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# What Makes Politicians' Instagram Posts Popular? Analyzing Social Media Strategies of Candidates and Office Holders with Computer Vision

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## Abstract

Previous research on the success of politicians' messages on social media has so far focused on a limited number of platforms, especially Facebook and Twitter, and predominately studied the effects of textual content. This research reported here applies computer vision analysis to a total of 59,020 image posts published by 172 Instagram accounts of U.S. politicians, both candidates and office holders, and examines how visual attributes influence audience engagement such as likes and comments. In particular, this study introduces an unsupervised approach that combines transfer learning and clustering techniques to discover hidden categories from large-scale visual data. The results reveal that different self-personalization strategies in visual media, for example, images featuring politicians in private, nonpolitical settings, showing faces, and displaying emotions, generally increase audience engagement. Yet, a significant portion of politician's Instagram posts still fell into the traditional, "politics-as-usual" type of political communication, showing professional settings and activities. The analysis explains how self-personalization is embodied in specific visual portrayals and how different self-presentation strategies affect audience engagement on a popular but less studied social media platform.

## Keywords

personalization, audience engagement, Instagram, virality, computer vision, image clustering, unsupervised learning

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While traditional political communication is often mediated by news coverage, social media platforms allow politicians to circumvent news gatekeepers to raise their profiles and directly communicate with citizens. As a consequence, there is growing interest in studying politicians' messages on social media and what makes them effective (Bene 2017; J. Lee and Xu 2018; McGregor et al. 2017; Metz et al. 2020; Rossini et al. 2018). Yet, this line of scholarship has so far focused on a limited number of platforms, especially Facebook and Twitter, while political communication is also vibrant on other social media platforms such as Instagram (Larsson 2019; O'Connell 2018). With 37 percent of U.S. adults reporting use of this site, Instagram has become the third most popular social media platform in the United States, following YouTube and Facebook.[1]

This research applies computer-assisted image analysis, or computer vision, to a total of 59,020 posts published by 172 Instagram accounts of U.S. politicians, including candidates and office holders, to examine how visual attributes influence audience engagement in the form of likes and comments. This study aims to advance our theoretical understanding of political communication on social media in several ways. First, previous studies tend to focus on how textual attributes influence the success of politicians' messages on social media (e.g., J. Lee and Xu 2018). Some studies have demonstrated the differential effects of using multimodal presentations—texts and visual elements—on user reactions (Bene 2017; Casas and Williams 2019; J. Lee and Xu 2018), yet the effects of specific visual attributes are less understood.

Research has also demonstrated the effectiveness of visuals in shaping viewers' judgment of politicians (Grabe and Bucy 2009; Joo et al. 2014; Peng 2018; Shah et al. 2016; Shah et al. 2015). There is a gap between the abundance of visuals in politicians' messages on social media and our understanding of how effectively different political messages influence audience engagement, however. To cite just one example, a common strategy on political social media is for candidates to personalize their campaigns, and empirical studies support the idea that self-personalization helps politicians gain favorable impressions (E.-J. Lee and Oh 2012; McGregor 2018; Meeks 2017). Yet there is a dearth of studies on the visual aspect of personalization. This study consequently engages with the concept of personalization and specifically examines how it is reflected in the visual representations of candidates and office holders.

Although the analysis of visual media is of theoretical importance, on a large scale it does pose methodological challenges to communication scholars. Researchers are now equipped with a wide range of natural language processing tools for analyzing textual data (Manikonda et al. 2016; McGregor et al. 2017; Peng 2017; Rossini et al. 2018). The field of computer vision, which trains computers to detect and recognize specific digital imagery, has also provided social scientists with potential tools of visual analysis (Joo et al. 2019; Peng 2018; Webb Williams et al. 2020). In particular, while scholars can utilize unsupervised learning tools such as topic modeling to discover latent patterns in a corpus of textual data, similar tools can also be useful for communication researchers to find potential categories in a large amount of visual media. This paper introduces an unsupervised approach that combines transfer learning and clustering to detect "visual topics" from digital images, in the hopes of enabling communication researchers to extract meaningful and interpretable patterns from the abundance of visual data that proliferates in today's political media environment.

## Personalization as a Multifaceted Concept

To provide a context for the analysis of candidate visual self-representations, this study highlights the concept of personalization, which has received growing attention in the scholarship of political social media strategy (Bene 2017; Larsson 2019; Meeks 2016; Metz et al. 2020). Scholars generally see personalization as a multifaceted concept. One prevalent approach proposes two components of personalization: (1) *individualization*, meaning that political communication increasingly focuses on specific candidates or politicians rather than parties, other institutions, or issues; and (2) *privatization*, which refers to the tendency of portrayals to depict politicians as private individuals rather than representatives of the people in public roles (Adam and Maier 2010; Holtz-Bacha et al. 2014; Van Aelst et al. 2012). Following this distinction, communications posted on politicians' personal social media accounts can be considered a form of individualized communication (Metz et al. 2020).

Beyond the individualization–privatization distinction, scholars have argued that the disclosure and expression of emotions should be conceptualized as another important element of personalization (Metz et al. 2020; Van Santen and Van Zoonen 2020). The emphasis on emotionalization, which describes communications about political events and experiences that are more distinctive for their emotionality than their policy substance, is recognized by Van Santen and Van Zoonen (2020) in their framework for assessing personalized political communications.

## Personalization and Social Media Engagement

A rich line of scholarship has examined what characteristics make online content popular or viral (Berger 2014). Noting that there is no consensus on the definition of "virality," this study takes a holistic view of virality as broadly encompassing a variety of online interaction behaviors such as viewing, liking, commenting, and sharing (Alhabash and McAlister 2015). Research has demonstrated that content that is likely to "go viral" and receive a substantial amount of engagement tends to provoke emotional arousal, contain information utility, and possess a novel or controversial quality (Berger 2014; Casas and Williams 2019). Interestingly, viral messages could be positive or negatively valenced, depending on the content domain.

