drink	−.008	.127
Food	.043	.102
Indoor	−.047	.163*
Others	.312*	−.050
Outdoor	.204*	.079
People	−.258*	.238*
Plant	.220*	.084
Object	.241*	−.020
Sky	.277*	.014
Text	−.165*	−.262*
Transportation	−.085	.103
Gini coefficient	−.277*	.020

Note. *$p < .05$.

Table 3 presents the correlations between the facial features of accounts and the public's responses. The results suggest that the accounts whose photos had more and larger faces had less engagement: *Number of faces*, *close-up*, and *face ratio* were negatively associated with engagement. The accounts whose photos expressed emotions of more *contempt*, *happiness*, *neutral*, and *surprise* had less engagement. And the accounts whose photos contained older and more female faces had less engagement. Concerning comment sentiment, accounts whose photos had more faces and more female faces received more positive comments. Also, accounts whose photos expressed happy emotions more strongly on the faces had more positive comments, but accounts whose photos expressed *anger* and *neutral* emotions more strongly had more negative comments.

Table 3. Correlations Between the Facial Features of Accounts and the Public's Responses.

	Engagement	Comment Sentiment
Number of faces	−.329*	.194*
Close-up	−.198*	−.101
Face ratio	−.229*	−.043
Age	−.338*	−.013
Gender	−.289*	.222*
Anger	−.098	−.208*
Contempt	−.166*	-.055
Disgust	−.117	.008
Fear	−.093	.020
Happiness	−.277*	.257*
Neutral	−.213*	−.184*
Sadness	−.144	−.118
Surprise	−.163*	.016

Note. *p < .05.

Table 4 presents the correlations between the pixel color features of accounts and the public's responses. As presented in the table, engagement is negatively associated with variances of red, green, blue, saturation, and value of photos. These results suggest that photos that were relatively calmer and less deviant in color were more helpful for the engagement of the accounts. The *red mean* was negatively associated with engagement. Concerning comment sentiment, accounts whose photos had higher *saturation mean* had more positive comments. And the negative correlation between *hue peaks* and comment sentiment indicates that mussier photos were associated with more negative comments to the accounts.

Table 4. Correlations Between the Pixel Color Features of Accounts and the Public's Responses.

	Engagement	Comment Sentiment
Red mean	−.161*	.036
Red variance	−.290*	.103
Green mean	−.099	−.008
Green variance	−.301*	.078
Blue mean	−.092	−.088
Blue variance	−.302*	.136
Saturation mean	.100	.209*
Saturation variance	−.190*	.120
Value mean	−.122	.025
Value variance	−.221*	.091
Hue peaks	−.012	−.189*

Note. *$p < .05$.

Table 5 presents the correlations between the visual features of accounts and the public's responses. The negative correlations of *colorfulness*, *contrast*, and *RGB contrast* with engagement suggest that accounts whose photos were more colorful and more vivid in contrast had less engagement. However, the positive correlation between *sharpness* and engagement indicates that accounts whose photos were clearer and more detailed had more engagement. Concerning comment sentiment, accounts whose photos were higher in *naturalness*, *color diversity*, and *color harmony* had more positive comments.

Table 5. Correlations Between the Visual Features of Accounts and the Public's Responses.

	Engagement	Comment Sentiment
Brightness	−.123	−.004
Colorfulness	−.152*	.128
Naturalness	−.098	.155*
Contrast	−.309*	.131
RGB contrast	−.320*	.142
Sharpness	.164*	−.086
Color diversity	−.075	.374*
Color harmony	−.080	.160*

Note. *$p < .05$.

Finally, predictive models were built and analyzed to examine how accurately photo features predict engagement and comment sentiment. Support vector regression models were trained with 10-fold cross-validation, and their root mean squared errors (RMSEs) were calculated (see Table 6). Their predictability was determined by comparing the RMSEs with the means and standard deviations (SDs) of engagement and comment sentiment: The mean engagement was 1469.868 (SD = 4021.130), and the mean comment sentiment was 0.284 (SD = 0.207). The comparison indicates that RMSE in engagement is relatively small considering the variation, and the photo features predicted engagement with an acceptable level of accuracy.

In contrast, it indicates that RMSE in comment sentiment is relatively large considering the variation, and the photo features did not predict comment sentiment properly.

Table 6. RMSEs of the 10-Fold Cross-Validation of Support Vector Regression to the Public's Responses.

	Engagement	Comment Sentiment
Content category features	36.708	0.378
Facial features	36.688	0.387
Pixel color features	36.713	0.388
Visual features	36.712	0.393
All features	36.712	0.368

Discussion and Conclusion

The major findings of this study are summarized and discussed as follows.

First, photos of people made up the largest share of NPOs' Instagram photos. It is no surprise that NPOs might show their activities by presenting people who were doing something in their photos. However, in previous studies, text rather than people was reported to be dominant in the Instagram photos of public health organizations (Kim & Kim, 2020) and a hashtag movement (Kim, Song, & Lee, 2020) possibly because texts embedded in photos can draw attention from the public more easily due to their bigger size and diverse style than caption texts. In fact, text was also crucial in the content of the photos in this study: It made up the second-largest share in the content category and was the third highest in confidence score of content tag. But the dominant share of people photos over text photos can be a distinctive characteristic of NPOs' Instagram photos because it shows that NPOs present themselves through photos that represent mainly people in them.

