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ORIGINAL ARTICLE

Same Candidates, Different Faces: Uncovering Media Bias in Visual Portrayals of Presidential Candidates with Computer Vision

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How do today's partisan media outlets produce ideological bias in their visual coverage of political candidates? Applying computer vision techniques, this study examined 13,026 images from 15 news websites about the two candidates in the 2016 U.S. presidential election. The analysis unveils a set of visual attributes (e.g., facial expressions, face size, skin condition) that were adopted by media outlets of varying ideologies to differentially portray these two candidates. In addition, this study recruited 596 crowdsourced workers to rate a subset of 1,200 images and demonstrated that some visual features also effectively shape viewers' perceptions of media slant and impressions of the candidates. For example, Clinton was portrayed with more expressions of happiness, which rendered her as more favorable, whereas Trump was associated with more expressions of anger, which made him look less positive but more dominant. These differences in facial expressions varied in line with media outlets' political leanings.

Keywords: Media Bias, Visual Bias, Face Perception, Trait Perception, Non-Verbal Communication, Computer Vision, Computational Social Science, Crowdsourcing.

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Increasingly, media outlets are explicitly labeling their political affiliations to market themselves (Groeling, 2013). In the hope of exposing media consumers to more balanced and diverse viewpoints, scholars have made various attempts to automatically label political slants in media content (Park, Kang, Chung, & Song, 2009). Given the difficulty in analyzing images on a large scale, prior research examining content bias across media outlets has been mostly limited to textual data (Groeling, 2013). Yet, visual content proliferates in the digital media environment and is widely used in political communication (Grabe & Bucy, 2009; Verser & Wicks, 2006). Empirical studies also demonstrate that visual attributes such as facial expressions and face

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size can effectively shape our impressions and voting preferences towards politicians (Mutz, 2007; Tiedens, 2001). This research gap regarding visual bias should require special attention today.

This study tackled the challenge of analyzing large-scale visual media by bridging communication research and computer vision, a field that trains computers to understand digital imagery (Szeliski, 2010). Applying computer vision techniques such as facial detection and emotional analysis, this study examined 13,026 images from 15 news websites covering the 2016 U.S. presidential candidates—Hillary Clinton and Donald Trump—regarding various visual features. Beyond this methodological contribution, this study also advances our understanding of visual bias in the following ways. First, while extensive research has been devoted to quantifying the direction and magnitude of partisan bias, relatively limited studies have examined the forms of bias in visual content. Based on the ideological positions of media outlets established by prior research (Budak, Goel, & Rao, 2016; Flaxman, Goel, & Rao, 2016; Mitchell, Gottfried, Kiley, & Matsa, 2014), this study reveals the specific portrayals that media outlets use to convey their partisan views about the two candidates. In addition, this research also recruited crowdsourced workers to rate a subsample of images on their perceptions of media slant and impressions of the two candidates. By doing so, this study further illuminates how different visual representations adopted by partisan media potentially affect audiences of varying ideologies.

Measuring partisan media bias in visual content

This study defines partisan bias as systematic patterns in media content that favor one political party, candidate, or ideology over another (Groeling, 2013; Waldman & Devitt, 1998). First, bias should be distinguished from slant in a specific piece of media content, as bias should be "systematic, rather than anecdotal, episodic, or fleeting" (Groeling, 2013, p. 133). In addition, as Entman (2007, p. 166) argued, to establish media bias, researchers need to show "patterns of slant that regularly prime audiences, consciously or unconsciously, to support the interests of particular holders or seekers of political power." Our operationalization of bias thus retires the notion that it is a deviation from the truth but instead incorporates its potential impact on audiences. If a piece of content is determined as favoring certain political actors, it is reasonable to expect that viewers exposed to it should form favorable impressions about the targets or at least perceive the intended slant. While prior research has proposed other types of partisan bias, such as coverage bias (which focuses on the volume of coverage), this study focused on presentation bias, which specifically deals with the favorability of media coverage toward one party or ideology over the other (D'Alessio & Allen, 2000; Groeling, 2013).

Previous attempts at measuring visual slant can be broadly categorized into two approaches. Some have used more objective measures by coding visual content on a checklist of features that researchers predefine as (un)favorable treatment of politicians. The criteria used to determine visual slant usually include a politician's nonverbal behaviors (e.g., facial expressions, hand gestures, activity), contextual features (e.g., photographic settings, other objects, and people in the same picture), and structural features (e.g., camera angle, color; Grabe & Bucy, 2009; Moriarty & Popovich, 1991; Verser & Wicks, 2006; Waldman & Devitt, 1998). This checklist approach offers nuanced understandings of how bias is embodied in specific visual portrayals, although, as scholars have noted, different visual features do not contribute equally to the favorability of images (Barrett & Barrington, 2005). It also remains unknown whether these attributes, selected by scholars, indeed influence audience interpretations (Lobinger & Brantner, 2015).

Others have used more subjective measures by instructing coders to rate the favorability of media content. For example, in Barrett and Barrington (2005), three coders rated photos of politicians on a "highly unfavorable" to "highly favorable" scale. In Hehman, Graber, Hoffman, and Gaertner (2012), six coders evaluated candidates in photos on warmth and competence. With crowdsourcing platforms like Amazon Mechanical Turk, scholars can recruit more coders from diverse demographic and ideological backgrounds to assess bias on a large scale (Budak et al., 2016). Nevertheless, this approach still relies on coders' subjective interpretations and answers only how much, but not how, media content is biased. As Grabe and Bucy (2009, p. 101) argued, "visual analyses should move beyond the 'positive versus negative' index measures and investigate more specific and nuanced character frame–building dimensions."

These two approaches can be regarded as not only different methods for quantifying bias, but also two routes of conceptualizing bias that complement each other. Partisan bias should first be established as systematic patterns of differential treatment of political actors in media content. However, differences alone do not guarantee favorability; it requires additional efforts to demonstrate that these patterns indeed (dis)advantage certain actors among audiences. This study thus integrated a content analysis that investigated whether the visual coverage of candidates does vary by media outlets with a survey that asked crowdsourced workers to rate the favorability of these pictures. By doing so, we hoped this research would reveal visual cues that (a) reveal media outlets' ideological positions and (b) influence audience perceptions of favorability.