Previous research on personalization sometimes assumes that personalized media coverage might disfavor political candidates, as this type of coverage might trivialize office seekers and render them irrelevant (Aday and Devitt 2001). However, empirical studies generally support the finding that self-personalization (and in particular, privatization) helps politicians emotionally connect with viewers and foster favorable impressions (Colliander et al. 2017; E.-J. Lee and Oh 2012; McGregor 2018; Meeks

2017). In experimental research, participants exposed to personalized tweets from candidates were more likely to report feeling a sense of parasocial interaction and social presence than those exposed to issue-oriented tweets alone (E.-J. Lee and Oh 2012; McGregor 2018). Viewers also perceived candidates who were presented in personalized terms on Twitter as more likable and capable of dealing with political issues than depersonalized candidates (Meeks 2017).

Analyses of social media data have shown that politicians' personalized posts garner more audience feedback in the form of likes and comments than depersonalized communications (Bene 2017; Larsson 2019; Metz et al. 2020). Among other reasons for this is that personalized content tends to be emotional, a content feature that drives virality (Berger 2014). In the Hungarian election of 2014, candidates' Facebook posts about family members attracted more likes and comments than posts about policy (Bene 2017). From an analysis of German parliament members' Facebook accounts, Metz et al. (2020) showed that posts disclosing politicians' private lives or emotional side induced more audience expressions of "sentiments" (i.e., likes and emojis) than depersonalized posts. Instagram, the focus of the present study, seems built for sharing personalized content. In an examination of posts generated by users of both Instagram and Twitter, Manikonda et al. (2016) showed that posts about nonpolitical content such as art, food, fitness, fashion, travel, friends, and family, prevailed on Instagram, whereas posts related to news, sports, and business were more popular on Twitter.

Despite the potential positive effects of personalization, research has documented that politicians still use social media in a traditional, "politics-as-usual" manner, that is, with a low level of personalization (Bene 2017; McGregor et al. 2017; Meeks 2016). Bene (2017) found that just 4 percent of candidates' Facebook posts during the 2014 Hungarian election could be classified as personal. McGregor et al. (2017) examined U.S. gubernatorial candidates that same year and revealed that only 7.3 percent of posts on Twitter and 9 percent on Facebook were personalized. Meeks (2016) analyzed U.S. Senate candidates' Twitter feeds in the 2012 election and found that 11.8 percent of the candidate tweets included elements of personalization.

## Personalization in Visual Media

How does personalization manifest itself in visual posts on Instagram? To answer this question, we first review research on personalization in textual contexts. From an analysis of campaign websites, Hermans and Vergeer (2013) identified three dimensions or foci of personalization: professional careers (e.g., official positions, political achievements), personal preferences (e.g., favorite music or sports), and family (e.g., marital status, children). Trimble et al. (2013) considered demographic and socially salient indicators of personalization, including gender, age, physical appearance, sexual identity/behavior, upbringing, marital status, and children.

In one of the few studies that systematically examined politicians' Instagram posts, O'Connell (2018) found that among the Instagram posts of members of Congress in the United States during the first six months of 2017, just 8.16 percent were categorized as personal, with the majority of posts (69.37%) classified as professional. Other types of posts also emerged, such as text description of political statements and issue positions (10.17%) and landscape photos featuring natural scenery without people (2.84%) (O'Connell 2018). Larsson (2019) analyzed the top 20 most liked and commented on Instagram posts from Norwegian party leaders and observed many posts reflect politicians' private lives. However, the analysis of personalization in visual media remains limited. Therefore, the current study adopted an unsupervised machine learning approach by first identifying the types of visual categories in politicians' Instagram posts. The first research question therefore asks:

> **Research Question 1 (RQ1):** What visual categories are presented in politicians' image posts on Instagram?

Given that previous research has found a positive influence of privatized communications on audience engagement, we would expect a similar outcome for visual representations of privatization. Therefore, the first hypothesis predicts that

> **Hypothesis 1 (H1):** Among the categories identified in RQ1, visual communications related to the nonpolitical, private lives of politicians are more likely to garner audience engagement (i.e., likes and comments) than communications related to the professional and political lives of politicians.

In the context of visual communication, showing faces might be a simple strategy of personalizing and cultivating close relationships with followers on social media. This research situates face disclosure as an aspect of personalization in visual media that is independent of privatization, as politicians can choose (or not) to show their faces both in professional and private settings. The strategy of showing faces should be particularly effective on a platform like Instagram, which is characterized by a prevalence of selfies (Deeb-Swihart et al. 2017). The act of self-disclosure, revealing personal information about oneself, often makes a person more liked by others (Collins and Miller 1994). Studies in computer-mediated communication also demonstrate that disclosing profile images fosters more favorable impressions among viewers (Feng et al. 2016).

Since humans are evolutionarily drawn to human faces (Valenza et al. 1996), it is possible that faces on social media will also be attention-getting (Bakhshi et al. 2014). Prior research has shown that on Instagram, pictures with faces are more likely to get likes and comments than posts without faces (Bakhshi et al. 2014). It is unclear, however, whether this tendency was due to people recognizing and engaging with faces they know or whether users are attracted to faces in general. Therefore, this study aims to isolate the effects of a politician's own face and contrast it with both the absence of any faces and the faces of others. We expect that images that foreground a politician's own face should get the highest engagement. We therefore predict that

> **Hypothesis 2 (H2):** Images with politicians' faces should attract more audience engagement than images without politicians' faces. Specifically, images with

politicians' *own* faces should get more engagement than images without faces (H2a) and images featuring only other people's faces (H2b).

Related to this, we expect that the relative size of a politician's face on the screen should also be positively associated with increased engagement, based on the tendency for larger objects to have higher visual saliency and a greater likelihood of attracting viewer attention (Proulx 2010). Therefore,

**Hypothesis 3 (H3):** The area that a politician's face occupies in an Instagram image should be positively associated with greater audience engagement.

