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Cross-Platform Emotions and Audience Engagement in Social Media Political Campaigning: Comparing Candidates' Facebook and Instagram Images in the 2020 US Election

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ABSTRACT

This study provides a cross-platform, longitudinal investigation of pictures depicting political candidates posted to Facebook and Instagram over a 15-month period during the 2020 US election (n = 4,977). After motivating an exploratory research design, we set out to expound: the extent of cross-platform image posting across Facebook and Instagram; the emotion expression of politicians across the two platforms; and the relationship between these emotions and post performance. Our analysis of eight political campaigns (seven Democratic challengers and the Republican incumbent) finds relatively high and stable levels of cross-posting candidate pictures across the two platforms. The exception is the incumbent campaign, where cross-posting activity rose in proximity to the primary elections. Regarding emotions, we utilize both computer vision and crowd coding to identify happiness as the dominant emotion on Facebook and Instagram. Overall, we detect little variation in candidate emotion expressions – across campaigns and across platforms. However, we do find differences in how platform audiences respond to emotions, proxied here through post performance. Results from binomial logistic regressions show that in comparison with Calm, posts exhibiting Anger are less likely to overperform on both Facebook and Instagram. Most interestingly, we find diverging patterns for Happiness, which performs better than Calm on Instagram but not on Facebook. We interpret these findings to suggest first, that Instagram users reward emotionality from politicians. Second and more importantly, we argue that differing audience responses to emotions – captured through social media metrics – may reveal a generation polarization in what different segments of the electorate prefer their political leaders to be.

Introduction

Research on images – as a medium of political communication – remains a small but burgeoning literature. Traditionally, political scholars have used the term *image* to describe a candidate's "perceived ethos" (Schill, 2012, p. 119), namely the presentation of their qualities or their reputation among voters. Empirically, this research on images has overwhelmingly focused on television, which is a qualitatively different technology than the still image. While understanding how candidates communicate their ethos through television remains important, most existing research on political images has very little to do with the actual *pictures* that campaigns disseminate.

We argue that the dearth of research on candidate pictures is largely due to a historical lack of their prominence for political campaigns in the United States.[1] Prior to social media, newspapers – either print or online news – were the primary purveyors of candidate pictures to the electorate. Campaigns themselves had comparatively few opportunities to share pictures widely, perhaps with the exception of pamphlets, direct mail, e-mail, and websites. Today, social media places pressure on campaigns to generate and communicate pictures of their candidates at an unprecedented rate, resulting in an unprecedented scale of campaign-issued images. Now more than ever, the candidate picture has become a widely utilized component of political campaigning. In recognizing the importance of candidate visuals for the modern campaign, political communication scholars have begun assessing how pictures work to advance campaign goals (Filimonov et al., 2016) or frame the personas of individual candidates during elections (Muñoz & Towner, 2017; Steffan, 2020).

This study takes a different approach. Here, we neither evaluate the role of political images to the campaign apparatus nor asses how images contribute to candidates' ethos construction. Instead, we treat candidate pictures as empirical artifacts that help shed light on three understudied aspects of digital campaigning. First, a cross-platform analysis of a single data type – candidate pictures – helps reveal the extent that campaign messaging differs across platforms. Theoretical models of social media campaigning argue that campaigns post platform-specific content, due in part to varying audiences across platforms. We posit that candidate pictures are conducive media for investigating such platform message divergence, since pictures could be varied across platforms without changing a post's core function (e.g., attacking an opponent or promoting a policy agenda). Similarly, an analysis of pictures provides an alternative method to measure cross-platform campaigning than text, where platforms typically exhibit more variation in character limits than in supported pixel requirements. Therefore, text-based analyses could lead to an overemphasis of platform difference, since texts may be more altered than pictures to accommodate platform architectures.

Second, we utilize the non-verbal aspects of candidate pictures to classify candidates' emotion expressions (or to be more terminologically precise to the field of psychology, "perceived emotions" from "facial configurations" [see, Barrett et al., 2019, pp. 45–46]). Emotions are receiving a renaissance of attention in political research, largely due to their purported impact on citizens' information processing and mobilization (Marcus et al., 2000). Moreover, research suggests that politicians can communicate emotions through pictures in ways that influence the participation of politically interested citizens (Jones et al., 2013). Since social media users who follow politicians likely rank high in political interest, the perceived emotions from candidate's faces may play a role in the persuasion and mobilization of citizens who follow candidates on social media.

Third, we explore whether social media audiences differ in responding to candidates' emotion expressions across platforms. Using post performance as a dependent variable, we assess whether social media audiences respond differently to the perceived emotions in candidates faces. If so, this would lend credence to the hypothesis that certain emotions – like happiness – are broad triggers of political mobilization, which we proxy here through social media post performance. However, if users respond differently to candidate emotions across platforms, this may signal that platform audiences are distinct in what qualities they value in political leaders.

Overall, we designed this study to illustrate what a scholarly focus on candidate pictures may reveal about digital campaign structures and audience engagement on social media. However, this study does not definitively answer whether the results we find are a direct result of campaign structures or audience perceptions. These topics are better researched through interviews with campaign staff and controlled experiments, respectively. Instead, our study is exploratory by design and meant to generate hypotheses for validation in future confirmatory research. We now outline our theoretical arguments for how pictures relate to campaign structures and audience engagement, before justifying our research design and presenting our results.

Platform Divergence and Convergence in Digital Campaigning

Recent scholarship argues that since platforms exhibit differences in their architectures and audiences, digital campaigners adapt their communication practices to platform idiosyncrasies (Bossetta, 2018; Boulianne & Larsson, 2021; Farkas & Bene, 2021; Kreiss et al., 2018; Steffan, 2020; Stier et al., 2018). Taken together, this scholarship makes the case for *platform divergence* in campaign communication: i.e., that campaigns craft tailored messages to each social media platform to accommodate their social and technological variance.

However, emerging empirical investigations into cross-platform campaigning yield mixed results about the extent of platform divergence. In the 2013 German federal election, Stier et al. (2018) find differences in how candidates promoted campaign events on Twitter and Facebook, but policy salience was stable across platforms. Comparing American presidential candidates' Facebook and Instagram posts in 2016, Bossetta (2018) finds that for three of the five top-polling candidates, over half of the content posted to Instagram was also present on Facebook. Similarly, Farkas and Bene's (2021) analysis of the 2018 Hungarian parliament election finds that 30% of Instagram posts were on Facebook. In a three-platform study of the 2019 Canadian election (Twitter, Instagram, and Facebook), Boulianne and Larsson (2021, p. 16) observe that "most of the content was cross-posted without changes to reflect the platform and/or what resonates on specific platforms."

