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Emergency Physicians and Personal Narratives Improve the Perceived Effectiveness of COVID-19 Public Health Recommendations on Social Media: A Randomized Experiment

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Abstract

Background: Containment of the coronavirus disease 2019 (COVID-19) pandemic requires the public to change behavior under social distancing mandates. Social media are important information dissemination platforms that can augment traditional channels communicating public health recommendations. The objective of the study is to assess the effectiveness of COVID-19 public health messaging on Twitter when delivered by emergency physicians and containing personal narratives.

Methods: On April 30, 2020, we randomly assigned 2007 U.S. adults to an online survey using a 2x2 factorial design. Participants rated 1 of 4 simulated Twitter posts varied by messenger type (emergency physician vs federal official) and content (personal narrative vs impersonal guidance). Main outcomes were: perceived message effectiveness (35-point scale); perceived attitude effectiveness (15-point scale); likelihood to share Tweets (7-point scale); and writing a letter to their governor to continue COVID-19 restrictions (write letter or none).

Results: The physician/personal message had the strongest effect and significantly improved all main messaging outcomes except for letter-writing. Unadjusted mean differences between physician/personal and federal/impersonal were: perceived messaging effectiveness (3.2 [95%CI, 2.4-4.0]); perceived attitude effectiveness (1.3 [95%CI, 0.8-1.7]); likelihood to share

(0.4 [95%CI, 0.15-0.7]). For letter-writing, physician/ personal made no significant impact compared to federal/ impersonal (odds ratio 1.14 [95%CI, 0.89-1.46]).

Conclusions: Emergency physicians sharing personal narratives on Twitter are perceived to be more effective at communicating COVID-19 health recommendations compared to federal officials sharing impersonal guidance.

INTRODUCTION

The coronavirus disease 2019 (COVID-19) crisis has exposed the critical need for clearly and consistently communicating public health guidelines anchored in the best available evidence. Yet, many voices are competing with public health officials, particularly given that social media outlets frequently supplant traditional news sources.[1] Amid this backdrop, the U.S. has had higher COVID-19-associated deaths and excess all-cause mortality compared to most peer countries.[2] Despite the alarming rate of viral transmission, the public has not had full compliance with pandemic guidelines.[3,4] Policymakers and public health officials therefore must be strategic in communicating pandemic-related messages to the public.

Emergency physicians can play a key role in disseminating and amplifying public health recommendations especially during a crisis.[5,6] Emergency departments experienced the severity of the initial COVID-19 viral surge and were challenged by a rapid response to the influx of ED patients.[7–9] Serving at the front lines of the epidemic, emergency physicians have played a prominent role as a trusted source in communicating COVID-19 updates and urging the public to stay home.[6,10,11] The effectiveness of public messaging can be influenced by the credibility of the messenger [12,13] and the content of the message.[14] However, there is little experimental data measuring the effectiveness of public health communication through personal narrative or by physicians, which has been commonly seen in social media posts during the COVID-19 pandemic.

Therefore, the goal of this study was to evaluate the effectiveness of a physician versus federal official and personal versus impersonal content in delivering COVID-19 public health recommendations on Twitter, a popular social media platform. We tested the following hypotheses: 1) Emergency physicians deliver a more effective message than federal officials; 2) Personal appeals are more effective than impersonal ones; and 3) The interaction of a physician messenger with a personal message is synergistic.

METHODS

Study Design and Setting

We conducted a preregistered randomized experiment using simulated Twitter accounts and posts that randomly manipulated messenger type and message content in a 2 × 2 between-subject factorial design. We launched the experiment on April 30, 2020, the day the White House-issued public restriction guidelines were set to expire, transferring decision-making responsibility on restrictions to state governments.

This trial was approved by the institutional review board at the University of Michigan. Written informed consent was obtained from participants before participation. This trial followed the Consolidated Standards of Reporting Trials (CONSORT)[15] guideline with suggested amendments for reporting nonpharmacologial treatments and factorial trials.[16]

Participants

We recruited U.S.-based adult participants from Lucid Theorem, a nationally representative crowdsourced online subject pool that is quota-sampled to match census demographics on age, gender, race/ethnicity, and region.[17] Participants were eligible if ≥18 years old. We included responses for analysis if ≥80% of study questions were complete. We assessed the impact of weighting the sample based on demographic characteristics of U.S. adults with Internet access as reported by the 2017 U.S. Census.[18] **(eTable 1 and eTable 2)** Participants in Lucid were compensated at a rate comparable to $1 per study. Median time to complete the study was 11 minutes.