This study also pays attention to politicians' facial expressions, which serve as important nonverbal cues (Grabe and Bucy 2009). Consistent with the argument that the expression of emotions should be conceptualized as an important element of personalization, Metz et al. (2020) found that Facebook posts published by politicians were more likely to invite expressed sentiments (likes and emojis) and comments if they involved emotional expressions of politicians or content with emotional appeal. Research has shown that emotional arousal, regardless of its positive or negative valence, drives content virality in general (Berger 2014). We thus expect that politicians' expressions of emotion should increase audience engagement. But does the direction of expressed emotion matter?

Indeed, it does. A recurring finding in the viral media literature is that negativity works effectively in propagating political messages on social media, especially Twitter (J. Lee and Xu 2018; Stromer-Galley et al. 2018). Analyzing tweets from candidates competing for U.S. governorships in 2014, Stromer-Galley et al. (2018) showed that candidates' attack messages got retweeted more than their advocacy tweets. J. Lee and Xu (2018) showed about half of Clinton and Trump's tweets in the 2016 presidential campaign were attack messages, which invited more retweets and likes than other types of messages.

While Twitter has developed a reputation for political hostility and negativity, Instagram has yet to fall into this bitter pattern and, as a primarily visual platform, might be more oriented toward positive self-presentation and sustaining social relationships than division. Some research confirms that the platform used drives the associated tone of communication. Manikonda et al. (2016) showed that the same group of users reported expressing more negative emotions and use of more work-related and swear words on Twitter, while reporting use of more social words related to home, family, and friends on Instagram.

During campaigns, displays of happiness typically make politicians look friendlier and more competent, leaving positive impressions among viewers (Joo et al. 2014; Peng 2018). We therefore expect that displays of happiness will also be associated with increased audience engagement. Yet, given some emerging platform-oriented norms, it is unclear if showing negative portrayals and expressions of emotion will be effective in driving engagement on Instagram, a platform that emphasizes positive self-presentations and social relationships. To explore these relationships, we propose a hypothesis and research question:

**Hypothesis 4 (H4):** Politicians' expression of positive emotion will be positively associated with increased audience engagement on Instagram.

**Research Question 2 (RQ2):** How does the expression of negative emotion by politicians influence audience engagement on Instagram?

## Computer Vision Methods in Computational Communication Research

In addition to documenting specific social media dynamics related to political messaging on Instagram, this paper aims to make a methodological contribution by exploring the potential of computer vision methods in analyzing political visuals. In the last decade, deep neural networks (DNNs) have become a popular technique for many computer vision tasks such as image classification. A DNN comprises an assemblage of connected neurons organized in multiple layers. In a feedforward DNN, each neuron receives inputs from neurons in the previous layer, performs computations, and passes outputs to connected neurons in the subsequent layer (Chollet 2017; Joo and Steinert-Threlkeld 2018). A convolutional neural network (CNN) is a specific category of DNN that has several types of layers, such as convolutional layers and max-pooling layers, that can handle the high dimensionality of image data (Chollet 2017; Joo and Steinert-Threlkeld 2018). A CNN learns local patterns from raw pixels of images. These patterns are (1) translation invariant, meaning that after a CNN learns a certain pattern in one part of an image, it can identify it in other places of the image, and (2) spatially hierarchical, meaning that after one CNN layer learns some small local patterns such as edges and color patches, the following layers can recognize more complicated and advanced patterns based on these simple patterns (Chollet 2017). These more complicated features are then used to recognize more complex and abstract visual concepts (Chollet 2017).

A review of the existing literature suggests that there are at least four approaches from the field of computer vision that can aid social scientists' endeavors in visual analysis. First, a wide range of open-source computer vision libraries (e.g., OpenFace) and commercial APIs (e.g., Face++, Microsoft Azure) can help researchers perform standardized and commonly used tasks, such as facial detection, emotion analysis, object detection, and optical character recognition (e.g., Peng 2018). Researchers can conveniently run analyses for a given input image, although they have to rely on a limited number of visual attributes preselected by these libraries or services. Researchers can also build prediction models for other outcomes using features provided by these tools (Joo et al. 2019).

Second, for supervised learning tasks, researchers can also prepare visual attributes by themselves and train a neural network to predict the labels (Joo and Steinert-Threlkeld 2018; Webb Williams et al. 2020). Typically, neural networks are trained on a large number, sometimes millions, of labeled images. With relatively small data sets, typically found in social sciences, researchers can resort to transfer learning techniques, that is, extracting features from (or fine-tuning) a pre-trained network that has been previously trained on a large data set (Chollet 2017). As noted, CNNs are able to recognize advanced and complicated features. These features are originally used to classify images in one training context, but they can be repurposed for a different task. By training a classifier with advanced features from pre-trained models and new labels, instead of training a brand-new model from raw pixels of images, researchers can achieve good accuracy with relatively small data sets.

Transfer learning has commonly been used for supervised learning, but scholars have also noted that this method can also be applied to unsupervised learning, for example, grouping objects in pictures into similar-looking categories (Guérin et al. 2017). Unlike supervised learning, unsupervised learning uncovers hidden patterns in data without pre-existing labels. The research reported here details a procedure of combining transfer learning (specifically, feature extraction) and clustering to detect visual topics from politicians' images.

Last, visual messages can not only be described in terms of content but also in terms of aesthetics. Scholars can now computationally calculate a variety of aesthetic features of images, including brightness, blur, color, and composition. Prior work has demonstrated associations between these visual attributes and outcomes such as image virality and aesthetic appeal (Ke et al. 2006; Peng and Jemmott 2018). Recent works have also started to harness the power of neural networks to assess the aesthetic appeal of images (Talebi and Milanfar 2018).

## Method

### *Sample*

The study sample, which was curated from a list of U.S. politicians in autumn 2018, included four groups: (1) candidates from the 2016 U.S. presidential primaries ($N$ = 29), including seventeen Republican, six Democratic, four third-party candidates (Gary Johnson, Jill Stein, Evan McMullin, and Darrell Castle), and two vice presidential candidates (Mike Pence, Tim Kaine); (2) governors ($N$ = 50); (3) senators in the 115th Congress ($N$ = 104), including four who ended their terms earlier; and (4) cabinet members of the Trump administration ($N$ = 30). Some politicians fell into multiple categories (e.g., Bernie Sanders). Duplicates were removed and a check was performed to make sure each politician in the database had an Instagram account. Private accounts and accounts with fewer than 20 posts were excluded. In some cases, a politician might have multiple accounts—these were kept in the sample. Altogether, 176 accounts representing 159 politicians (women = 19.5%, Democrat = 39.6%, Republican = 56.6%, mean age = 62.4), were included in the analysis.