Across four national contexts – Germany, the United States, Hungary and Canada – empirical research finds that national-level campaigns recycle content across platforms, thereby constituting an argument for *platform convergence*. Understanding whether campaigns communicate platform-specific messages (divergence) or cross-post the same content on multiple platforms (convergence) has significant implications for digital campaigning theory. In particular, if cross-posting is a recurring and stable feature of digital campaigning, then findings from single-platform studies may hold more generalizability than is currently acknowledged. Conversely, if cross-posting comprises only a fraction of digital campaigning, then removing cross-posts from datasets will still help ascertain what content is truly platform-specific and why.

Therefore, our first point of inquiry is to uncover whether candidate pictures are customized to fit the expected norms of different platforms – what Kreiss et al. (2018, p. 20) refer to as "genres" – or, alternatively, whether broader structural forces work to incentivize convergence in candidate visual communication across platforms. Although campaigns can be highly resourced in terms of money, staff, and digital-savvy, all campaign communication is circumscribed by structural constraints that may incentivize cross-platform posting. We typologize these constraints, which we argue work to "institutionalize" campaign visual communication (Haim & Jungblut, 2021, p. 59), into three categories: candidate consistency, campaign factors, and platform design.

Candidate consistency is the first constraint to platform divergence and relates to how "candidate image" is traditionally construed in the literature, i.e., as an ethos-building or political marketing construct (Schill, 2012). Kreiss et al. (2018) note how campaigners customize candidates' social media communication to help portray an authentic image of their candidate. At the same time, maintaining a coherent message and electable persona is also an important facet of presidential campaigning (Stromer-Galley, 2019), and candidates may risk appearing inauthentic if they are depicted as various and incongruous versions of themselves across platforms. Therefore, platform divergence would expect candidates to adapt their messages to fit specific platform norms; however, the risk of appearing inauthentic through "flip-flopping" personas would seemingly incentivize platform convergence to help maintain a coherent and carefully crafted character.

The second series of factors supporting platform convergence are three structural constraints endogenous to political campaigns: *temporal, contextual*, and *organizational*. Time-pressure in a campaign environment compels staff to produce content regularly over short intervals, and developing posts that are applicable across multiple platforms is cheaper and more efficient than developing platform-specific content. Similarly, unexpected contextual events that arise over the course of a campaign – such as a negative press piece or an attack from an opponent – can compound time-pressure, and rapid response may take precedence over deeply considering the degree of fit between post content and various audiences. Even outside of rapid response scenarios, most campaigns follow an organizational hierarchy in designing, creating, and approving social media posts (Penney, 2017). Campaigns therefore benefit from a lean post approval pipeline, since cluttering workflows by involving multiple pieces of content at various stages of editing and approval is likely to create inefficiencies between copywriters, designers, and campaign managers. Thus, factors endogenous to political campaign operation – particularly temporal, contextual, and organizational constraints – generate incentives for campaigns to focus on a single, cross-platform strategy (platform convergence) rather than multiple, platform-specific ones (platform divergence). We posit that these incentives are particularly strong for candidate pictures, since they likely require more resources to design, produce, and approve than text copy or the distribution of links from external sources.

Third, *platform design* is a crucial structural component to consider regarding the extent of platform convergence or divergence. Social media platforms have different digital architectures (Bossetta, 2018), which can either necessitate platform divergence (by requiring different media formats) or support platform convergence (by allowing for recycling messages that are interoperable with multiple platforms' functionalities). Following this logic, it would make little sense to compare candidate pictures on a platform that supports image uploading and one that does not.

Therefore, we opt here to compare candidate pictures on Facebook and Instagram. Both platforms are under researched relative to Twitter, whose user base is a fraction of either platform we study (and therefore arguably less impactful as a medium for voter contact). In addition to this motivation, our platform selection is guided by two technical criteria. First, data from both platforms is accessible through CrowdTangle Team (2020), a public insights tool owned and operated by Meta. Second, the functionalities of Facebook and Instagram are not particularly varied in supporting image uploads, with the potential caveat that Instagram *requires* an image (or video) to be posted (whereas Facebook does not). Since both platforms exhibit comparatively similar functionality and are owned by the same parent company, we consider our platform comparison akin to a "most similar cases" research design. Here, significant differences in candidate pictures would provide strong evidence for platform divergence, namely in catering to different audience expectations across the two platforms.

The emerging cross-platform research on candidate pictures appears to suggest such a divergence. Steffan (2020, p. 3110) compared framing strategies in candidate pictures across six countries and found that when aggregated, the framing strategies differed between Facebook and Instagram (presumably indicating different images across the two platforms). By contrast, Farkas and Bene (2021) compared Facebook and Instagram images in Hungary and found that candidate pictures were often cross-posted, but they comprised different proportions of overall content for each platform. To us, this suggests that while campaigns likely cross-post *some* content, they post *additional* content to certain platforms in a way that biases results toward platform divergence in aggregated statistical models. Therefore, we hone our analysis to one data-type, candidate pictures, which we argue are ripe for platform convergence on account of the aforementioned structural incentives: candidate consistency, campaign constraints, and platform design. We pose our first research question:

RQ1: Do campaigns exhibit platform convergence or divergence when posting candidate pictures to Facebook and Instagram?

Emotion Expression and Post Performance in Social Media Campaigning

An important component of pictures is that they are able to convey non-verbal information such as facial expressions, which can be used to make political arguments and shape voters' impressions of candidates (Schill, 2012). At a biological level, facial expressions are an important medium for primate communication and have long been associated with the communication of emotions (Darwin, 1872). More recently, political psychologists argue that voters' *internal* emotional states impact their mobilization behavior (Marcus et al., 2000), and there is some evidence to suggest that *external* emotion communication through politicians' faces – or what Jones et al. (2013) refer to as "target affect" – can influence voters' self-reported political participation. To be clear, this does not imply that specific emotions are transferred directly from politicians' faces into voters' brains (i.e., that a happy face induces happiness in voters). Rather, we argue that particular facial configurations captured in politicians' pictures can be perceived by voters to indicate an inferable emotion (Barrett et al., 2019).

To date, much of the research categorizing emotions in social media pictures has focused on binary assessments of whether posts are emotionally-laden or not (Metz et al., 2020) or has adopted a two-dimensional valence dimension of positive and negative sentiment (Farkas & Bene, 2021; Peng, 2021). Studies focusing on discrete emotion categories tend to find that campaigns depict candidates and supporters as happy (Haim & Jungblut, 2021). While it is plausible to expect that campaigns predominantly depict candidates as happy when in control of their messaging (and thus unbound from media gatekeeping), there may also be incentives to communicate anger and negativity, which Bene (2017) suggests contributes to post virality. Apart from a general disposition toward communicating happiness, we currently know little about: whether other types of discrete emotions are perceptible through politicians' facial configurations, whether they vary across platforms, and whether they affect user engagement differently. Therefore, we ask:

RQ2: What emotions do candidates express through their facial configurations in Facebook and Instagram pictures?