Next, three photo clusters were detected and found to be different in terms of their content- and pixel-level characteristics. The photos in the first cluster were largely of animals and contained small faces of young boys in outdoor settings. They were calmer in color than photos in other clusters. The photos in the second cluster were mainly of humans, especially faces looking happy. The photos in the third cluster were mostly of texts. They were generally brighter and more luminous than photos in other clusters. These clusters revealed the major elements of the visual representations in NPOs' Instagram photos. Although previous studies had analyzed visual data of NPOs (Auger, 2013; Waters & Jones, 2011), their analyses were centered on the purpose of the posts rather than their visual representations. To the best of the authors' knowledge, these detailed visual representations in NPOs' SM photos are being reported for the first time in this study.

In addition, three account clusters that differed in terms of their content- and pixel-level characteristics were found. The accounts in the first cluster were mainly of human rights and relief/aid organizations, and their photos were mainly of people, who expressed a happy emotion on their faces. The accounts in the second cluster were largely of ecological and environmental organizations, and their photos featured mainly animals with young boys in outdoor settings. Their photos were also calmer in color than those in other clusters. The accounts in the third cluster were mostly of social movement organizations concerning various issues, and their photos were mainly of text. Their photos were brighter and more luminous than those in other clusters. Although the organizations in the same cluster were not perfectly identical in terms of their activities, it can be possibly said that NPOs' field of activities tended to be reflected in the characteristics of photos on their Instagram accounts. In the literature, SM accounts of individual users were clustered and the differences among clusters were examined (Dietz et al., 2020). But this approach was rarely adopted for investigating organizational accounts, especially in terms of their visual representations. Thus, it is not easy to find similar results in the literature, and the results seem to be reported for the first time in this study.

Finally, one aspect of photo features was found to be associated with the public's responses. Engagement was positively correlated with the share of photos of natural settings but negatively correlated with the share of photos of people and text and the Gini coefficient. More and larger faces in photos were linked to less engagement, as were emotions such as contempt, happiness, neutrality, and surprise. Older faces and more female faces were linked to less engagement as well. Being calm in color, clearer, and more detailed in photos were positively associated with engagement but being colorful and vivid in contrast were negatively associated with it. Comment sentiment was positively correlated with the share of photos of indoor settings and people but negatively correlated with the share of photos of text. More faces and more female faces were linked to more positive comments. Happy emotion was linked to more positive comments, but anger and neutral emotions were linked to more negative comments. Being more saturated in photos was positively associated with the comment sentiment, but being mussy was negatively associated with it. Also, it was found that the engagement was predicted from the photo features with an acceptable level of accuracy, whereas the comment sentiment was not. Although a few studies on NPOs' SM communication have reported that posts containing visual materials had higher levels of engagement than others (Guidry, Jin, Orr, Messner, & Meganck, 2017; Smith, 2018), they rarely investigated exactly what characteristics of the posts contributed to the higher engagement. Additionally, the sentiments expressed in the comments made to the posts were scarcely used to examine the public's responses. Thus, it is hard to find prior works whose results can be compared with this study's results, which can be novel about NPOs' SM communication.

The above findings have implications for understanding NPOs' visual self-presentation on SM. The first and the second findings reveal that photos with which characteristics were used by NPOs for presenting themselves and engaging with the public: The overall content shows the major objects represented in the photos, and the photo clusters manifest the key elements and their characteristics of NPOs' visual self-presentation. The third finding shows that photos differed by NPOs' activity domains: This suggests that a similar strategy in visual presentation is shared among NPOs in the same domain. And the fourth finding indicates that photos with certain characteristics were associated with more (or less) positive public responses. These findings may contribute to our knowledge about NPOs' visual self-presentation by identifying what NPOs show to the public and how the organizations communicate with them. Photos have not been actively investigated in terms of their use in organizational communication on SM, and the findings of this study may fill this gap. The findings can have implications in that they expand the theoretical perspective of self-presentation to one by visual material. At the same time, the findings can have practical implications for NPOs in that they may help them to make their messages more appealing and receive better responses from the public. In methodological aspects, this study has shown that the clustering method can be useful for analyzing photo data. It has also illustrated how DNN-based features and other photo features can be used together; the former is better for performance, while the latter is better for human understanding. In addition, this study used various pixel-level features, which show the different and important aspects of photos that content analysis cannot.

The limitation of this study is that the relationships between post characteristics and the public's responses have not been considered from the theoretical perspectives of strategic communication. Future research is suggested to investigate the organizations' strategic goals and their relationships with the characteristics of their SNS posts based on theoretical frameworks such as information-community-action (Lovejoy & Saxton, 2012). Additionally, organizations in a particular field of activity, for example, medical, environmental, artistic, or political organizations, can be examined to understand how they visually represent themselves in SM photos. Furthermore, future research can investigate the link between organizations' offline activities and online visual representations.