This study retrieved each politician's entire Instagram feed published before 31 August 2018, along with each post's caption, publication date, and numbers of likes and comments.[2] Only publicly accessible posts from politicians were downloaded. The data collection occurred during the first week of September 2018. Videos were excluded from the data set. Regarding "carousel" posts, a type of Instagram post that contained multiple photos for viewers to swipe through, only the cover image was kept. The final sample included 59,020 images. Each account had 335.3 image posts on average ($SD$ = 415.7, $Mdn$ = 219.5).

### *Visual Categories*

The analysis adopted an unsupervised approach that combined transfer learning and clustering to categorize a large amount of visual data (Guérin et al. 2017). This procedure first converted each image to a vector of features with a pre-trained neural network. To decide which pre-trained model to use for feature extraction, it is important to consider the similarity between the data on which a model has been trained and the data to be analyzed. Many publicly available pre-trained models are trained on the ImageNet Large Scale Visual Recognition Challenge data set, which contains approximately 1.4 million labeled images grouped into 1,000 categories (Chollet 2017). The ImageNet data set uses categories mostly related to animals (e.g., *stingray*) and everyday objects (e.g., *joystick, volleyball*) and is frequently used for a general-purpose image classification task.

However, regarding politicians' images, one crucial aspect that distinguishes professional and personal photos is the setting in which politicians present themselves. The analysis thus integrated a data set about scene categorization, the Places365 data set, which contains about 1.8 million images of 365 scene categories (Zhou et al. 2017). Some scene categories in the Places365 data set clearly related to politicians' professional lives, such as *office, legislative chamber*, and *conference center*, whereas other categories like *kitchen* and *soccer field* were more reflective of politicians' private lives. Therefore, the analysis utilized a VGG16 model pre-trained on a combination of the ImageNet and Places365 data sets.[3]

Next, the analysis fed each image into this pre-trained model and extracted features from the third to last layer (fc2). The extracted features had 4,096 dimensions. A principal component analysis (PCA) was applied on these dimensions with scikit-learn, a machine learning library in Python. The first 200 factors (explaining 64.6% of the variance) were used in clustering.

The analysis then applied a commonly used clustering algorithm *k*-means. One challenge in *k*-means clustering is to choose the optimal number of clusters. This research adopted an approach that kept human interpretation in the loop. First, the model was repeatedly run with the number of clusters ranging from five to fifteen. Second, in each clustering solution, twenty images were randomly selected for inspection from each cluster and exploratorily examined to confirm whether the images classified into each cluster formulated a coherent category. This step of inspection identified four broad categories in the data set (see Table 1).

The first category, labeled "professional/political setting," featured people in professional or political settings, such as governmental buildings, legislative chambers, press conferences, offices, conference rooms, rallies, and protests. The second category, labeled "text/illustration," was comprised mostly of textual messages, figures, and illustrations. Politicians published this type of post to get their messages out, including policy positions, event announcements, and supporter mobilization efforts. These two categories were more related to the professional side of holding or seeking political office. The third category, "personal setting," showed individuals in private or nonpolitical settings, such as bars, restaurants, shops, gyms, homes, vehicles, streets, nature scenes, and settings that did not have clear visual cues related to politics (e.g.,

**Table 1.** Examples of Images in Each Category.

| Category | URL | Account | Short Description |
|---|---|---|---|
| Professional/political setting | https://www.instagram.com/p/INR3qlyqwf/ | philbryantms | Phil Bryant speaking to an audience in a chamber. |
| | https://instagram.com/p/mYZd1kubsZ/ | kirstengillibrand | Kirsten Gillibrand participating in a panel discussion at a conference. |
| | https://www.instagram.com/p/1_5sCfxiOA/ | massgovernor | Charlie Baker signing an executive order. |
| Text/illustration | https://www.instagram.com/p/7yBMaPrJuw/ | senjoniernst | Joni Ernst sharing a picture of the POW/MIA Flag. |
| | https://www.instagram.com/p/BVAf17rgYwG/ | realdonaldtrump | A quote from Donald Trump criticizing the "FAKE MSM." |
| | https://www.instagram.com/p/BYRSRV3D-P2/ | kamalaharris | Kamala Harris posting a message about Women's Equality Day. |
| Personal setting | https://www.instagram.com/p/BUFesB4jGcC/ | senatormenendez | Bob Menendez with his mother. |
| | https://www.instagram.com/p/Bgw-zhQBzgz/ | nikkihaley | Nikki Haley with her dog. |
| | https://instagram.com/p/33npEfhPGu/ | govmikehuckabee | Mike Huckabee chatting with people in a restaurant. |
| Architecture/landscape | https://www.instagram.com/p/BeHE18znfQh/ | Senatormartinheinrich | Martin Heinrich sharing a photo of White Sands National Monument. |
| | https://www.instagram.com/p/BHbClW7hJoh/ | nygovcuomo | Andrew M. Cuomo sharing a photo of One World Trade Center. |
| | https://www.instagram.com/p/7_Go_rkEyF/ | senatortimscott | Tim Scott sharing a photo of Lake Greenwood. |