Further undergirding our motivation for posing RQ2 is that the presence of emotionality appears to increase users' post engagement on social media (Metz et al., 2020). Focusing specifically on faces in candidate pictures, Peng (2021) finds that Instagram images where the politician displays happiness, as well as a grouped category of non-happy "negative" emotions, were both positively associated with higher like counts. Typically in the literature, the argument for studying post reactions is that they increase the organic visibility of posts by triggering exposure via platform algorithms (Bene, 2017; Boulianne & Larsson, 2021; Farkas & Bene, 2021). Thus, garnering more user interactions contributes to how a post "performs" on a platform.

We seek to understand how emotions affect post performance. However, by adopting a cross-platform approach, we also aim to assess whether emotion categories affect post performance universally or vary by platform audiences. Our interest in this comparison lies in the presumption that a user's interaction with a post on social media is a form of low-resource mobilization (especially since this interaction carries with it a degree of social risk by potentially making one's political preferences visible to others). Thus, we consider user interaction with a candidate picture to signal some degree of personal investment in political self-expression. If emotional categories perceived in politicians' faces variably affect post performance across Facebook and Instagram, this would seemingly signal that platform audiences differ in the emotions they prefer candidates to communicate. While admittedly a speculative leap, we suggest that post reactions could signal differing demands placed on politicians by platform audiences, who may hold differential worldviews about what traits a political leader should exhibit. To probe this potentially powerful use of observational social media data, we ask:

RQ3: How do candidates' emotional expressions relate to post performance across Facebook and Instagram?

Research Design

To answer these unexplored research questions, we opt for an exploratory research design. In contrast to confirmatory research, which tests theory-driven hypotheses and expects empirical findings to hold across populations (i.e., findings are data-independent), exploratory research aims to generate hypotheses for future confirmation and replication (Stebbins, 2001). In particular, an exploratory research design acknowledges that findings are data-dependent, which is particularly applicable to studies of American presidential campaigns for three reasons: the unique regulatory environment, election-specific contextual factors, and changes in platform development.

First, campaigns in the United States operate in a unique regulatory environment that allows for high levels of fundraising, voter data acquisition that is transferable across cycles, and the purchasing of third-party commercial data (Kreiss, 2016). Second, electoral campaigns are context-dependent, and idiosyncratic factors such as race competitiveness, prior election results, and challenger/incumbent dynamics influence the deployment of social media for voter contact (Auter & Fine, 2018). Third, platform developers continuously update their products in ways that influence the content, curation, and reach of social media posts (Bossetta, 2020). Therefore, findings from past election cycles are not necessarily ground-truths for developing theory-driven hypothesis to apply to future cycles. To meet this challenge of "temporal validity" in social media studies, scholars are calling for "purely descriptive" research that can help inform follow-up confirmatory research, such as experiments (Munger, 2019, p. 1).

Taken together, we consider these three aspects of American digital campaigning to warrant a data-dependent, exploratory research design without *a priori* hypotheses formulation. Instead, we pose open-ended research questions to guide a content analysis exploring: RQ1) the degree of cross-platform image posting across Facebook and Instagram; RQ2) the emotional expression of politicians displayed in images on the two platforms; and RQ3) the relationship between emotion expression and post performance. Since we iteratively and inductively developed the methods applied to the first two research questions, we did not preregister an analysis plan. However, in the study's open data repository,[2] we provide all images, data, and code used to generate our results and figures. In line with exploratory research designs, we report all significant p-values as descriptive (i.e., uncovering associations between variables) rather than inferential (De Groot, 2014), and our analysis is interpreted in a way that generates testable hypotheses for future confirmatory research. We outline each step of our methodology below.

Methodology

Step 1: Data Collection and Preprocessing

First, we retrieved all posts from eight candidates' verified Facebook and Instagram accounts using the "historical search" feature of CrowdTangle Team (2020). The candidates include the Republican incumbent (Donald Trump) and seven Democratic challengers (Joe Biden, Michael Bloomberg, Pete Buttigieg, Amy Klobuchar, Bernie Sanders, Tom Steyer, and Elizabeth Warren). We focus on these challengers because they were the highest polling (according to the Real Clear Politics polling average) and qualified for the Democratic debate immediately preceding Super Tuesday.

The period of data collection is January 1^{st}, 2019 – April 1^{st}, 2020. This period encapsulates when the challengers announced their presidential bids (with Warren being the first on February 9, 2019) to when they exited the race (the exceptions being Biden and Sanders, with Sanders ending his campaign one week after data collection). In total, we collected 23,424 posts from Facebook and 6,859 posts from Instagram.

Using custom-built tools in Python, we downloaded all images from the candidates' official Facebook and Instagram accounts. To identify pictures, we relied on the "Type" metadata provided by Crowdtangle: i.e., posts labeled with "Photo" on Facebook and "Photo" or "Album" on Instagram. Thus, our dataset does not reflect the overall corpus of images that may appear in candidate's posts (e.g., from embedded hyperlinks), but we do capture the candidate pictures explicitly uploaded by campaigns. In total, we collected 4,147 images from Facebook and 4,033 from Instagram.

In this study, we are specifically interested in the emotions perceptible from candidates' facial configurations. Therefore, we manually removed all images that did not contain the candidate in the picture. Non-candidate pictures included screenshots of tweets from Twitter, infographics, pictures promoting merchandise, and images depicting only supporters or family members. We also remove pictures depicting only political opponents, which were surprisingly few (n = 76). We then named each of the images that contained candidates with a unique identifier, which we constructed to be a concatenation of: the account handle, the post's date, timestamp (in Eastern Time), and the platform where it was posted ("FB" or "IG"). For example, a Facebook post issued by the Biden campaign on July 4th at 6:30pm would be: "joebiden_2020-07-04183000EDT_FB." With this naming scheme, we gave a unique id to each image based on their candidate, timestamp, and platform.

Step 2: Cross-Platform Image Detection and Sorting

To answer RQ1 and quantify the extent of cross-platform image posting, we utilized a mix of computational clustering and manual sorting. Early on, we noticed that campaigns often posted the same image multiple times, but the text or graphics overlaying the image would be different (for example, changing a call-to-action or name of a state). For terminological clarity, we refer to the image underlying any text or graphics as a "core image," and "duplicates" as images with the same core image *and* the same overlying text or graphics. To identify duplicates, we first grouped images into clusters if they shared the same core image. Then, we could identify which images in these clusters were exact duplicates posted across platforms (i.e., cross-platform posts).