Selection of visual features

The first step in our approach was to select visual features that could be captured by computer vision applications on a large scale and that should, theoretically, reflect media bias. Based on previous scholarship on visual bias, social cognition, and political psychology, this study focused on the following features:

Facial orientation

Current facial detection algorithms often show facial orientation in three angles: pitch refers to the extent of a head bowing down or raising up; roll reflects the extent of a head tilting to the left or to the right; and yaw shows the extent of a face turning to the left or to the right (Figure 1). The pitch angle can be seen as a proxy of camera angle, a criterion frequently used in prior research to indicate visual favorability. A low camera angle (face pitching upward) is regarded as a better portrayal, as it could convey a sense of dominance and power compared with a high angle (face pitching downward; Grabe & Bucy, 2009; Waldman & Devitt, 1998). It is unclear, however, if the other two angles—roll and yaw—are related to visual bias.

Face size and location

As a cue for judging interpersonal distance, face size might pose mixed impacts on perceptions of other people. On one hand, compared with a long shot, a close-up portrait makes a person seem closer to viewers, thus appearing more intimate or dominant (in the sense of face-to-face confrontation; Archer, Iritani, Kimes, & Barrios, 1983; Grabe & Bucy, 2009). On the other hand, an extreme close-up might be a negative portrayal, as it resembles an extremely close physical distance that violates the notion of personal space. It also brings a person's face under detailed scrutiny, revealing skin flaws or awkward expressions (Grabe & Bucy, 2009). In addition, prior research has also claimed that featuring a candidate dominating the photo or as the center of attention positively portrays the candidate (Verser & Wicks, 2006). A photo that locates a politician's face closer to the center should cast the person in a better light.

Facial expressions

Facial expressions of emotion—motions or positions of facial muscles that convey the emotional state (Ekman & Friesen, 2003)—have also been used to evaluate visual bias. Looking happy or confident is usually coded as a positive representation of politicians, while frowning or looking sad, worried, or tired is seen as negative (Moriarty & Popovich, 1991; Waldman & Devitt, 1998). Happy faces are also perceived as more trustworthy, attractive, and dominant (Knutson, 1996; Oosterhof & Todorov, 2008; Sutherland et al., 2013). Besides coding facial expressions on a positive–negative spectrum, scholars have also argued for distinctions among discrete emotions. Ekman and Friesen (2003) identified six basic facial expressions: happiness, sadness, fear, anger, surprise, and disgust. Grabe and Bucy (2009) also distinguished among anger/threat, fear/evasion, and happiness/reassurance. Different negative emotions may produce distinct impressions: for example, individuals showing anger or disgust are often perceived as more dominant and powerful than those showing sadness or fear (Knutson, 1996).

Eye and mouth status

Eye status is another criterion frequently used to evaluate the favorability of photographs. Looking directly at the camera or at someone in pictures is coded as a positive portrayal of the candidate, whereas closed eyes portray a politician negatively (Moriarty & Popovich, 1991; Verser & Wicks, 2006). Research has shown that eye

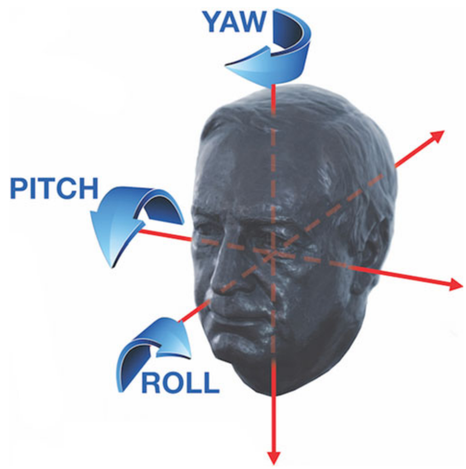

Figure 1 Facial orientation in pitch, roll, and yaw angles. Credit: Kyle Cassidy.

openness could make people look more intelligent and attractive (Talamas, Mavor, Axelsson, Sundelin, & Perrett, 2016). Mouth openness should also be an indicator of favorability. Prior research has regarded exhibiting dynamic behaviors such as speaking as a favorable depiction of politicians (Verser & Wicks, 2006). Mouth openness also reflects the intensity of smiling, although it can also indicate yelling and shouting that convey aggressiveness.

Skin condition

Skin condition has rarely been examined in visual bias literature, but its effects are frequently documented in face perception research. First, darkening a face's skin tone often leads to more negative reactions to it (Alter, Stern, Granot, & Balcetis, 2016; Ronquillo et al., 2007). An analysis of news articles showed that how positively an article portrayed a person correlated with the person's skin lightness in the article's visuals (Alter et al., 2016). Facial skin coloration is another important cue in impression formation. Skin redness and yellowness can be used as cues for inferring health status (Stephen, Smith, Stirrat, & Perrett, 2009). Signaling increased blood flow, facial redness is also linked to perceptions of attractiveness, dominance, and aggressiveness (Stephen, Oldham, Perrett, & Barton, 2012). Lastly, faces with healthier skin are often rated as more attractive, whereas skin imperfections such as wrinkles and uneven pigmentation make a person look older, less healthy, and less attractive (Fink, Grammer, & Matts, 2006; Jones, Little, Burt, & Perrett, 2004).

Other people

In prior research, presenting a cheering crowd or attentive colleagues together with a politician has often been coded as a positive representation, whereas featuring the politician alone or with inattentive crowds or colleagues has been seen as negative (Moriarty & Popovich, 1991; Verser & Wicks, 2006). Being accompanied by other people in pictures would also make a person appear more attractive than being photographed alone (Walker & Vul, 2014). Therefore, the presence of other people in pictures, as well as their facial expressions and eye openness, can also be proxies of media bias.

Visual bias across liberal and conservative media outlets

Having proposed a list of computer vision features that should theoretically reflect media bias, this study then asked how bias would be embodied in differential portrayals of politicians. Past research on partisan bias often focused on whether the media deviates from the norm of balance and exhibits an overall liberal or conservative bias, but no consistent patterns have emerged. For example, regarding television news, D'Alessio and Allen's (2000) meta-analysis revealed a detectable but small pro-Democrat bias, whereas Grabe and Bucy (2009) found a persistent pro-Republican one. Given the rise of partisan media outlets that explicitly favor one side instead of sticking to the norms of objectivity and balance, scholarship has gradually shifted to quantifying bias at the individual media outlet level (Budak et al., 2016). Regarding visual bias, research has shown that media outlets like newspapers (Barrett & Barrington, 2005) and websites (Hehman et al., 2012) indeed publish photos that portray candidates they endorse more favorably than the candidates' opponents. Therefore, we should expect that liberal media portrayed Clinton better than Trump and conservative media acted reversely prior to the election. However, it remains unknown what visual cues are adopted by media outlets of various political affiliations in their (un)favorable treatment of politicians, which is one focus of this study.