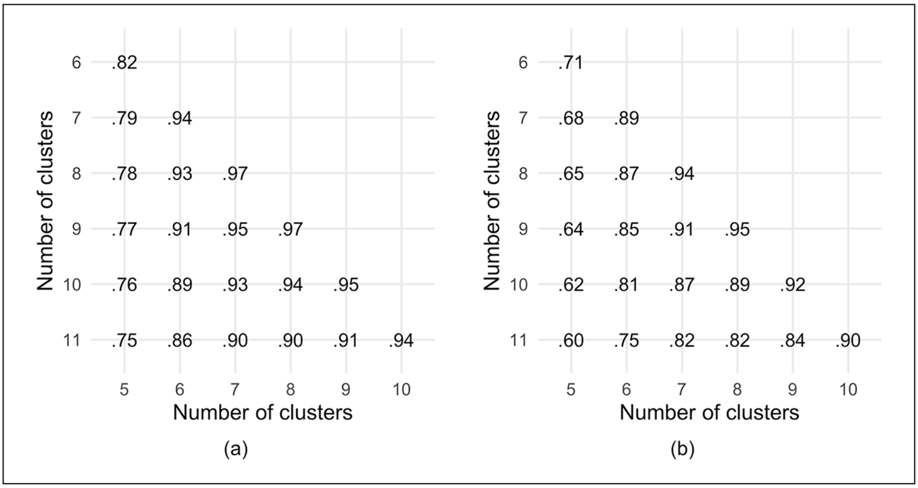


**Figure 1.** Agreement on visual categories coded from different clustering solutions: (a) percent agreement and (b) Cohen's kappa.

a blurred background or wall). The fourth category, "architecture/landscape," featured views of buildings, structures, and landscapes, often in the absence of people. These latter two categories were more related to the nonpolitical or private side of politicians.

Next, each cluster in each solution was then assigned to one of the four categories based on the twenty images selected from each cluster. This step applied the assigned category to all of the images within that cluster. For example, if one cluster was assigned to the "architecture/landscape" category, the label "architecture/landscape" was then assumed to apply to every image in that cluster. This step of analysis also suggested that when the number of clusters was too many (e.g., more than twelve clusters), some clusters did not have the majority of images (>50%) clearly fitting into one category. These solutions were removed from consideration.[4]

Two additional steps were taken to validate this process. To begin with, the agreement between each pair of clustering solutions (5–11 clusters) regarding whether images were consistently assigned to the same category was calculated. With the exception of the five-cluster solution, the assigned categories based on different clustering solutions were relatively consistent. There was generally over 80 or 90 percent agreement among different clustering solutions (Figure 1) and the percentages of images in each category in the data set were also similar (Figure 2), suggesting this method classified images into the four categories in a relatively reliably way.

In addition, a total of six clustering solutions (6–11 clusters) were selected for further validation. For each solution, twenty images were randomly inspected from the four categories and checked for whether they matched their assigned categories. Results suggested that in general, 75 to 95 percent of the images in each of the four categories were classified correctly. The current study presents the results from the

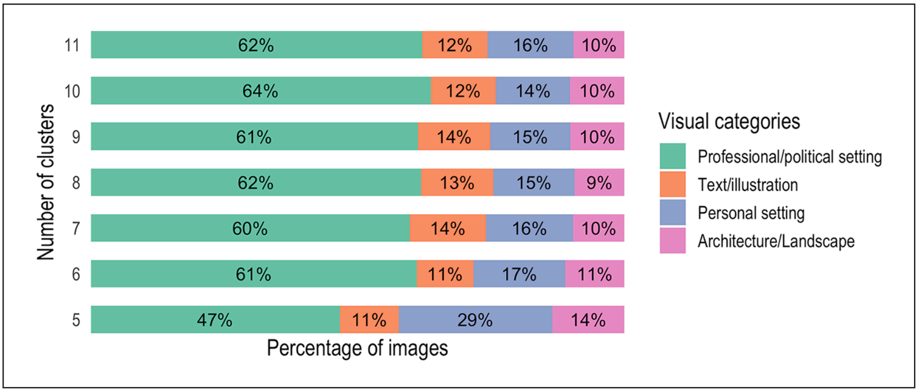


**Figure 2.** Percentages of images assigned to the four categories based on different clustering solutions.

11-cluster solution, in which 90, 80, 80, and 80 percent of the images in the four categories were identified correctly, respectively (see Supplementary Information file).

## *Facial Analysis*

For facial analysis of the politician images, this study used Face++, a computer vision API that specializes in facial detection and recognition. A target face set that included faces of all the politicians sampled in this study was first prepared.[5] For each image in the data set, the facial recognition algorithm detected whether the image featured a face or not. Next, for each detected face, the algorithm compared this face to all the faces in the target face set and returned the most similar-looking face. The majority (72.7%) of posts contained at least one face ($M = 3.0$, $SD = 4.4$). Each post had on average 0.44 ($SD = 0.57$) faces belonging to the politician who owned the account and 2.56 ($SD = 4.19$) faces of other people. A manual validation suggested that the facial recognition algorithm accurately identified politicians' faces, especially when faces were near-frontal, not blocked, not blurry, and not too small (see Supplementary Information file).

Based on the facial recognition results, the analysis compared four types of images to isolate the effects of a politician's own face compared to other people's faces: images with no face (27.3%), images with only the politician's face (7.9%), images with only faces of other people (31.7%), images with both the politician's face and other people's faces (33.0%).

For politicians' face size and emotional expression, the analysis only included images ($N = 24{,}190$, 41.0%) that contained at least one face of the politician. First, Face++ provided the location of the face as a rectangle. The analysis calculated how much area the politician's face occupied in the whole image, measured as the ratio between the size of the facial rectangle and the whole image (Peng 2018). Natural log transformation was applied for easier interpretation. In addition, Face++ also provided the probability of occurrence for seven discrete emotional expressions (i.e., happiness, anger, sadness, disgust, surprise, fear, and neutral emotion) ranging from 0 to 1. The analysis included the expression of happiness ($M = 0.64$, $SD = 0.43$) and combined negative emotions (all other emotions detected except happiness and neutral, $M = 0.16$, $SD = 0.29$) in the politician' faces. Since all the emotions added to a constant of one, neutral expressions were treated as the baseline for comparison. For pictures featuring multiple faces of the same politician (e.g., a photo collage), average values were used.

### Control Variables

The analysis controlled for (1) aesthetic features commonly found to influence image popularity, including brightness, contrast, colorfulness, and visual complexity (see Supplementary Information file); (2) the number of days between the day when the account's first post in the data set was published and the day when this particular post was published; (3) characteristics of each post's caption, including word count and percentages of positive/negative emotion words (calculated by Linguistic Inquiry and Word Count) as well as the numbers of mentions (@) and hashtags (#); (4) politician characteristics, including gender, age, race, party affiliation, and political role (e.g., senator, governors, presidential candidate, cabinet member); and (5) account characteristics, including the numbers of followers, accounts following, and posts.