To identify clusters of core images, we sorted candidate pictures into eight folders, one for each candidate. We then combined facial feature tagging and *k*-means clustering to group core images into clusters. Similar to topic modeling, *k*-means clustering is an unsupervised clustering approach that attempts to group data points into a user-specified number of *k*-clusters. To provide input data for the clustering algorithm, we ran each image through the convolutional neural network VGG19 (Simoyan & Zisserman, 2015). In order to use an unsupervised clustering approach, we removed VGG19′s classification layer and only used it to extract facial features as input data for the *k*-means algorithm. Put another way, we transformed faces into a series of dots (via VGG19′s facial feature tagging) that could then be algorithmically clustered.

For each candidate, we clustered the images using different values for *k*, until we arrived at a *k* value that seemed to cluster the majority of images well. We then added the resulting cluster number to the image id. However, the clustering algorithm did not perfectly cluster images, especially in cases where the orientation, size, or graphics of the pictures differed. We therefore inspected the clusters to identify images missed or wrongly assigned by the clustering algorithm, and we manually assigned these images to the appropriate core image cluster (and changed the image id name accordingly).

At this stage, clusters could consist of pairs of two images (signaling cross-platform duplicates); or, they could consist of larger clusters comprising the same core images but with different text or graphical variations. For both cluster types, we manually identified duplicates (where both the picture and overlying graphics or text were the same) and were posted across platforms by observing the "FB" or "IG" label assigned to the image id. For each candidate, we placed these duplicate pairs in an "Exact Duplicates" folder, alongside the folders for larger "Core Image" clusters and "Platform-Specific" images (which only appeared once in the data). The purpose of this division is that we can annotate only one core image from each cluster, and then copy that annotation to all other images within the same cluster (since the underlying core image is the same). We encourage readers to visit the study's data repository, where we provide all images sorted by "Exact Duplicate" image pairs, "Core Images" clusters, and "Platform-Specific" candidate pictures per campaign.

Step 3: Emotion Classification with Computer Vision and the Crowd

To answer RQ2 and classify politicians' facial expressions with emotion labels, we utilized a combination of computer vision and crowd coding. First, we built a dataset of unique candidate pictures (n = 3,277) comprising: a) a randomly selected single image from every core image cluster together with b) all platform-specific images in the dataset. We then ran these images through Amazon Web Service's Rekognition API, which offers face and "emotion detection" using computer vision. The emotion classifications provided by the algorithm are: Happy, Sad, Angry, Confused, Disgusted, Surprised, Calm, Fear, and Unknown. We chose the Rekognition API since these emotion classifications align well with the three emotion systems comprising Affective Intelligence Theory: *enthusiasm* (Happy, Sad), *aversion* (Anger, Disgust), and *anxiety* (Calm, Surprised, Confused, and Fear). The Rekognition API labels each detected face with an emotion, along with a confidence score up to 99.99%.

To provide an initial validation for Rekogntion's emotion classifications, we designed an image classification task for crowd coding via Amazon's MTurk. To construct a sample for crowd coding, we selected all images where candidates were labeled with emotion scores over 99% confidence (n = 473). The vast majority of these high confidence classifications were Happy (407), followed by Calm (40), Angry (20), Sad (4), Surprised (1), and Fear (1). Given the uneven distribution between Happy and non-Happy images, we constructed a dataset of all non-Happy images (66) and a random sample of 5 Happy images from each candidate (40). We tasked five crowd coders with labeling each of these 106 images with one emotion from Rekognition's categories (i.e., a choice-to-array task, which helps structure coders' perceptions of emotions [Barrett et al., 2019]). Coders were unaware of Rekognition's prediction when labeling, and we removed "Unknown" as an option to force a classification choice. The instruction posed to the coders was: "Choose the emotion displayed by the politician's face," alongside the option to select one of the eight emotion categories. We paid each coder $0.04 USD per image, and the median time took by coders was 12 seconds. This yields an hourly rate of $12 (300 images per hour x $0.04 per image = $12).

After taking majority agreement from the five coders for each image, we found that the crowd labels matched perfectly with Rekognition's classifications for Happy. Majority crowd agreement and Rekognition's labels aligned for all 40 Happy images, and for 35 of them, all five coders unanimously labeled Happy. We therefore consider the Rekognition API's classifications strongly validated for Happy at 99% confidence or higher. However, agreement was less consistent for other emotions. Therefore, we decided to crowd code all unique images with two exceptions.

The first exception was the sample of 106 images that we already sent to coders. For the second exception, we removed images where the candidate's face was not depicted or clearly decipherable in the image. This could occur because the candidate was depicted from behind, their face was too small or blurry to be seen (such as in shots of large crowds), or the image was a collage of multiple photos (rendering the task confusing for coders). These images are labeled as "Unsubmitted" (n = 392) and can be viewed in the data repository.[3] We chose not to submit these images to the crowd, since coder agreement might be an artifact of random selection rather than a perceptible emotion.

Even though our initial crowd coding sample validated Rekognition's Happy classifications at 99% confidence or higher, we sent high confidence Happy images to the crowd as an extra robustness check. *If* crowd coders could not consistently arrive at majority agreement with Rekognition's high confidence Happy images, this would signal a clear flaw in the crowd coding method.

Holding out the original 106 crowd coded image sample and 392 Unsubmitted images, we sent the remaining 2,779 core images to the crowd. We again paid coders $0.04 per image, but opted for three coders instead of five (five coders increases costs by 40% with only 3% gains on accuracy in more demanding text classification tasks [Guo et al., 2020]). If two coders agreed on an emotion label, we assigned that label to the image. If coders could not reach a majority agreement, we assigned "Unclassified" to the image. In a last step, if the image was part of a core image cluster (i.e., not unique to the dataset), we copied the label – whether an emotion, Unclassified, or Unsubmitted – to all other images in the same cluster (since the underlying core image is the same).

Overall, 58 crowd coders took part in the coding. We inspected the metadata of their coding results, looking for renegade coders who only marked one emotion or took the exact same time in performing each task (signaling bot activity). Based on these inspections, we have no reason to suspect that the labels are invalid. Moreover, our robustness check of leaving Rekognition-labeled Happy images (at 99%+ confidence) in the data helps validate the coding. Crowd coders reached majority agreement for these Happy images in 395 of 398[4] cases (99%). In the data repository we include all crowd coding results, with worker ID's anonymized to protect their anonymity.