Study Procedures

Participants accessed the online survey (Qualtrics, Provo UT) through their personal electronic devices and gave consent blinded to the study objectives. They first underwent a pre-treatment attention assessment with the correct answer embedded in the instruction stem.[19] We randomized participants to 1 of 4 treatment arms with simulated Twitter posts and they answered a series of questions to measure primary outcomes. This was followed by a second attention check to recall the messenger's occupation which was a means of assessing that participants read the post and had received the intervention. Lastly, participants were invited to take a stay-at-home pledge, write a letter to their governor, and to answer additional covariate questions.

Twitter Stimuli and Randomization

We created images of a Twitter account and message for experimental exposures. We used the same male actor for the emergency physician (dressed in scrubs and a surgical cap) and the non-physician federal official (business clothes). The background photo was a building selected to plausibly appear as either a federal building or hospital. We took other Twitter metrics (date joined, number of accounts followed and followers) from an exemplar emergency physician Twitter account which were the same across conditions.

For message content, we compared the effect of a personal versus impersonal message. The personal message was based on "the identifiable victim effect", that having more identifiable information about a victim increases caring.[20] In contrast, the language for the impersonal message was used directly from a mass federal communication mailed on postcards to 130 million U.S. households[21] as part of the "President's Coronavirus Guidelines for America" and from the White House "Opening up America Again" guidelines.[22,23]

The two messages had approximately the same number of words (personal:61, impersonal:55) and delivered a similar three-part message: (1) young people are at risk; (2) public activity restrictions should continue; and (3) continuing restrictions would reduce the risk of viral resurgence. (**Figure 1**).

Simple random assignment was accomplished via the randomizer tool in Qualtrics. Each participant was assigned to 1 of 4 possible treatment arms with equal probability: 498 to physician/personal (PP); 505 to physician/impersonal (PI); 505 to federal/personal (FP), and 499 to federal/impersonal (FI).

Primary Outcome Measures

To evaluate the effect of messages, we measured (1) perceived message effectiveness (PME), (2) perceived attitude effectiveness (PAE), and (3) behavioral outcomes: likelihood to share, write a letter to a governor. The PME scale was intended to measure the message's emotional impact, and was adapted from a scale used in the context of smoking cessation research.[24] Participants evaluated the messages as: memorable, grabbed my attention, powerful, meaningful, and convincing on a 7-point Likert scale "Strongly disagree" to "Strongly agree" (coded 1-7), summed to a 35-point rating. (Supplement section 5) We modified the original scale by removing subscale "informative," due to COVID-19 information saturation. The modified scale demonstrates high reliability (α=.93) and an eigenvalue of 3.96 accounting for 79.2% of the variance, similar to the original scale reliability (α=.94) and eigenvalue of 4.22 accounting for 70% of the variance.

The perceived attitude effectiveness (PAE) scale was intended to measure the message's effect on attitudes, and was adapted from a scale used in smoking cessation research.[25] Participants evaluated whether the message (1) "Made me concerned about the health effects of lifting restrictions on public activity"; (2) "Made lifting restrictions less appealing"; (3) "Discourages me from supporting opening America up right now" on a 5-point Likert scale, "Not effective at all" to "Extremely effective" (coded 1-5), summed to a 15-point rating. The modified scale demonstrates high reliability (α=.88) and one-factor dimension that accounted for 81.3% of the variance, similar to the original scale reliability (α=.93) and a general factor that accounted for 82.6% of the variance.

We measured likelihood to share the Tweet as an estimator of the messages' behavioral impact. This was measured on a 7-point Likert scale "Extremely unlikely" to "Extremely likely" (coded 1-7). Self-reported willingness to share social media posts has previously been correlated with increased sharing in reality.[26]

Lastly, we asked participants whether they were interested in writing a letter to their state governor (yes/no). Participants who agreed were provided a free-text response box to write to the governor (not a form letter) and were truthfully informed we would send this letter anonymously, which we did via state government online communication forms. Because of the cognitive effort involved, the letter-writing task is less susceptible to desirability bias.[27]

Secondary Outcome Measures

As an exploratory outcome, we asked participants to take a pledge (yes/no) to stay inside to fight COVID-19. Pledging has been a popular way in the COVID-19 pandemic for concerned groups to encourage social distancing.[28] Prior research indicates that pledging to engage in prosocial behavior (*e.g.*, voting, environmental protection) has a small but significant effect on increasing the desired outcome.[29]