## Results

With an R package lme4, a series of multilevel regression analyses ($N = 59{,}020$) examined what visual features predicted audience engagement for each image post (Table 2). The analyses treated accounts ($N = 176$) as random effects. Visual categories, facial features, and control variables mentioned earlier were included as fixed effects. To facilitate statistical analysis, natural log transformation was applied to the two highly skewed dependent variables, the numbers of likes (skew = 7.5) and comments (skew = 230.1) a photo received.

### Visual Categories

RQ1 asks what visual categories are present in politicians' images. As noted, the clustering method identified four broad categories (Table 1), including two related to the professional and political side of politicians, *professional/political setting* (62.1%) and *text/illustration* (12.3%), and two related to the personal side of politicians, *personal setting* (16.1%) and *architecture/landscape* (9.5%).

The analysis then looked at how audiences liked different visual categories (H1). The category professional/political setting was treated as the reference group. The other politics-related category, text/illustration, did not significantly differ from the

**Table 2.** Multilevel Analyses Predicting the Numbers of Likes and Comments.

| | Likes | (Log-Trans.) | Comments | (Log-Trans.) |
|---|---|---|---|---|
| | *b* | 95% CI | *b* | 95% CI |
| Estimates of fixed effects | | | | |
| Politician characteristics | | | | |
| Women | 0.18 | [−0.18, 0.54] | 0.01 | [−0.23, 0.25] |
| (ref. = Republican) Democrat | −0.01 | [−0.31, 0.28] | −0.10 | [−0.29, 0.10] |
| Independent | 0.57 | [−0.20, 1.35] | 0.33 | [−0.18, 0.84] |
| (ref. = mixed[a]) Senate | −1.07*** | [−1.64, −0.50] | −0.75*** | [−1.13, −0.38] |
| Governor | −0.59 | [−1.19, 0.01] | −0.53* | [−0.93, −0.14] |
| Cabinet | −0.31 | [−1.12, 0.49] | −0.12 | [−0.66, 0.41] |
| Presidential candidate | 0.24 | [−0.45, 0.92] | 0.04 | [−0.41, 0.50] |
| Nonwhite | −0.40 | [−1.00, 0.21] | −0.44* | [−0.84, −0.04] |
| Age | 0.00 | [−0.01, 0.02] | 0.01 | [0.00, 0.02] |
| Visual category (ref. = professional/political setting) | | | | |
| Text/illustration | −0.01 | [−0.03, 0.01] | 0.12*** | [0.10, 0.15] |
| Personal setting | 0.19*** | [0.17, 0.21] | 0.15*** | [0.13, 0.17] |
| Architecture/ landscape | 0.14*** | [0.12, 0.16] | 0.00 | [−0.03, 0.02] |
| Face category (ref. = no faces) | | | | |
| Politician's face only | 0.26*** | [0.23, 0.28] | 0.30*** | [0.27, 0.33] |
| Other faces only | 0.06*** | [0.04, 0.08] | 0.02* | [0.00, 0.04] |
| Politician with other faces | 0.12*** | [0.10, 0.13] | 0.07*** | [0.05, 0.09] |
| Standard deviations of random effects | | | | |
| Accounts ($N$ = 176) | 0.92 | | 0.60 | |
| Residual | 0.62 | | 0.76 | |

*Note.* $N$ = 59,020. Unstandardized regression coefficients are shown. The full results including all the control variables are in the Supplementary Information file (Table S1). CI = confidence interval.
a. Politicians belonging to multiple categories.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

reference category. In comparison, the personal setting category ($b = 0.19, p < .001$) and the architecture/landscape category positively contributed to likes ($b = 0.14$, $p < .001$). The outcome variable was log-transformed. Compared with images in the reference category, images in these two categories attracted more likes by 21 and 15 percent, respectively.

The engagement pattern was slightly different for comments. Compared with the professional setting category, the text/illustration category attracted more comments by 13 percent ($b = 0.12, p < .001$). Regarding nonpolitical categories, the personal setting category still invited a large number of comments with a 16 percent increase

($b = 0.15$, $p < .001$). But the architecture/landscape cluster, although aesthetically appealing and likable, did not influence comments. Overall, the hypothesis (H1) that nonpolitical, personal categories would receive more audience engagement was well-supported regarding likes, but only received partial support regarding comments. Consistent with H1, the personal setting category received more comments than the professional setting category. Yet, the architecture/landscape category, another nonpolitical category, did not significantly differ from the professional setting category and actually received fewer comments than the text/illustration category, which contradicted H1.

## *Face Disclosure*

To examine the effects of face disclosure, images without faces were treated as the reference group. Compared to pictures with no faces, the other three categories, images featuring only the politician ($b = 0.26$, $p < .001$), images featuring only other people ($b = 0.06$, $p < .001$), and images featuring the politician with other people ($b = 0.12$, $p < .001$), were all associated with an increase in likes. Images with only the politician's face received the highest increase in likes (29%), followed by images featuring the politician with other people (12%) and images featuring other people's faces only (6%).

A similar pattern occurred for comments. Images with faces received more comments, with posts only featuring the politician's face resulting in the highest increase of 35 percent ($b = 0.30$, $p < .001$). Images featuring the politician with other people and images with other faces were associated with a 7 percent ($b = 0.07$, $p < .001$) and 2 percent ($b = 0.02$, $p = .045$) increase in comments, respectively. In summary, faces, in general, drove audience engagement. Images featuring politicians' own faces only were the most effective in spurring engagement, followed by images featuring politicians with other faces, images containing only other faces, and images without faces.[6] H2a and H2b were supported.