Step 4: Assessing the Relationship between Emotions and Post Performance

To answer RQ3 and explore associations between candidates' emotion expression and post performance, we run multiple binomial logistic regressions with the emotion classifications as the main independent variables. We operationalize our dependent variable, post performance, as the Overperforming Score provided by Crowdtangle. The Overperforming Score is calculated by dividing the actual number of interactions by an expected, "benchmark" number of interactions (see Gamur, n.d). The benchmark number is calculated by averaging the number of interactions that fall within the interquartile range of the previous 100 posts of the same type (e.g., link, video, or image post). Crowdtangle clocks these benchmark averages at several timepoints (e.g., at 15 minutes, at one hour, and at 5 hours), meaning that the score is sensitive to how posts garner interactions over their life cycle. A post is considered overperforming by CrowdTangle if its interactions meet or exceed the benchmark average of the past 100 posts of the same post type (yielding an Overperforming Score > 0).

Although Crowdtangle clearly outlines how the Overperforming Score is calculated[5] (Gamur, n.d), the score is difficult to externally validate since we do not have access to post performance at various stages in its life cycle or the weighting scheme that Crowdtangle uses. Therefore, in the Appendix (Table S7), we also report OLS regressions with log-scaled aggregated engagement metrics as the dependent variable, which is the current academic standard (see Boulianne & Larsson, 2021). Our main results do not significantly change; however, we prefer reporting the Overperforming Score here for the following three reasons.

First, the Overperforming Score is conducive to cross-platform analysis, since it calculates post performance based on platform-specific metrics. Since Facebook and Instagram have different user engagement functionalities and metrics (particularly for reactions and sharing), a similarly-derived performance score is arguably preferable to wrangling interactions data from one platform to be comparable with those of another. Our analyses in the Appendix support this notion (Tables S6 and S7). When testing interactions as a dependent variable in OLS regressions, we obtained different results in a single model that combined interaction metrics from both platforms, versus running two platform-specific models. However, when using Overperforming Scores as a dependent variable in logistic regressions, results from combined and platform-specific models yielded similar results (Table S5). To us, this suggests that user engagement metrics are platform-specific and do not represent an apples-to-apples comparison across platforms. Therefore, we argue that the Overperforming Score offers a more comparable measure of post performance across Facebook and Instagram relative to user interactions. However, a clear drawback is that the metric is only available for platforms covered by Crowdtangle (currently Facebook, Instagram, and Reddit).

Second, Crowdtangle's benchmark estimate is an average of how a post performs at various time points in its life cycle. Thus, the Overperforming Score incorporates a temporal nuance not captured by raw interaction metrics. Although we cannot externally validate this temporal clocking, we have no reason to suspect the Overperforming Score is not a scientifically valid measurement.[6] Third, since the benchmark estimate is a rolling average calculated by the previous 100 posts, the Overperforming Score helps control for fluctuations in candidates' social media followership. Candidate accounts may grow over the course of a campaign with increased notoriety and targeted strategies to grow their follower counts. Iteratively updating the performance benchmark provides a coarse control mechanism for how posts perform relative to an account's follower growth.

CrowdTangle's Overperforming Score is a continuous variable that can be positive or negative (signaling underperformance). Continuous variables are suitable for OLS regressions, but our tests show that the distribution of the residuals in an OLS model with Overperforming Scores as a dependent variable are not normally distributed even after log-transformation (Appendix, Figure S2). Therefore, we opt for binomial logistic regressions and transform the Overperforming Score into a dummy variable. Posts with an Overperforming Score > 0 are coded "1" and all others are coded "0."

To investigate the relationship between emotions and post performance across platforms, we run a binomial logistic regression model for each platform. The emotion classifications are categorical, independent variables. We choose Calm as the reference category, since Calm is arguably a "neutral" emotion baseline. To ease interpretation, we remove images with the following emotions: Confused, Disgust, Fear, Surprised, Unclassified and Unsubmitted. None of these categories were statistically significant. In the Appendix, we also report the results of a single logistic regression with both platforms combined (Table S5) and OLS models using interactions as the dependent variable without (Table S6) and with individual candidates (Table S7). Our main results do not change, and readers may replicate, adjust, and compare these models using the scripts provided in the repository.

Results

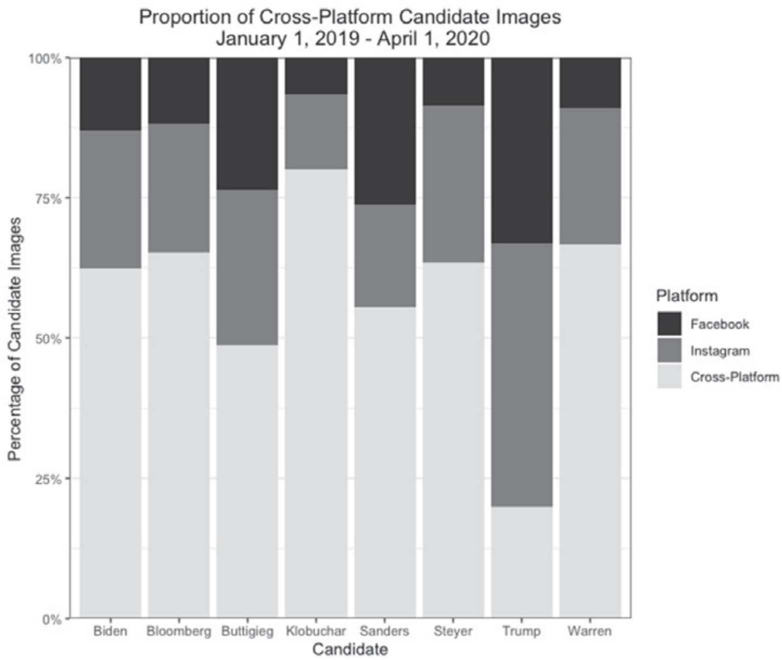
We first sought to uncover the proportion of images depicting candidates (or "candidate pictures") that were cross-posted to Facebook and Instagram. Table 1 reports the total number of image posts, the number of candidate pictures, the identified cross-platform image pairs, and the proportion of candidate pictures that were cross-posted.[7]

To answer RQ1, our clustering and sorting process identified that overall, 57% of candidate pictures on Facebook were cross-posted to Instagram. For Instagram, 50% of candidate pictures were also cross-posted on Facebook. These proportions (shown in the two right-most columns in Table 1) are calculated by dividing the number of "cross-platform pairs" by the "candidate pictures" for each campaign. The proportions represent the percentage likelihood that a randomly drawn candidate image would not be unique to that platform. Figure 1 renders this graphically[8] by reporting the proportions of cross-posted candidate pictures, compared to those specific to Facebook and Instagram.