Covariate Measures

We incorporated additional variables in a covariate-adjusted model and to explore heterogeneous treatment effects using demographic information provided by Lucid (age, education, race/ethnicity, sex, household income, political party, state), which we supplemented with survey questions on overall health, marital status, population density, number in household, employment status, and political ideology. We also collected variables related to health behaviors, policy positions, and messaging receptiveness: anxiety about coronavirus, trust in federal officials and physicians,[30] economy vs public health trade-off,[31] political engagement,[32] consumption of media bias via AllSides rankings,[33] empathy (using the empathic concern subscale of the Brief Interpersonal Reactivity Index[34]), and news exposure frequency. Finally, we incorporated data on the extent of COVID-19 cases and restrictions based on the participant's state of residence (Supplement section 3).

Statistical Analysis

Sample size was determined from a pilot survey with 601 Lucid participants conducted two weeks prior and not included in the final study. We estimated with 438 participants per treatment arm (N =1752), the minimum detectable effect at 80% power using a 2-sided hypothesis test ($\alpha = .05$) is approximately 0.10 standardized units for a bivariate outcome difference of letter-writing.

The statistical analysis plan was pre-registered prior to data collection through the Open Science Framework (Supplement Section 9). We compared demographic characteristics and outcomes across groups by analysis of variance and T-Test for continuous variables and $\chi 2$ test and Z-test of proportions for categorical variables. As recommended for the accurate reporting of factorial studies,[16] we present three major comparisons: (1) 4-level treatment effects; (2) each factor pooled (messenger and message content); and (3) interaction between factors. Assumptions for each statistical test were evaluated using standard diagnostic tests and no major violations were found.

We estimated treatment effects using ordinary least-squares linear regression and logistic regression on the 4-level treatment factor, with federal impersonal as the omitted reference category. Regression models were covariate-adjusted to maximize the precision of estimated treatment effects. Covariates were selected by items expected to be associated with social distancing, then manually backward selected for inclusion based on the strength of the association with the outcome and Akaike information criterion (AIC) of the model fit: race/ethnicity, marital status, political party, gender, COVID-19 anxiety, news frequency, and economy vs public health trade-off. All models were assessed for violations of basic assumptions and no major violations were found. Participants with missing value for a variable were included with a missing data indicator for that variable.

We also examined whether subgroups of participants were affected differently by treatments using generalized random forest, a machine learning algorithm that estimates treatment effect heterogeneity as a function of each participant's covariate profile by nonparametric statistical estimation based on random forests.[35] Understanding how demographics may contribute to different responses to messaging can help in creating tailored content for specific groups at higher- risk for COVID-19.[4] Identifying these groups would create opportunities for audience segmentation - varying messaging strategies to address different groups - as demonstrated in climate science communication literature.[36] We assessed the effect heterogeneity specifically for PME because as an emotion-based rapid cognition, we hypothesized it would be more likely to be influenced by demographic profiles.[37] R version 3.5.2 (R Foundation for Statistical Computing) was used for statistical analyses, and the grf package was used for Causal Forests.[38]

RESULTS

Of 2090 participants who entered the survey, 2007 consented, were randomized, and completed the survey with ≥80% data (**eFigure 1**). All participants that were randomized were included in the analysis. Participants' mean age was 45 years (SD 16.7 years), 51% (n=1034) were female, 10.6% (n=214) were Black, and 11.6% (n=234) were Hispanic. Baseline characteristics and covariates were well-balanced across the four treatment arms (**Table 1, eTable 3**).

Main Outcomes

For the 4-level treatment results, participants rated PME, PAE and likelihood to share significantly higher in the physician/personal (PP) condition compared with the federal/impersonal (FI) condition, with largest effect on PME (**Figure 2**). Unadjusted estimated effects of PP versus FI are presented here with outcome means (**eTable 4**); remaining comparisons are shown in **eTable 5**. For the PME 35-point scale outcome, the means were: PP 28.52 (SD 6.81) versus FI 25.32 (SD 6.95) (difference 3.2 [95%CI, 2.37 to 4.02] $p<0.001$). For the PAE 15-point scale, the means were: PP 11.02 (SD 3.66) versus FI 9.77 (3.54) (difference 1.26 [95%CI, 0.81 to 1.7] $p<0.001$). For the likelihood to share 7-point scale, the means were: PP 4.99 (2.09) vs FI 4.59 (2.13); (difference 0.4 [95%CI, 0.15 to 0.66] p=0.003). There was no significant difference across treatment arms of letter-writing to the governor to continue public activity restrictions (odds ratio for PP compared to FI was 1.14 [95%CI, 0.89-1.46]). The proportion letter-writing was 50.6% for PP vs 47.3% for FI (difference 3.3% [95%CI, -3.1%to 9.7%] p=0.33). There was similarly no significant effect on the pledge to stay home secondary outcome: mean PP 90.6% vs FI 90.0% p=0.99. As expected, adjusted means had similar effect estimates with more precise confidence intervals (**eTable 6**).