## *Face Size and Emotional Expressions*

Last, the analysis investigated the effects of politicians' face size and emotional expressions. The following multilevel analyses only included images featuring politician's faces ($N = 24{,}190$; Table 3). First, compared with images featuring a politician's face only, images featuring both the politician and other faces received fewer likes by 10 percent ($b = -0.11$, $p < .001$) and fewer comments by 15 percent ($b = -0.17$, $p < .001$), confirming the previous observation that the politician's own face attracted the most engagement. Face size positively contributed to both likes ($b = 0.10$, $p < .001$) and comments ($b = 0.11$, $p < .001$), supporting H3. When face size doubled, a post's likes and comments increased by 7 and 8 percent, respectively.

Regarding emotional expressions, the expression of neutral emotion was treated as the baseline for comparison. Facial displays of happiness positively influenced likes ($b = 0.06$, $p < .001$): indeed, happy faces received 7 percent more likes than neutral

**Table 3.** Multilevel Analyses Predicting the Numbers of Likes and Comments (Only Including Images Containing the Politician's Face).

| | Likes | (Log-Trans.) | Comments | (Log-Trans.) |
|---|---|---|---|---|
| | *b* | 95% CI | *b* | 95% CI |
| Estimates of Fixed Effects | | | | |
| Visual category (ref. = professional/political setting) | | | | |
| Text/illustration | 0.09** | [0.03, 0.15] | 0.31*** | [0.23, 0.38] |
| Personal setting | 0.13*** | [0.10, 0.15] | 0.07*** | [0.04, 0.11] |
| Architecture/ landscape | 0.29*** | [0.21, 0.36] | 0.16*** | [0.07, 0.25] |
| Face category (ref. = Politician's face only) | | | | |
| Politician with other faces | −0.11*** | [−0.13, −0.09] | −0.17*** | [−0.19, −0.14] |
| Facial features | | | | |
| Face size (log-trans.) | 0.10*** | [0.09, 0.11] | 0.11*** | [0.10, 0.12] |
| Happiness | 0.06*** | [0.04, 0.09] | 0.00 | [−0.03, 0.03] |
| Negative emotions | 0.06*** | [0.02, 0.09] | 0.04 | [−0.01, 0.08] |
| Standard deviations of random effects | | | | |
| Accounts ($N$ = 176) | 0.90 | | 0.60 | |
| Residual | 0.60 | | 0.76 | |

*Note.* $N$ = 24,190. Unstandardized regression coefficients are shown. The full results including all the control variables are in the Supplementary Information file (Table S2). CI = confidence interval.
*$p < .05$. **$p < .01$. ***$p < .001$.

faces. However, happiness did not influence the number of comments. H4 thus received partial support only regarding likes. Regarding RQ2, the expression of negative emotion increased a post's likes by 6 percent ($b = 0.06$, $p < .001$), but did not influence comments.

## Discussion

In summary, this research advances our understanding of politicians' use of social media platforms, specifically Instagram, and how different self-personalization strategies influence audience engagement. This study specifies different self-personalization strategies in visual media, for example, appearing in private, nonpolitical settings, showing one's face, and displaying emotions, and empirically shows that these strategies generally increase audience engagement. Beyond contributing to a theoretical dialogue with the social media political communication literature, this study also illustrates the potential of applying computer vision techniques in political communication research. In particular, this study describes an unsupervised approach to analysis that combines transfer learning and clustering to extract "visual topics" from large-scale visual media, which could be applied in future research.[7]

### *Personalization Strategies on Social Media*

The analysis reported here examined the effects of different content categories on audience engagement, with an emphasis on the role of privatization. A significant portion of politician's Instagram posts still fell into the traditional, "politics-as-usual" type of political communication, showing professional activities, but this type of content was generally less successful in attracting engagement. Instead, nonpolitical and private content from politicians generally attracted more engagement such as likes and, less consistently, comments from audiences than political content. This result echoes previous studies showing that politicians' personalized content often receives more audience reactions on Facebook (Bene 2017; Metz et al. 2020).

Due to the "social" nature of social media platforms, users might prefer more intimate content from politicians and expect them to communicate and share aspects of their daily lives more like an everyday person than like a politician (Bene 2017). The preference for personalized content could also be due to a "novelty" factor: As politicians' Instagram feeds remain preoccupied with more traditional type of self-portrayals, personalized pictures garner more likes and comments because they are still somewhat unusual for politicians to share, thus receiving greater attention from viewers.

This study also reveals that some content categories distinctly influence the volume of likes and comments, indicating that social media users might have different psychological motivations when liking and commenting on politicians' posts. Because political visuals are more intuitive than textual messages and don't require linguistic parsing, liking an image might be less cognitively demanding than commenting on a message (Alhabash and McAlister 2015). Liking also typically signals a positive evaluation of a media message while comments can be of mixed sentiment (Peng and Jemmott 2018).

In the results, textual messages used by politicians, while not getting many likes, led to substantially more comments. This revealed that texts added to visual images could provoke more thoughts or cognitive efforts among viewers, reinforcing previous findings from Facebook that text posts from politicians get more comments than likes (Bene 2017). In comparison, images of architecture and landscape, while attracting a large number of likes, failed to get many comments. This type of image might be aesthetically likable and serve as "eye candy" in politicians' newsfeeds but does not provoke conversations among followers.[8]

This study also examined the effectiveness of showing faces as a personalization strategy in visual media. Prior research has shown that on social media, pictures with faces are more likely to get likes and comments than pictures without faces (Bakhshi et al. 2014). It is unknown, however, whether this tendency is due to the fact that people engage with generic faces or that people are attracted to the faces of account holders they are following. This research showed that although the presence of faces did increase audience engagement overall, politicians' own faces were the most effective in enhancing audience engagement. This finding indicates that social media users react positively to images with faces primarily because they can recognize them and build a kind of social connection.

In addition, larger faces also garnered more attention and engagement from audiences. This finding is consistent with research on "face-ism," which posits that the prominence of faces in visual representations tend to make a person look more favorable (Archer et al. 1983), but might contradict some findings that large faces in media outlets can elicit negative evaluation of politicians (Peng 2018). This could be due to the fact that politicians' Instagram posts are generally positive self-presentations and do not feature extreme close-ups, which tend to be associated with negative portrayals in news outlets (Grabe and Bucy 2009).