The analysis of partisan bias was further complicated in this case because the past election had both a female and a male candidate. Although this research can uncover differences in visual representations of Trump and Clinton, it is difficult to attribute these differences solely to partisan bias or gender bias, as some attributes related to favorability are also linked to gender. For example, faces are often shown as more prominent in visual depictions of men than those of women, a phenomenon termed as "face-ism" in prior research (Archer et al., 1983). Gender is also stereotypically linked to different emotions: anger is often seen as more masculine, signifying aggressiveness and dominance, whereas happiness, sadness, and fear are seen as more feminine, showing friendliness or weakness (Plant, Hyde, Keltner, & Devine, 2000). Therefore, instead of focusing on the overall contrast between Clinton and Trump, this study asked whether the differential treatment between the two candidates varied by media outlets' ideological positions, thus uncovering visual cues that signalled their political orientation.

> RQ1: Which visual features—facial orientation (pitch, roll, yaw angles), face size, face location, facial expressions (e.g., happiness, anger, sadness), eye openness, eye gaze direction, mouth openness, facial skin condition (lightness, redness,

yellowness, health), presence of other people, other people's facial expressions, and eye openness—were used by liberal and conservative media to differently portray Clinton and Trump?

Favorability and its dimensions

As noted earlier, the notion of favorability in media bias implies that biased content should indeed advantage certain political actors among media consumers. One important function of visual media in political communication is to convey cues that help us judge politicians' traits and characters (e.g., warmth, competence; Lobinger & Brantner, 2016), which in turn could influence voting preferences (Caprara & Zimbardo, 2004). Nevertheless, the majority of media bias studies often see bias as a single unfavorable-versus-favorable spectrum, which might not capture the diverse effects of visual portrayals on viewers' impressions. For example, showing the negative emotion of anger might make a person look unfriendly, but simultaneously dominant (Knutson, 1996; Tiedens, 2001). In addition, different traits also correspond to gender stereotypes: women are expected to be more friendly and kind, whereas men are perceived to be more assertive and aggressive (Prentice & Carranza, 2002). This study thus asked whether different visual representations of politicians actually affect viewers' perceptions of media slant, as well as evaluations of politicians, on separate trait dimensions.

Prior research is still divided on what specific dimensions govern our judgment of people from visual portrayals. Research in person perception claims that two fundamental dimensions underlie our judgments of people: one dimension (communion) captures traits related to perceived intent and could be further divided into two sub-dimensions, warmth (e.g., sociable, friendly) and morality (e.g., trustworthy, sincere); and the other dimension (agency) captures traits about perceived ability and incorporates two sub-dimensions as well, competence (e.g., intelligent, competent) and dominance (e.g., dominant, assertive; Abele et al., 2016). Evaluating politicians could be seen as a specific case of person perception. Caprara and Zimbardo (2004) also found a two-factor structure in judging personalities of politicians—energy and agreeableness—which largely overlap agency and communion.

Research in face perception also proposes that we use multiple dimensions to infer traits from human faces. The first dimension, labeled as valence, incorporates traits related to warmth, morality, and competence, indicating an overall favorability in impressions. The second dimension reflects only dominance (Oosterhof & Todorov, 2008). Attractiveness has also been proposed as a third factor in perceiving human faces (Sutherland et al., 2013). In this study, news photographs of politicians include not only their faces, but also social information such as their interactions with other people. Therefore, this study first examined the structure underlying viewers' perceptions of candidates in images and then investigated whether visual features influence these dimensions differently. Here, this study proposes two research questions regarding the potential effects of various visual features.

RQ2: Among the visual features proposed in RQ1, what features could best predict viewers' judgment of media slant in images of the two candidates?
RQ3: (a) Among warmth, morality, competence, dominance, and attractiveness, what dimensions underlie people's perceptions of candidates in news photographs? (b) And what visual features proposed in RQ1 could best predict audience perceptions of these dimensions?

Method

Data preparation

Prior research has already placed a list of popular news websites on the liberal–conservative spectrum. This research combined insights from several recent studies: one that averaged crowdsourced workers' perceived slant of each media outlet's news articles (Budak et al., 2016) and two using aggregated political orientation of each outlet's audience as a proxy of its ideological position (Flaxman et al., 2016; Mitchell et al., 2014). The sample included eight liberal sites (Daily Kos, *Slate*, *The New York Times*, *The Huffington Post*, *The Washington Post*, MSNBC, BBC, CNN), four relatively neutral sites (USA Today, Reuters, NBC News, *The Wall Street Journal*), and three conservative sites (Fox News, Breitbart, and TheBlaze). With Google search, the study searched for images of the two candidates limited to a specific news site (e.g., "Hillary Clinton site:cnn.com"). A total of 20,702 still images were retrieved in the last week of November 2016.[1] All images were transformed to JPEG format and large images were resized so both width and height did not exceed 1000 pixels.

With a computer vision service, Face++, this study then identified images with visible faces of the two candidates. The analysis first prepared a face set that included the two candidates. Next, for each image, the analysis detected whether this image contained faces (facial detection). For each detected face, Face++ compared this face to faces in the face set and returned the most similar-looking face, along with a confidence score of the two faces belonging to the same person (facial recognition).[2] Pictures without faces of Clinton or Trump were excluded. Based on the URLs of images returned by Google, this study then determined the date of each photo. The majority of URLs embedded the date when an article or a photo was published. For remaining images, a combination of web scraping and manual checking was used. Images from 2015–2016 ($N = 13{,}026$; 6,543 for Clinton) were kept in further analysis (Figure 2).