Figure 1 shows that for Democratic challengers, at least 49% of candidate pictures were posted cross-platform (the lowest being Buttigieg), with Klobuchar's campaign cross-posting candidate pictures most frequently (80%). The outlier is the Trump campaign, where only 20% of images depicting the candidate were cross-platform. Trump's high degree of platform divergence may relate to his incumbency status. That is, Trump's social media accounts may have been used to communicate certain presidential affairs to specific

Table 1. Overview of image posts, candidate pictures, and cross-platform duplicate pairs.

	Image Posts		Candidate Pictures		Cross-Platform Pairs	Proportion of Cross-Platform Candidate Pictures	
	Facebook	Instagram	Facebook	Instagram		Facebook	Instagram
Biden	339	311	176	225	125	71%	55%
Bloomberg	262	265	157	192	114	73%	59%
Buttigieg	291	271	223	236	112	50%	47%
Klobuchar	222	407	171	199	148	87%	75%
Sanders	1,737	1059	696	581	354	51%	61%
Steyer	154	277	117	173	92	79%	53%
Trump	660	725	424	561	98	23%	17%
Warren	482	718	358	488	282	79%	58%
Total	***4,147***	***4,033***	***2,322***	***2,655***	***1,325***	***57%***	***50%***



	Biden	Bloomberg	Buttigieg	Klobuchar	Sanders	Steyer	Trump	Warren
Facebook	13%	12%	23.5%	6.5%	26.5%	9%	33%	9%
Instagram	25%	23%	27.5%	13.5%	18%	28%	47%	24%
Cross-Platform	62%	65%	49%	80%	55.5%	63%	20%	67%

Figure 1. Proportion of cross-platform and platform-specific candidate pictures.

audiences, rather than cross-posting to his entire social media following. To probe further into why the incumbent cross-posted less than challenger campaigns, we visualized a longitudinal time series of the data. Figure 2 depicts this time series, where the y-axis is the percentage of cross-posted candidate pictures relative to all candidate pictures posted per day. To interpret trendlines, we applied a LOESS smoothing interpolation to the data. The gray ranges indicate the 95% confidence interval for where the true proportion of cross-platform image posting lies on a given day (x-axis).

Figure 2 shows a clear tendency for the Trump campaign's candidate image cross-posting to increase with closer proximity to primary elections (the vertical line indicates Super Tuesday). Thus, cross-posting may be a tactic aimed at delivering a unified message close to voting day; or, it might be a strategic attempt to reach the broadest online audience possible ahead of the vote. While the relative proportion of cross-platform images fluctuates for Democratic challengers, most indicate an uptick in cross-posting immediately ahead of Super Tuesday. In the Appendix (Figure S1), we report another temporal dimension of cross-posting: campaigns generally cross-post candidate pictures across platforms within minutes – not hours or days.

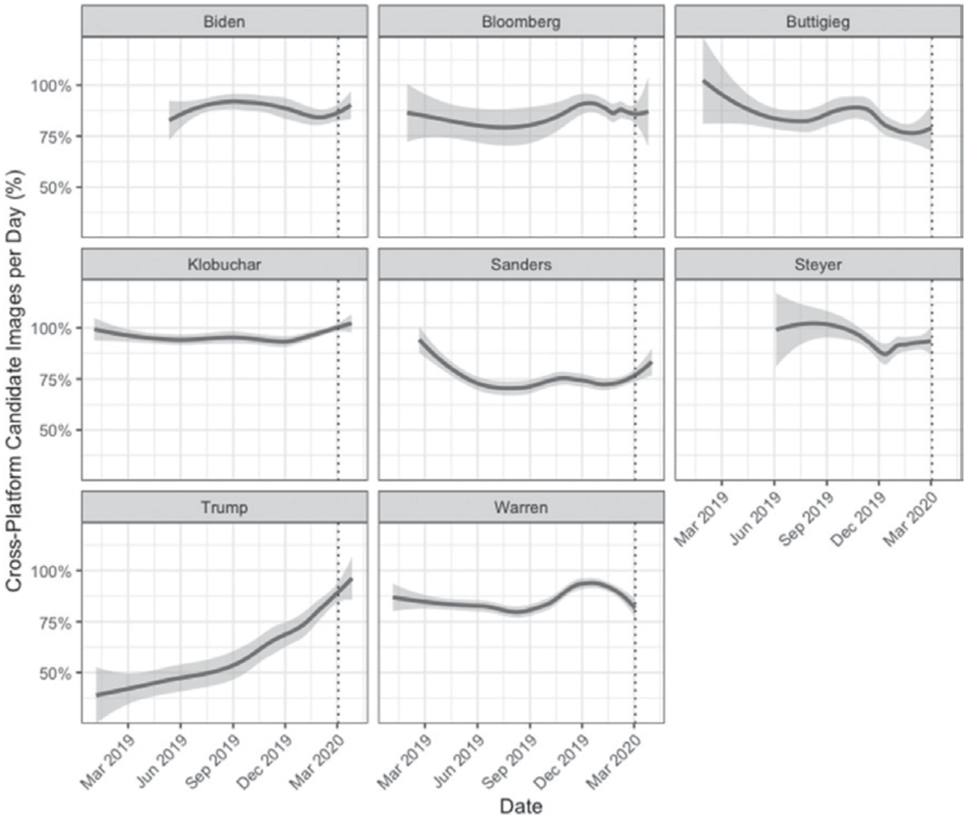


Figure 2. Time series of cross-platform candidate pictures relative to all candidate pictures.

Emotional Self-Presentation and Post Performance across Platforms

RQ2 asked about the emotions perceptible from candidates' faces and whether they differ on Facebook and Instagram. Figure 3 shows the proportion of emotion classifications, with raw numbers reported in the Appendix (Table S2).

Figure 3 shows that for all candidates, Happy is the dominant emotion perceived across platforms, followed by Calm. Interestingly, variation in emotions across platforms is virtually minimal. We include Unclassified images (those where crowd coders did not reach majority agreement) and Unsubmitted images (those that we did submit to the crowd) in Figure 3, since their inclusion shows the proportion of images where an emotion could be agreeably inferred. Overall, 13% of candidate pictures were Unclassified, which raises an interesting question of whether all candidate pictures convey a clearly perceptible emotion. As can be seen in the study's data repository, many Unclassified images depicted the candidate speaking or in motion, where coders (as well as the Rekognition API) seem to struggle in assigning an emotion label.