This study also shows the positive effect of displaying emotions as a personalizing strategy on audience engagement. Prior research on virality suggests that content with the capacity to provoke emotional arousal, regardless of valence, is likely to go viral (Berger 2014). Similarly, the current study found that facial expressions of both positive and negative emotion increase likes for politicians at a higher rate than visual portrayals showing neutral emotion. This pattern is also consistent with our observations regarding captions (see Supplementary Information file): posts with captions containing either positively or negatively valenced words were associated with more likes and comments. Therefore, although Instagram is generally oriented toward positive self-presentation and building social connections, users might still be drawn to negative messages from politicians when it comes to politics.

### *Effects of Personalization beyond Audience Engagement*

While this research reveals the effectiveness of personalization strategies in visual content regarding audience engagement, future studies can investigate how personalization influences user activity beyond social media engagement. Prior research has shown that personalization can elicit more positive impressions and make viewers feel more connected with a politician (E.-J. Lee and Oh 2012; McGregor 2018). By personalizing on social media, politicians might present themselves as relatable and approachable, but this strategy might also render themselves as less serious contenders and distract viewers from more substantial issues such as their policy positions.

Experimental studies have revealed an innuendo effect in person perception that reveals the weaknesses of certain study designs: when media coverage of a politician only focuses on one of the two trait dimensions, warmth and competence (i.e., only as friendly or only as competent), viewers would rate the politician more negative on the other dimension (Koch and Obermaier 2016). In addition, while personalization might produce positive effects among less politically involved viewers, more politically engaged voters could be less drawn to personalized coverage and prefer policy pronouncements; hence, sharing images in this case could further develop negative feelings toward politicians (E.-J. Lee and Oh 2012).

Nevertheless, politicians on social media platforms rarely use personalized content alone. Consistent with prior research (O'Connell 2018), the results show that personalized content is outweighed by more traditional, "politics-as-usual" posts. It is unlikely that personalized posts on Instagram overshadow politicians' delivery of policy stances or display of more politically relevant qualities. Future studies can examine how a combination of varying self-presentation strategies, which represents a more realistic scenario on social media, affects the evaluation of politicians.

### *Limitations and Future Research*

While this study provides valuable insights into Instagram, a popular but less examined platform (Larsson 2019; O'Connell 2018), the choice of examining this particular platform might shape the observations of this research. The majority of Instagram users do not turn to this site for political content. Only 32 percent of Instagram users reported getting news on this platform, compared with 71 percent on Twitter and 67 percent on Facebook.[9] This might contribute to the pattern of nonpolitical content performing better in getting people's attention. Regarding interaction behaviors, Instagram prioritizes liking over other interaction behaviors such as reposting, which might encourage more positive self-portrayals. Hence, a direction for future research might be to look beyond a single social media platform and compare audience responses to politicians' self-presentations across different sites.

This research also shows that computer vision techniques can greatly expand the scope of visual analysis in political communication and demonstrates the utility of an unsupervised approach to categorizing political visuals. The proposed approach is not without limitations. Certain images were assigned to the wrong categories. Some misclassifications could be due to the tendency of the clustering algorithm grouping visually similar-looking images based on transfer learning features without knowing the actual content of the images. For example, some pictures of still objects such as a medal were categorized as text/illustration, as these images often had words or patterns that looked similar to captioned images.

Also, some images might be ambiguous and can be assigned into multiple categories. For example, an image showing a text statement on a natural scene background might be assigned to both the text and the landscape category. If such images are prevalent in the data set, it might be more appropriate to apply a mixed-membership clustering method instead of the single-membership method used in this study, *k*-means. In addition, although the pre-trained models used in this study were primarily about everyday objects and scenes, it is unknown if the extracted features might still incorporate gender, racial, or cultural biases, which should be further investigated. Future research can experiment with different pre-trained models, clustering algorithms, and analytical procedures to improve the performance of this approach.

Future research can also apply computer vision methods to analyze political videos on social media. Videos have been frequently used in political communication and some studies have already applied computational methods in analyzing effects of political videos (Joo et al. 2019; Shah et al. 2016; Shah et al. 2015). Combining computational textual analysis and visual analysis is another promising research direction. While this study only looked at the number of comments given to politicians' posts, analyzing social media users' comments should give us more insights into viewers' interpretations of these visual portrayals.

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## Supplemental Material

Supplemental material for this article is available online.

## Notes

1. https://www.pewinternet.org/fact-sheet/social-media/
2. For data collection, this study used a program called 4K Stogram (https://www.4kdownload.com/products/product-stogram) to download each account's posts and a Python script to retrieve each post's meta data (e.g., caption, number of likes and comments) using Selenium. For more discussion about the ethics of web scraping in computational communication research, see Freelon (2018).
3. The pre-trained model (VGG16-hybrid1365) is available at https://github.com/GKalliatakis/Keras-VGG16-places365.
4. The randomly selected images from each cluster, the assigned categories, and the randomly selected images from each category are available at https://osf.io/9fmw5/
5. To prepare the target face set, Google image search was used to download a collection of images of each politician. For each politician, the face set included three pictures that featured only one frontal face of the politician that was of good resolution and was in focus.
6. The differences among the four categories regarding likes and comments were all statistically significant, as indicated by additional regression analyses using the images with other faces only and images featuring politicians with others as the reference groups.
7. Supporting data and Python codes can be found at https://osf.io/9fmw5/ and https://github.com/yilangpeng/transfer-learning-clustering
8. As indicated by Tables 2 and 3, there might be interaction effects between visual categories and face categories. The analysis exploratorily tested this possibility by adding the

products of the three dummy variables for visual categories (*text/illustration*, *personal setting*, and *architecture/landscape*) and the three dummy variables for face-related categories (*politician only*, *other people only*, *both*) in the regression models (see Supplementary Information file Table S3). In general, the effects of showing the politician's faces in attracting likes and comments were weaker in the *professional setting* category than the effects for the other three categories.

9. https://www.journalism.org/2018/09/10/news-use-across-social-media-platforms-2018/

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