Participant ratings

From Amazon Mechanical Turk, 596 U.S. crowdsourced workers who had completed at least 100 tasks with an approval rate above 98% were recruited to rate a subset of 1,200 images randomly selected from the sample (40 for each candidate and each outlet). Each participant rated a random set of 20 images for each candidate. On average, each image received 19.9 ratings ($SD = 1.66$, range $= 18$–32).[3]

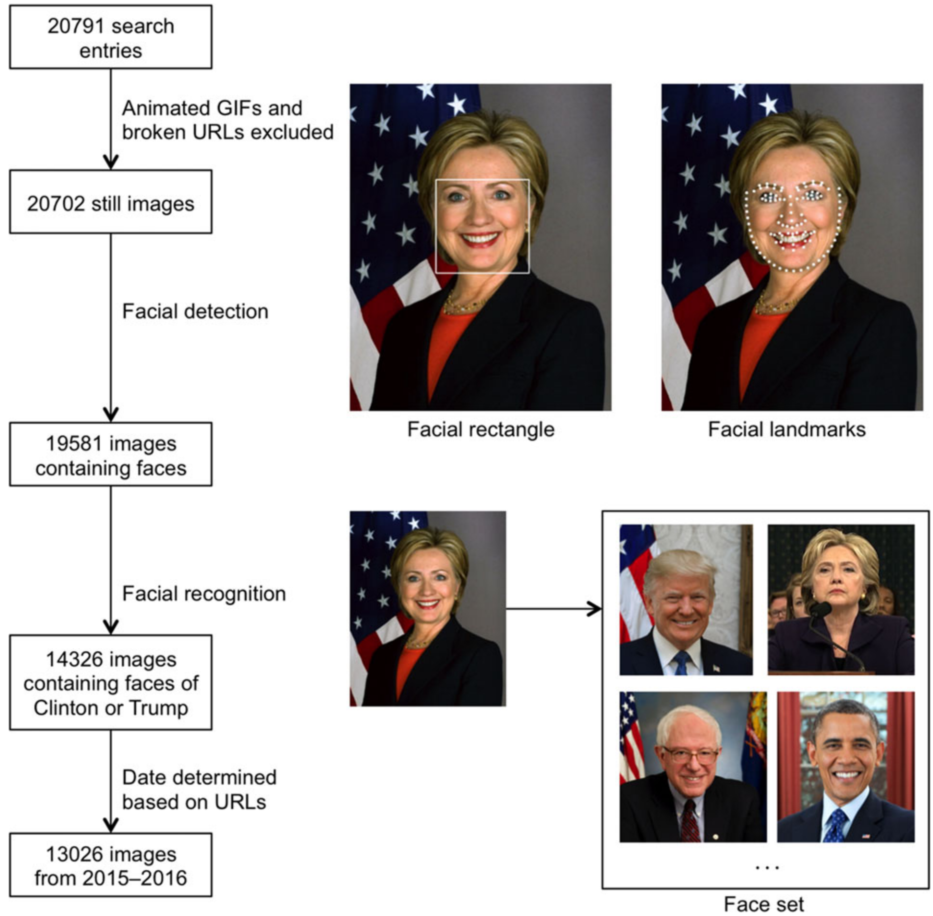

Figure 2 Data preparation procedures.

Ratings of each image were averaged across participants and used in the later analysis (Oosterhof & Todorov, 2008).

Each image was rated on the following questions.

1. Perceived slant: on five-point scales, participants rated how an image negatively or positively (1 = extremely negative, 5 = extremely positive) and unfavorably or favorably (1 = extremely unfavorable, 5 = extremely favorable) portrayed a candidate ($\alpha = .99$; $M_{\text{Clinton}} = 3.32$, $SD = .47$; $M_{\text{Trump}} = 2.84$, $SD = .58$).
2. Traits perceptions: on five-point scales (1 = strongly disagree; 5 = strongly agree), participants rated in each image whether the candidate looked friendly, warm, honest, trustworthy, dominant, assertive, competent, intelligent, attractive, youthful, and healthy. These adjectives correspond to various constructs proposed in prior research (Table 3; Abele et al., 2016; Oosterhof & Todorov, 2008; Sutherland et al., 2013).

Table 3 Principal Component Analysis of Perceived Traits

		All (N = 1200)		Clinton (600)		Trump (600)	
Constructs	Items	1	2	1	2	1	2
Communion (warmth)	Friendly (.89)	**.87**	−.38	**.85**	−.44	**.82**	−.43
	Warm (.88)	**.89**	−.35	**.87**	−.41	**.86**	−.40
Communion (morality)	Honest (.65)	**.95**	−.01	**.94**	−.01	**.94**	−.05
	Trustworthy (.69)	**.96**	−.01	**.95**	−.02	**.94**	−.03
Agency (dominance)	Dominant (.64)	.29	**.92**	.29	**.91**	.47	**.84**
	Assertive (.67)	.35	**.89**	.35	**.89**	.45	**.84**
Agency (competence)	Competent (.73)	**.92**	.24	**.88**	.35	**.92**	.20
	Intelligent (.74)	**.90**	.22	**.85**	.38	**.91**	.19
Attractiveness	Attractive (.78)	**.94**	−.12	**.93**	−.15	**.91**	−.13
	Youthful (.78)	**.85**	−.24	**.85**	−.28	**.79**	−.28
	Healthy (.73)	**.93**	−.02	**.92**	−.07	**.90**	−.02
Variance explained		66.5%	22.4%	62.2%	26.6%	61.1%	25.1%

Note: Inter-rater reliability for each item is provided in brackets. Factor loadings larger than .5 are shown in bold.

3. Perceived facial expression: given the subjectivity in human perceptions of facial expressions, this study also asked 396 participants to rate a subsample of 800 images to determine the extent to which the candidates' faces displayed anger, disgust, fear, happiness, sadness, surprise, and emotional neutrality (1 = *not at all*, 5 = *to the full extent*). These ratings were used to validate emotional analysis results from computer vision services.

Computer vision analysis

For each image, Face++ provided the yaw, roll, and pitch angles that represented facial orientation. Face++ also provided each face's location in the picture as a facial rectangle that bounded the face region (Figure 2). Face size was calculated as the ratio between the size of the face rectangle and the size of the image. Face location was calculated as $1–2 \times d_1/d_2$, in which d_1 was the distance between the face rectangle's center and the picture's center, and d_2 was the length of the picture's diagonal. A higher value indicated that the face was closer to the center. Face++ also provided the extent of eye openness and mouth openness, as well as eye gaze direction, as a three-dimensional vector. The analysis calculated the angle between the gaze direction and the image, so a higher value approaching 90 degrees would indicate the eye was looking towards the camera rather than looking elsewhere. Values for eye openness and eye gaze direction were averaged across both eyes.

Regarding facial expressions, prior research has shown that computer vision tools can accurately detect happiness, but might not identify other facial expressions well (Dehghan, Ortiz, Shu, & Masood, 2017). The analysis thus compared emotions detected by four popular emotion analysis services—Microsoft, Face++, Sighthound, and Google Vision—with participants' perceived emotions (Table 1). All services detected happiness well, with Microsoft performing best ($r = .85$). Microsoft also predicted anger ($r = .54$) and emotional neutrality ($r = .63$) relatively accurately. Yet, the detection of other emotions, such as fear and sadness, was not satisfactory. Therefore, scores of anger, happiness, and emotional neutrality from Microsoft were used and other emotions were excluded from the analysis. Where Microsoft failed to detect a candidate's face in a picture, Face++'s results were used.