Table 2 presents the results of our binomial logistic regressions, which examine the relationship between emotions and post performance on Facebook and Instagram (RQ3).[9] To facilitate interpretation, we only report emotion categories that showed a statistically significant relationship ($p < .05$) with post performance on either platform. For logistic

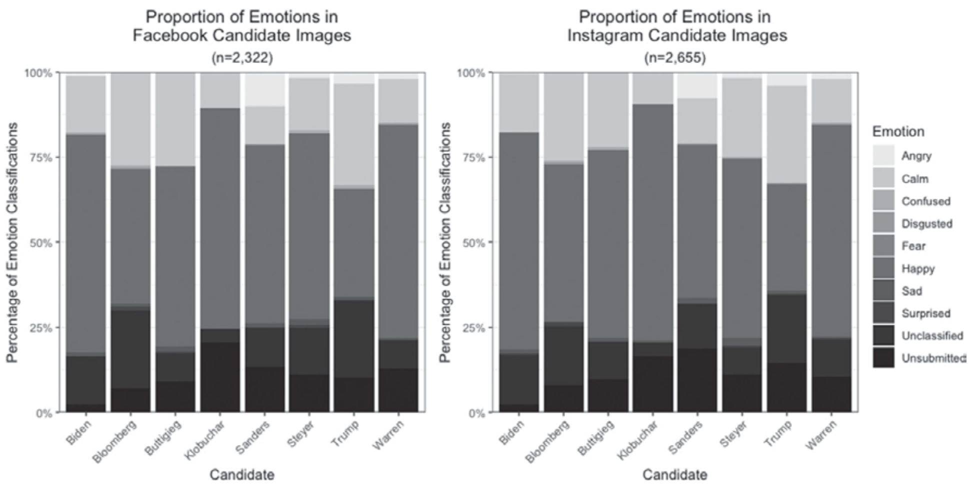


Figure 3. Emotion classifications per candidate and platform.

Table 2. Multiple binomial logistic regressions on post overperformance (DV) and emotions (IV).

	Facebook		Instagram	
	Coefficient	Odds Ratio (95% CI)	Coefficient	Odds Ratio (95% CI)
Angry	−1.271***	0.28***	−0.936*	0.39*
	(0.35)	(0.14, 0.56)	(0.44)	(0.17, 0.93)
Happy	−0.472***	0.62***	0.45***	1.56***
	(0.13)	(0.49, 0.80)	(0.13)	(1.2, 2.03)
Sad	0.229	1.26	1.289**	3.63**
	(0.45)	(0.52, 3.04)	(0.40)	(1.66, 7.94)
Intercept	−0.858***	-	−1.58***	-
	(0.11)	-	(0.12)	-
N	1730		1942	
Log-likelihood	−915		−1010	
AIC	1837		2028	

regressions, coefficients and odds ratios of the independent variables should be interpreted as relative changes to the reference category, which is Calm. Therefore, our models show how different emotion classifications relate to post overperformance relative to an emotional baseline of "Calm."

Table 2 reveals four key results. First, the emotion classifications that have a statistically significant relationship with post performance are Angry, Happy, and Sad. Second, Angry appears to be negatively associated with post performance on both platforms,[10] relative to Calm. Third and most interestingly, we find diverging patterns for Happy. Relative to Calm, pictures depicting politicians as Happy were *less likely* to overperform on Facebook but *more likely* to overperform on Instagram. Fourth, candidate pictures displaying Sad (i.e., showing compassion or empathy) were more likely to overperform relative to Calm on Instagram, but not on Facebook.

The differences in the statistical strength of Angry and Sad's association to overperformance across platforms, as well as the diverging directions of Happy, suggest an overall difference in how audiences react to emotions perceived in candidates' faces across platforms (at least in relation to Calm). Viewed holistically, we interpret these results to suggest that Instagram users generally reward "emotionality" – understood as conveying emotions different from Calm – from political leaders in comparison to Facebook users. However, we caution that our results are not outright predictions of emotions on post performance; rather, they highlight nuances across platforms when viewed comparatively, relative to the neutral emotional baseline of Calm.

Discussion and Conclusion

This study investigates American digital campaigning from three underexplored perspectives: cross-platform campaigning, the emotions communicated by candidates through pictures, and the comparative relationship between these emotions and post performance on Facebook and Instagram. While our analysis deals with one type of data – pictures of candidates – we consider a limited scope of analysis conducive to methodological rigor, which is vital to conduct strict cross-platform analysis. Our findings, while limited to the data-type and platforms we study, hold broader significance for future research designs in the field. Therefore, and in line with the expected output of exploratory research (De Groot, 2014), in discussing our results we offer testable hypotheses as outputs of our study, rather than motivating drivers.

Answering RQ1, we find high levels of cross-posting candidate pictures on Facebook and Instagram, signaling platform convergence. Since we only analyzed candidate pictures, we cannot generalize about the extent of platform convergence or divergence for other social media data-types or platforms. However, our specialized focus has three key strengths. First, it allows us to posit that researchers should expect some degree of convergence in candidate pictures across platforms that support them, especially since personalization appears to be "a general feature of social media visual communication" (Farkas & Bene, 2021, p. 137). Second and related, this may indicate that findings from prior studies of campaign visuals on Instagram (e.g., Filimonov et al., 2016; Muñoz & Towner, 2017) may be more generalizable than previously perceived.

Put another way, our findings provoke the question of whether previously observed platform differences are partially attributable to methodological artifact – namely, the statistical comparison of aggregated social media data across platforms. By focusing narrowly on candidate pictures, we show that they are often cross-posted and virtually identical across platforms in terms of the perceived emotions from candidates' faces (platform convergence). However, candidate pictures comprise a higher proportion of overall content on Instagram compared to Facebook (platform divergence). Thus, if we had calculated the amount of cross-posted pictures relative to overall posts on each platform, we would find strong evidence for platform divergence. We therefore encourage scholars interested in cross-platform campaigning to carefully consider the trade-offs between analyses of a singular data-type and those of aggregate posts. Furthermore, we contend that to truly isolate platform differences in digital campaigning from the campaign supply-side, researchers first need to identify and remove cross-posted content before conducting their analysis, whether that analysis be qualitative or quantitative.

The third strength of our limited analytical scope, and a core motivation for our design, is that exploratory research is conducive to conceptualizing the relationship between campaign structure and agency. Like Haim and Jungblut (2021), we think that structural forces shape campaigns' practices of visual communication. Although these relationships are difficult to isolate, exploratory research is well-suited to investigate them. Our results suggest that most campaigns increase cross-posting ahead of primary elections (Figure 2), a finding that was particularly pronounced for the incumbent campaign. We suggest that temporal and organizational constraints incentivize cross-posting as elections draw closer, leading to a testable hypothesis for future research: *cross-posting should increase with closer proximity to voting day, as candidates attempt to mobilize the broadest audience possible under time-pressure.*

Answering RQ2, we find virtually no variation in the perceived emotions from candidates faces across Facebook and Instagram. This suggests that certain media types are likely to exhibit convergence across platforms, especially if they are costly to design, produce, and approve. This leads to our second offered hypothesis: *resource-intensive content like images and videos are likely to be cross-platform, vis-à-vis text-only posts and existing content hyperlinked from external sources.* Methodologically, answering RQ2 showed the promise for using computer vision tools in emotions research. However, we caution that existing computer vision tools are most reliably utilized as "happy detectors," which suits studies of candidate pictures due to the predominance of happiness we find (i.e., they can be used as computational filtering mechanisms).