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Appendix

Table A.1. Mean Comparison of Photo Features Among Photo Clusters.

	Photo Cluster 1	Photo Cluster 2	Photo Cluster 3	*F*
Number of faces	0.480	1.143	0.907	2491.656*
Close-up	0.008	0.021	0.016	1878.424*
Face ratio	0.010	0.027	0.021	2493.122*
Age	7.349	14.274	13.065	3374.192*
Gender	0.272	0.675	0.525	1989.083*
Anger	0.002	0.003	0.003	58.702*
Contempt	0.001	0.002	0.002	104.635*
Disgust	0.000	0.001	0.000	44.273*
Fear	0.000	0.001	0.000	17.323*
Happiness	0.118	0.301	0.224	4756.800*
Neutrality	0.101	0.191	0.160	1649.153*
Sadness	0.005	0.012	0.008	352.617*
Surprise	0.003	0.007	0.005	123.822*
Red mean	123.472	130.274	136.873	1095.044*
Red variance	4051.330	4641.390	4688.264	1877.462*
Green mean	118.814	119.973	128.908	763.495*
Green variance	3756.449	4355.245	4369.470	2131.476*
Blue mean	112.298	114.001	125.149	1116.023*
Blue variance	3789.375	4339.063	4281.177	1470.344*
Saturation mean	87.960	87.251	84.789	61.734*
Saturation variance	3174.841	3613.542	3611.034	874.489*
Value mean	139.343	143.672	153.066	1256.663*
Value variance	3834.395	4278.847	4134.439	1045.385*
Hue peaks	2.110	2.107	2.139	18.382*
Brightness	119.465	122.374	130.863	939.720*
Colorfulness	42.438	47.052	48.423	956.439*
Naturalness	0.471	0.522	0.505	319.023*
Contrast	56.684	61.093	60.401	1849.119*
RGB contrast	104.422	112.959	112.226	2480.590*
Sharpness	71459.821	66439.359	65841.337	186.558*
Color diversity	2.066	2.102	2.049	907.873*

Color harmony	45.592	48.511	46.783	179.025*

Note. *$p < .05$.

Table A.2. Mean Comparison of Photo Features Among Account Clusters.

	Account Cluster 1	Account Cluster 2	Account Cluster 3	*F*
Abstract	0.033	0.086	0.058	30.089*
Animal	0.001	0.087	0.002	49.080*
Building	0.012	0.018	0.011	2.554
Dark	0.004	0.011	0.005	14.181*
Drink	0.001	0.001	0.002	1.336
Food	0.005	0.009	0.004	2.300
Indoor	0.027	0.021	0.018	2.132
Others	0.138	0.275	0.141	66.480*
Outdoor	0.098	0.171	0.047	43.587*
People	0.507	0.131	0.250	170.140*
Plant	0.009	0.054	0.008	69.537*
Object	0.004	0.024	0.003	34.300*
Sky	0.004	0.030	0.008	44.873*
Text	0.151	0.079	0.440	201.043*
Transportation	0.005	0.003	0.003	5.583*
Gini	0.766	0.640	0.765	60.678*
Number of faces	1.290	0.258	0.919	76.333*
Close-up	0.021	0.005	0.016	25.907*
Face ratio	0.028	0.006	0.020	36.105*
Age	16.106	4.766	13.579	66.808*
Gender	0.774	0.138	0.576	45.428*
Anger	0.004	0.001	0.003	11.079*
Contempt	0.002	0.001	0.002	23.054*
Disgust	0.001	0.000	0.000	21.690*
Fear	0.001	0.000	0.000	10.576*
Happiness	0.324	0.063	0.219	59.634*
Neutrality	0.201	0.069	0.140	35.474*
Sadness	0.013	0.003	0.006	37.383*
Surprise	0.007	0.002	0.004	18.223*
Red mean	130.226	121.510	142.323	34.361*
Red variance	4757.124	3908.676	4703.374	44.286*
Green mean	119.991	117.366	134.064	34.953*
Green variance	4476.648	3620.188	4393.730	40.851*
Blue mean	113.478	108.128	131.603	68.946*

Blue variance	4500.419	3685.210	4249.262	33.794*
Saturation mean	87.794	88.283	83.273	3.581*
Saturation variance	3702.092	3064.637	3689.869	19.459*
Value mean	143.598	136.282	159.639	52.339*
Value variance	4417.878	3779.290	4017.688	30.531*
Hue peaks	2.090	2.094	2.198	10.694*
Brightness	122.311	117.552	136.255	42.378*
Colorfulness	47.847	41.109	50.802	17.349*
Naturalness	0.533	0.493	0.498	4.128*
Contrast	62.256	56.028	59.978	45.208*
RGB contrast	115.014	102.893	112.084	48.423*
Sharpness	66363.885	80895.013	63215.494	13.481*
Color diversity	2.125	2.079	2.028	38.682*
Color harmony	49.775	44.438	44.991	22.556*

Note. $*p < .05$.