Face++ provided facial landmarks of each face, which were locations of important face components, such as face contour, eyes, and mouth (Figure 2). Based on facial landmarks, the analysis then identified the facial skin region as the facial region excluding eyebrows, eyes, nose, and mouth. The image was transformed into the CIELab color space. Lightness, redness, and yellowness of facial skin were calculated as the average L, a, and b values, respectively, of pixels inside the facial skin region (Stephen et al., 2012). In addition, Face++ also returned likelihoods about a face's skin condition. Skin health was calculated as the difference between the likelihood that the skin was healthy and average likelihood that the skin showed different types of ill conditions, such as dark circles and stains.[4]

The number of other people's faces detected by Face++ was used to indicate whether a candidate was presented with other people or not. If the candidate was accompanied by multiple individuals in an image, the means of other faces' happiness and eye openness were used as predictors. For a small portion of images with multiple faces of the same candidate (e.g., Trump standing in front of a screen showing his face; .9%), face-related visual attributes were averaged across the candidate's faces. The number of repetitions of the candidate's face was included as a control variable. A few computationally-calculated aesthetical features were also included as control variables, including brightness and contrast, measured as the mean and the standard deviation of all pixels' perceived luminance values; colorfulness, based on the combination of R, G, and B pixels in the RGB color space (Peng & Jemmott, 2018); and image size and aspect ratio, measured as the product and the quotient of an image's width and height.

Results

The study first examined whether the treatment between Clinton and Trump differed between liberal and conservative media regarding various visual features (RQ1). The analysis constructed a candidate variable (0 = Clinton, 1 = Trump) and a media outlet variable (1 = liberal media, 2 = relatively neutral, 3 = conservative media) based on the ideological positions of media outlets, as quantified by prior research (see Method section). A series of moderated multiple regressions were conducted (Jaccard & Turrisi, 2003), with each regression using the candidate variable, the media outlet variable, and their interaction to predict one visual feature (Table 2). For each visual feature, a statistically-significant coefficient of the

Table 1 Correlations Between Human-Perceived and Computer Vision Services–Detected Facial Expressions

	Face++	Microsoft	Sighthound	Google Vision
Anger (.88)	.29***	.54***	.31***	.23***
Disgust (.81)	.25***	.36***	.09*	NA
Fear (.50)	.08*	.19***	.11**	NA
Happiness (.96)	.79***	.85***	.71***	.80***
Sadness (.64)	.04	.28***	.18***	.17***
Surprise (.77)	.24***	.39***	.23***	.36***
Neutral (.74)	.46***	.67***	.36***	NA
N	791	738	783	772

Note: Analyses were performed on images containing only one face of the candidate ($N = 791$). The sample size varied, as some faces detected by Face++ were not detected by other services. NA = not available. The inter-rater reliability for each item is provided in brackets. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2 Distribution of Visual Features Across Candidates and Media Outlets

	Candidate	Media Outlet	Candidate × Media Outlet
Face orientation: Pitch	.14***	−.01	.02
Roll	−.11***	.02*	−.02
Yaw	−.02	.01	−.01
Face size	.14***	.06***	−.12***
Face location	−.09***	.18***	−.02
Facial expressions: Happiness	−.46***	−.06***	.08***
Anger	.42***	.02†	−.06**
Neutral	.09***	.01	.02
Eye openness	−.30***	−.01	.04†
Eye gaze	−.22***	.03*	−.01
Mouth openness	−.11***	.00	−.03
Skin condition: Skin lightness	−.19***	.03**	−.04†
Skin redness	.40***	.01	.02
Skin yellowness	.08***	.04**	.02
Skin health	−.09***	−.05***	.07**
Number of other people's faces	−.12***	−.03**	.07**
Other faces' happiness	−.04	−.01	.02
Other faces' eye openness	.13***	.02	.00

Note: $N = 13026$ ($N = 4939$ for other faces' happiness and eye openness). Candidate: 0 = Clinton, 1 = Trump. Media outlet: 1 = liberal, 2 = neutral, 3 = conservative. Each line represents one regression model. Standardized coefficients are shown. $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

candidate variable would imply that media overall portrayed the two candidates differently regarding that feature. As noted earlier, this difference could be a mix of partisan and gender biases, or characteristics of these two candidates (e.g., Trump and Clinton differ in their skin tones). A significant interaction would imply that the size of this difference was moderated by media outlets' political orientations, suggesting the presence of partisan bias.

In overall media coverage, compared with Clinton, Trump images had larger faces ($\beta = .14$), showed less happiness ($\beta = -.46$) but more anger ($\beta = .42$), and portrayed less healthy facial skin ($\beta = -.09$) and fewer other people's faces ($\beta = -.12$, all *p*s $< .001$). As indicated by significant interactions, these gaps regarding face size ($\beta = -.12$, $p < .001$), happiness ($\beta = .08$, $p < .001$), anger ($\beta = -.06$, $p = .002$), skin health ($\beta = .07$, $p = .002$), and number of other faces ($\beta = .07$, $p = .001$) narrowed or reversed as the media outlets' political orientations moved from liberal to conservative (Figure 3), implying that these attributes were adopted by outlets to differentially portray the two candidates. For example, regarding happiness, the gap between Clinton and Trump was 32 overall (on a 1–100 scale), and was wider in liberal media (34) than in conservative media (27). The gap was most pronounced in Daily Kos (46) and least in Breitbart (23), two sites situated at two extreme ends of the ideological spectrum. Face size served as another example. While liberal and relatively neutral outlets almost universally portrayed Trump images with larger faces than Clinton, the gap diminished or reversed in conservative sites such as Fox News, TheBlaze, and Breitbart. A similar pattern occurred for skin health. With two outliers (*The New York Times* and *The Huffington Post*), liberal media, especially Daily Kos and Slate, portrayed Clinton with healthier facial skin, but this gap narrowed in conservative media.

Having shown what visual features were adopted by media outlets of varying positions as signals of their political leanings, the analysis then investigated whether these features indeed impacted viewers' perceptions (RQ2). The inter-rater reliability (IRR) of participants' ratings was calculated based on intraclass correlation coefficients (see Kim, 2014, p. 167). The IRR for perceived slant was quite high (.87), suggesting a high degree of agreement among participants. An ordinary least squares regression used computer vision features to predict averaged perceived slant, controlled for which candidate an image featured (Figure 4a). Given that raters were randomly assigned to a large pool of images, it was unlikely that the raters' characteristics would be exactly the same across all the images. The model thus controlled for the number of raters assigned to each image and the aggregated characteristics of each image's raters, including percentages of raters who were women and White and means of raters' ages, education levels, and political orientations. Detected emotional neutrality highly correlated with happiness ($r = -.71$, $p < .001$), and was therefore removed from the model. All variance inflation factors were below 3.