Finding Happy as the predominant emotion in candidate pictures is unsurprising. Campaigns are likely to portray their candidate positively when, enabled by social media, they have control over their messaging and do not need to appeal to media logics (Haim & Jungblut, 2021). *However*, the similarity we observe in emotion communication across platforms renders our findings about differential audience responses to them all the more robust. We consider the most interesting and important aspect of our study to be this: *the variation we observe in audience engagement with emotions may signal differential preferences in what qualities social media audiences value in their political leaders.*

To answer RQ3, we find significant differences in how emotions relate to post performance on Facebook and Instagram. While our finding that happiness performs better than Calm on Instagram aligns with Peng's (2021) study, our cross-platform approach suggests that happiness is not a universal driver of post performance. We find that relative to Calm, perceived happiness in politicians' faces is negatively associated with post performance on Facebook. This may indicate that an older audience demographic on Facebook prefers leaders to project Calm, signaling strength, stability, and control. Meanwhile, a younger audience demographic on Instagram may prefer their political rulers to project emotionality, such as being approachable (Happy) or showing compassion (Sad). Even the relationship between Anger and post performance, which was negative for both platforms, appeared to be weaker for Instagram. Together, this may point to a generation polarization in what qualities platform audiences prefer in political leaders, motivating our third hypothesis for future research: *the reception of emotions will differ across platforms, with (younger) Instagram users privileging emotional communication.*

While offering these hypotheses for future research, we acknowledge that our study is limited to the data-type we study: organically-posted candidate pictures from campaign accounts on two platforms. We do not study candidate pictures in social media advertising, since currently there are questions regarding the completeness of data delivered by the Facebook Ad Library API. However, existing research suggests that Facebook ads from candidate accounts aim to positively promote candidates (Fowler et al., 2021) and most often depict them as happy (Schmøkel & Bossetta, 2021). Still, in analyzing only candidate accounts, we may be overlooking other aspects of digital campaigning that issue divisive messages with different emotions. For example, Cohen (2021, p. 131) argues that industry trends point to outside groups issuing negative ads in a way that "protect the candidate's image and give the campaign wiggle room to disavow ads they don't like." Thus, the levels of happiness we find may be the result of a carefully curated candidate image through "front-facing" social media channels. Entirely different emotions could be conveyed – likely via ads – by SuperPACs or dark money groups. We strongly encourage scholars to collect content issued by these entities and test the effect of their images on users in controlled experimental designs.

Despite the limitations of our study, we hope its design inspires deeper thinking about candidate pictures and the utility of social media data more generally. Rather than focus on what images achieve for campaigns or how they impact voters' perceptions, we honed our analysis to candidate pictures to keep our comparative analysis tight and controlled. Through doing so, we aim to show how an exploratory, descriptive, and cross-platform analysis of observational data can generate hypotheses around broader campaigning phenomena, such as the relationship between electoral structures and campaign agency or what post interactions may reveal about voters' democratic preferences.

To conclude, our findings suggest more convergence than divergence in campaigns' visual communication on social media. However, differentiated audience responses to the emotions conveyed in these pictures warrant more attention to how audiences respond to politician's facial expressions across platforms. The audience engagement observed here may reflect that the electorate holds differential worldviews regarding the traits they prefer political rulers to possess and project. The exploratory analysis of social media data may be a promising way to crowd source these insights, which can be validated in future confirmatory research to drive social science forward.

Notes

1. In many European countries, by contrast, election posters installed in public spaces have historically played a more prominent role in picturing candidates (partially as a means to differentiate candidates in party-list proportional representation voting).
2. https://osf.io/g69tr/.
3. Per the request of an anonymous reviewer, the breakdown of Unsubmitted core images by campaign and platform is: Biden (FB: 2, IG: 7), Bloomberg (FB: 3, IG: 14), Buttigieg (FB: 9, IG: 22), Klobuchar (FB: 21, IG: 17), Sanders (FB: 53, IG: 69), Steyer (FB: 14, IG: 6), Trump (FB: 40, IG: 56), Warren (FB: 19, IG: 40).
4. While Rekognition identified 407 high confidence Happy images, we removed 9 as "Unsubmitted" because they were collages of multiple pictures.

5. To ensure readers are aware of how the score was calculated at the time of study, we include a PDF file of the blog post outlining the calculation in the data repository.
6. Some researchers may be skeptical that, due to its commercial orientation, the Overperforming Score should not be trusted by scientists. For instance, it may be the case that the Overperforming Score is weighted to inflate overperformance to encourage more posting from marketers or publishers. On the other hand, Meta has an incentive to show these actors what posts perform poorly, in order to encourage them to produce more engaging content. We acknowledge the non-transparency of the measure, but we consider the benefits of leveraging Meta's internal data (e.g., temporal clocking and follower counts at the time of posting) to outweigh the analytical risks. To mitigate such risks, we provide robustness checks using OLS on raw engagement metrics in the Appendix.
7. An extended table with the number of overall posts and core images per platform is included in the Appendix (Table S1). Here we report only exact duplicates, meaning cross-posting figures would be slightly higher if we calculated cross-posting by core images.
8. All figures are optimized for readers with color blindness or color vision deficiencies by using color pallets from the "viridis" R package (Garnier, 2018).
9. A descriptive overview of the number of overperforming posts (per candidate, emotion, and platform), is provided in the Appendix (Tables S4 and S5). Overall, the majority of posts in our dataset tend to underperform, resulting in high negative skewness of −15.
10. We alert readers that in a single binomial model (Appendix, Table S5), the relative difference in Anger's relationship to post performance on Facebook and Instagram is not statistically significant. The difference is highly significant for Happy and slightly significant for Sad.

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Data availability statement

The data described in this article are openly available in the Open Science Framework at https://osf.io/g69tr/?view_only=31243a92935a439d8791e625fc20d5a2.

Open Scholarship

This article has earned the Center for Open Science badges for Open Data and Open Materials through Open Practices Disclosure. The data and materials are openly accessible at https://osf.io/g69tr/?view_only=31243a92935a439d8791e625fc20d5a2.

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