Among all the attributes, expressions of happiness had the largest effect size ($\beta = .48$). Images with large face sizes ($\beta = -.19$) and expressions of anger ($\beta = -.15$) were rated as negative portrayals of candidates, whereas skin health ($\beta = .09$; all *p*s $< .001$) positively contributed to favorability. These results showed a large

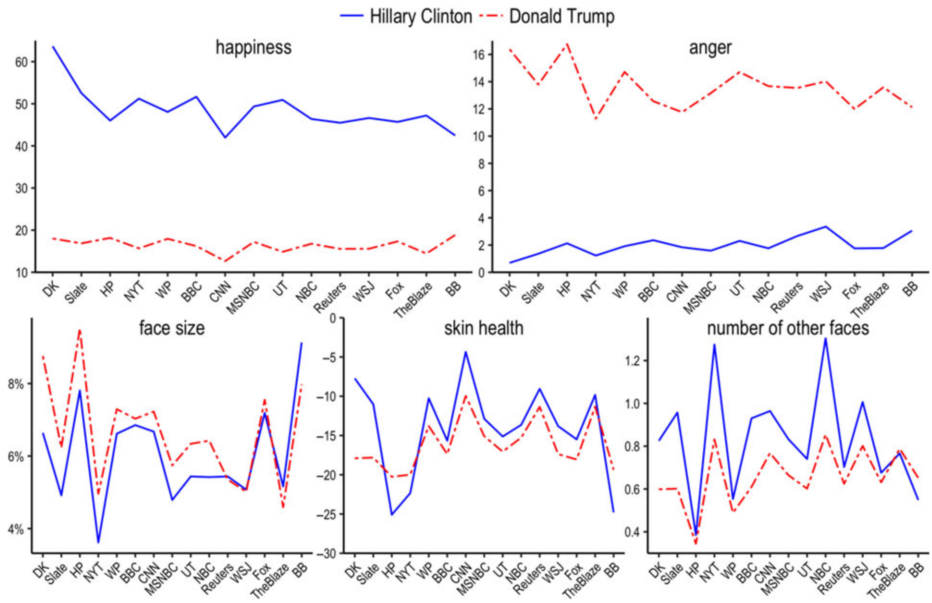

Figure 3 Distribution of visual features across media outlets and candidates. *Note*: BB = Breitbart; DK = Daily Kos; HP = *The Huffington Post*; NYT = *The New York Times*; UT = USA Today; WP = *The Washington Post*; WSJ = *The Wall Street Journal*. Scales: happiness/anger, 0–100; skin health, −100–100; face size, 0–100%.

overlap between visual features that differentiated liberal and conservative media and features that influenced audience perceptions of favorability. Based on unstandardized coefficients, a completely happy face, a completely angry face, and a face with perfectly healthy skin would impact a picture's favorability by +.8, −.7, and +.4, respectively, on a 5-point scale. In addition, mouth openness ($\beta = .10$, $p < .001$) and other faces' happiness ($\beta = .07$, $p = .002$) also slightly enhanced perceived favorability.

Next, this study looked at the dimensionality in the evaluation of traits from photographs (RQ3a). The IRR in perceiving different traits ranged from .64 to .89, indicating reasonably high agreement among participants, particularly for traits related to warmth, competence, and attractiveness, but less for dominance and morality (Table 3). A two-factor structure emerged from exploratory factor analyses. Two terms related to dominance (dominant and assertive) loaded on one factor (IRR = .68; $\alpha = .95$; $M_{\text{Clinton}} = 3.25$, $SD = .45$; $M_{\text{Trump}} = 3.25$, $SD = .46$). Warmth, morality, competence, and attractiveness did not form distinct concepts, as some prior research had implied; instead, these traits converged on another factor, referred to as valence (IRR = .77; $\alpha = .98$; $M_{\text{Clinton}} = 3.09$, $SD = .51$; $M_{\text{Trump}} = 2.57$, $SD = .41$; Table 3).

The analysis then looked at what visual features impacted audience perceptions on these two factors (RQ3b). Interestingly, the valence dimension highly correlated with perceived slant ($r = .93$, $p < .001$). Most features predicting perceived slant

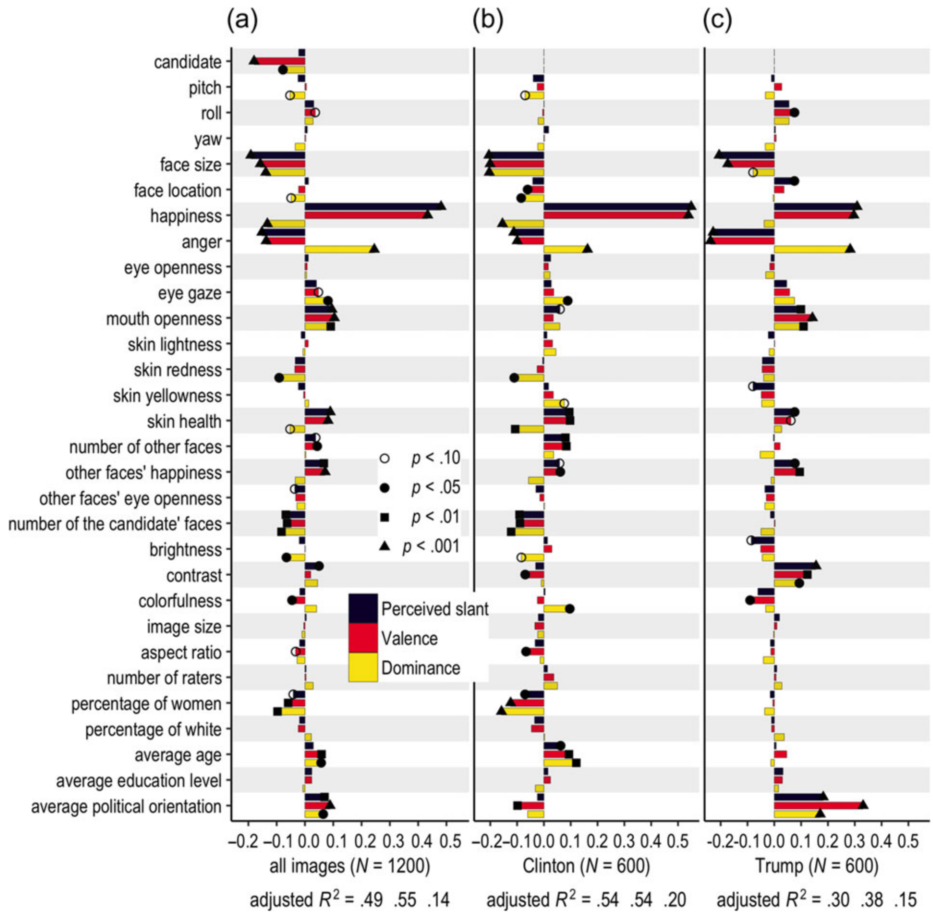

Figure 4 Effects of visual features on perceived slant, valence, and dominance. *Note*: Regarding other faces' happiness and eye openness, mean substitution was applied to photos with only the candidate' faces. Candidate: 1 = Trump, 0 = Clinton. The three adjusted R^2 values are in the order of predicting perceived slant, valence, and dominance.

also influenced judgment on the valance dimension, including face size (β = −.16), happiness (β = .43), anger (β = −.14), mouth openness (β = .10), skin health (β = .08), and other faces' happiness (β = .07, all *p*s < .001). The number of other faces also slightly increased valence (β = .04, *p* = .03; Figure 4a).

In contrast, the effects of visual attributes on dominance, which correlated with perceived slant only to some degree (*r* = .23, *p* < .001), showed a different pattern. A few attributes influenced dominance in the same direction of predicting valence, such as face size (β = −.14, *p* < .001) and mouth openness (β = .09, *p* = .01). Yet anger (β = .25) increased dominance, while happiness (β = −.13, both *p*s < .001) acted negatively: these measures were in the opposite directions of predicting valence. Completely happy and angry faces would impact dominance by −.1 and

+.8 on a 5-point scale, respectively. Skin redness ($\beta = -.09$, $p = .01$) and eye gaze ($\beta = .08$, $p = .02$) also had small effects on dominance (Figure 4a).

Discussion

In summary, this research advances our understanding of visual bias in the following ways. First, by integrating the objective checklist and subjective rating approaches developed in prior research, this study extends conventional analysis, which often focuses on the magnitude and direction of bias, to understanding how partisan media bias is constructed in visual portrayals of politicians and how these portrayals then influence audience interpretations. Regarding audience perceptions, this research also extends visual favorability from a single positive–negative spectrum to a two-factor space that includes valence and dominance. Different visual cues can exert both similar and reversed impacts on perceptions of these two dimensions. And last, this research also demonstrates that the use of computer vision tools greatly expands the scope of visual analysis and could better equip communication scholars to study visual content, which is becoming increasingly ubiquitous in our media environment.

Partisan bias in visual content

With a few exceptions, visual features that differentiate liberal from conservative media largely overlap features that impact viewers' perceptions of slant, including facial expressions, face size, and skin condition. Facial expressions, and particularly happiness, play essential roles in shaping participants' perceptions of media slant and impressions of politicians. Indeed, in face perception literature, perceived happiness in faces and valance-related traits such as trustworthiness, intelligence, and attractiveness often load on the same dimension in factor analysis (Oosterhof & Todorov, 2008; Sutherland et al., 2013). In interviews, Lobinger and Brantner (2015) also found that viewers heavily relied on politicians' facial expressions to judge the slant in news images. Therefore, computationally-detected happiness in politicians' faces could be a simplified but efficient proxy of visual slant. This measure might be particularly useful for information platforms that primarily circulate visual data, such as Instagram and YouTube.

One genre of negative portrayals in media coverage might require further attention: images featuring candidates with a large face, occupying almost the entire image, which highlights their skin flaws and negative emotional expressions.[5] Prior research in face-ism, which often compares full-body with half-body images, has shown a positive influence of facial prominence on impression formation (Archer et al., 1983). The negative impact of face size found in this study somewhat contradicts face-ism, but echoes what Mutz (2007) has termed as "in-your-face politics" in television discourse and Grabe and Bucy's (2009) interpretation of extreme close-ups. Close-up shots of politicians make them seem to be in the face of viewers and create a sense of discomfort and uneasiness among viewers, which could intensify viewers' preexisting negative feelings towards them. Furthermore, in fashion and advertising, media professionals can manipulate skin condition (e.g., remove wrinkles) to make models look more attractive in photos. In political coverage, media outlets might also intentionally make a politician look unfavorable by highlighting facial skin flaws. We should also note that both candidates examined here are White. The effects of skin condition might be more complicated if politicians of other races are considered, which could be an arena for future research.

Audience perceptions of favorability

Echoing prior research, this study revealed the multiple dimensions people use to evaluate politicians and highlights the need to study the effects of visual portrayals on different trait perceptions (Grabe & Bucy, 2009). Confirming previous research in face perception, a two-factor structure emerged from the data (Oosterhof & Todorov, 2008). While perceived slant converges with the valence dimension, dominance forms a separate dimension that should require further attention. These two factors do not completely converge. For example, some pictures intended to make candidates look bad by emphasizing their angry expressions and aggressive behaviors, like yelling and shouting, might simultaneously render them as more powerful and dominant.

Prior research has frequently shown the effects of trait perceptions on voting preferences (Caprara & Zimbardo, 2004), but where do people get their impressions of politicians? This study suggests that visual portrayals of politicians might be one source of trait perceptions. In the results, across different media outlets, Trump images expressed more anger and less happiness than Clinton, which should make him look less favorable and friendly but more dominant and aggressive. Indeed, a study conducted before the election showed that people considered Clinton as more caring and competent and Trump as more dominant (Kakkar & Sivanathan, 2017). Furthermore, trait perceptions on different dimensions might have distinct impacts on candidate preferences. Voters might prefer more dominant, aggressive leaders to more competent or caring ones when feeling threatened by outsiders or in uncertain situations (Kakkar & Sivanathan, 2017). Future work could experimentally examine how dominance in visual portrayals influences viewers' judgment of candidates and subsequent voting behaviors.

With the increasing visibility of female politicians in contemporary politics, it is also important to further bridge partisan bias and gender bias research. Gender bias might operate on multiple levels. First, media content might associate different norms with female and male politicians. In the results, Trump was portrayed using images with larger faces, less happiness, more anger, and fewer people around than Clinton. This could result from an unfavorable treatment of Trump across media outlets, as well as gender bias in face-ism and gender stereotypes that expect women to be more friendly and sociable and less aggressive (Archer et al., 1983; Prentice & Carranza, 2002). Moreover, the effects of visual cues on audience perceptions might differ between female and male politicians. Additional ordinary least squares regressions using photos of Clinton and Trump partially affirmed this possibility (Figure 4b and c). For example, the positive impact of happiness on perceived slant was more salient regarding Clinton's images than Trump's, potentially reflecting the gender norm in facial expressions that it was more proper or rewarding for women than men to smile (Plant et al., 2000). The negative effect of face size on dominance was also more pronounced for Clinton than Trump. Nevertheless, neither Clinton nor Trump represents all female or male politicians. Future research could include multiple female and male politicians to better study the interplay between political and gender biases.

The diversity in audience interpretations of visual content might also require our attention (Lobinger & Brantner, 2016). As Figure 4b and c shows, photos of candidates that matched (mismatched) viewers' political orientation were rated as more positive (negative), independently from visual attributes. This pattern was especially salient for Trump, a controversial figure who invited polarized responses from participants. As one crowdsourced worker commented at the end of the rating survey: "It was very difficult to rank Trump anything but the lowest in honesty no matter what the picture was." We also see that, compared with slant and valence, viewers' agreement on dominance was relatively low. This shows that crowdsourced workers can reach an agreement regarding certain evaluations, but there might be some inherent variability in people's interpretations of visual dominance, which requires further study. Future research could also study how other individual characteristics, such as political knowledge and visual literacy, might affect how viewers attend to and process visual portrayals of politicians.

Computer vision, limitations, and future research

This research demonstrates the potential of applying computer vision tools in analyzing large-scale visual media. However, several limitations exist. Current face detection services only work well with near-frontal faces. If algorithms fail to detect faces in a photo, this might already indicate an unfavorable portrayal of politicians (e.g., blocking a politician's face); therefore, this study's findings should only apply to images featuring identifiable faces of politicians. In addition, the computer vision services examined could not accurately identify facial expressions such as fear and sadness. This is unfortunate, as different negative emotions often produce differing effects regarding the evaluation of valence and dominance (Knutson, 1996). Nevertheless, this low accuracy could partially be due to the consideration that some expressions were not prevalent in the dataset and some were highly ambiguous: raters themselves couldn't agree upon which face should count as fearful (IRR = .50). Also, visual features such as politicians' gestures and activities might also reflect media bias, but could not be captured by the currently-available computer vision services. As the field of computer vision grows, future research could also incorporate these attributes.

One limitation of this study is that the images were resized and decontextualized from their original content. News stories associated with images may further influence how photos of politicians are picked up by media practitioners and interpreted by audiences. The design components in news websites might also reflect media bias. For example, the size of a photo might reflect the visibility a media outlet intends to give to a politician and influence readers' allocation of attention (Barrett & Barrington, 2005). Bringing tools of already widely-applied computational textual analysis, the next step in this line of research might be multi-modal analyses that investigate the interplay between textual and visual biases in media outlets. This study also only looked at still images, which are only one component of visual political communication. Future work might also apply computer vision techniques to analyze moving images, such as online videos.

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Notes

1 Although BBC is a British outlet, it attracts a sizable U.S. readership and has been classified as left-leaning by prior research (Mitchell et al., 2014), so it was included in our sample. Two strategies were used to address the concern about the potential bias in search engine results: (a) this study predefined a list of media sources and limited each search to one source, so whether Google prioritized certain sources should have had a limited impact on the results; and (b) all the images returned by Google were retrieved, so whether Google ranked certain types of entries ahead of others should not have generated substantial biases in the data.

2 The face set included the two candidates and their family members (e.g., Ivanka Trump), running mates (e.g., Tim Kaine), competitors (e.g., Bernie Sanders), third-party candidates (e.g., Gary Johnson), and other figures who frequently appeared in the campaign (e.g., Barack Obama). For each person, the face set included about 10 images that covered a diversity of facial expressions and luminance conditions. To validate results from Face++, the study manually coded 400 images selected from all the retrieved images on whether the image had visible faces of Clinton and Trump. The analysis tried a series of thresholds (.60, .65, .70, …, .95) as cut-off points to accept whether the face should be determined as Clinton or Trump. The overall accuracy rate was maximized when the threshold of .75 was used both for identifying Clinton (accuracy = 97.75%, false negative = 2%) and Trump (accuracy = 97.25%, false negative = 1.5%).

3 Participants reported their gender (female = 50.0%), age (M = 39.3, SD = 12.6), race/ethnicity (multiple answers allowed: Hispanic = 7.6%; African American = 8.6%; Asian = 8.1%; White = 83.2%), education (high school or less = 7.9%; some college = 21.0%; Associate's degree = 13.7%; Bachelor's degree = 37.4%; Master's degree or higher =

19.8%), political ideology ($M = 3.73$, $SD = 1.78$; 1 = *extremely liberal*, 7 = *extremely conservative*), and party affiliation ($M = 3.86$, $SD = 2.13$; 1 = *strong Democrat*, 7 = *strong Republican*). The last two ($r = .82$) were combined into one political orientation scale. A screening survey sampled a roughly equal number of women and men and of Democrats (34.3%) and Republicans (33.8%).

4 To assess the accuracy in other computer vision features, on three-point scales (2 = in the middle/can't decide), this study also manually coded a subset of 150 images on pitch (1 = head bowing, 3 = raising; $r = .60$), roll (1 = head tilting right, 3 = left; $r = .72$), and yaw (1 = facing right, 3 = left; $r = .78$) angles of the face; eye (1 = closed, 3 = open; $r = .71$) and mouth openness (1 = closed, 3 = open; $r = .67$); eye gaze direction (1 = looking elsewhere; 3 = nearly vertical to the image; $r = .50$); and skin health (1 = visible skin flaws, 3 = smooth and healthy; $r = .48$), which well correlated with computationally calculated features.

5 Face size negatively correlated with skin health ($r = -.21$) and happiness ($r = -.09$), implying that media combined these features to portray a candidate positively/negatively. Using regressions, tests of interactions suggested that the impact of happiness (but not skin health) on slant ($\beta = -.04$, $p = .048$) and valence ($\beta = -.05$, $p = .012$) was larger for images with smaller faces. Given the potential mixed effect of face size, the quadratic term of face size was also tested and was significant in predicting slant ($\beta = .09$, $p = .007$) and valence ($\beta = .09$, $p = .009$), implying that images with extremely large faces did not further reduce favorability compared with only fairly large ones.

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