The average effects of the messenger and message are presented in **eTable 7**. The pooled treatment effect of both personal content and physician messenger had a statistically significant impact on both PME and PAE. Cohen's D, a standardized measure of effect size, is presented here to facilitate comparing across different scales-- 0.2 is considered a small effect and 0.5 a medium effect.[39] The average personal content had a stronger effect compared to physician messenger for PME (0.40 [95%CI, 0.28 to 0.52] p<0.001 versus 0.25 [95%CI, 0.13 to 0.37] p<0.001) and PAE (0.22 [95%CI, 0.10 to 0.35] p<0.001 versus 0.16 [95%CI, 0.04 to 0.29] p=0.009), respectively. Conversely, personal content did not significantly increase likelihood to share, while the physician messenger retained a positive effect (0.17 [95%CI, 0.05 to 0.30] p=0.006). We found a negative interaction for PME such that physicians had an incrementally increased score compared to federal officials when presenting for the impersonal context, but less so for the personal narrative (-1.18 [95% CI, -2.35 to -0.02]; P=0.045). No significant interactions were found for the other primary outcomes.

Sensitivity Analysis Attention Check Question

We presented participants with two attention checks. Most participants passed the post-outcome measured manipulation check, correctly selecting the occupation in the Twitter profile (81.1%, n=1628). Far fewer passed the pre-exposure check in which the correct answer was hidden within the instruction paragraph (52.1%, n=1046). The groups were similar in treatment effects but had slightly stronger effects in the groups with higher levels of attention checks. (eTable 8, **eFigure 2**)

Treatment Effect Heterogeneity

We did not find significant heterogeneity in causal forest-estimated treatment effects of the personal message on PME. Causal forest was trained on many key variables, and test set predictions and CIs were assessed (**Figure 3**). While some patterns visually emerged among the variables specifically selected for graphical illustration based on hypothesised effect heterogeneity- political ideology, health status, age, and race/ ethnicity- all individual confidence intervals overlapped, coinciding with the null global test.

DISCUSSION

To our knowledge, this is the first large-scale, nationally representative, pre-registered, randomized experiment to directly estimate the effect of a physician versus federal official messenger and message content of simulated social media posts on individual perceptions, attitudes, and behavior. We found that public health messages delivered by physicians and personal messages elicited stronger emotions, greater changes in attitudes and an increased willingness to disseminate the message than when federal officials delivered impersonal messages. We did not observe differences in a stay-at-home pledge (which was near ceiling), nor in willingness to write a letter to the governor to continue restrictions. These findings suggest that to emergency physicians sharing personal stories on social media may be more effective in increasing general adherence to public health guidelines than federal officials sharing impersonal messages. Complementary communication campaigns are still needed to augment these recommendations in order to change pandemic related individual behavior.

Our study adds important findings of source effects and messaging content on a non-traditional communication platform during this public health crisis. We demonstrate that trusted messengers can alter opinions on contentious public policy issues consistent with prior experiments finding a medical scientist and physician increased support for antimicrobial resistance policy[12] and comparative effectiveness research,[13] respectively. The framing of health messages also matters. Similar to identifiable victim effect findings, we found enhanced emotional and attitudinal impact when the message was to help a single, identifiable person (i.e. the COVID-19 victim who was a friend) compared to the concept of helping the many, unidentifiable others.[20,40] Moreover, findings of increased public health messaging effectiveness from personal narratives is also supported by organ donation literature, which has shown that when viewers are more emotionally involved in a television narrative they were more likely to become organ donors if the show encouraged donation.[41]

We also assessed heterogeneous treatment effects to determine if there were distinct subpopulations which were impacted by the intervention differently, a finding which would be helpful for tailoring messaging for different groups. Despite a rigorous investigation harnessing machine learning tools, we found no significant impact of any participant characteristic, on the extent or direction of the message's impact, specifically examining political ideology, health status, age, and race/ ethnicity. Although we did not observe a differential impact of the emergency physician or federal official on lower income or minority participants, underserved populations may have lower trust in physicians than those included in our study,[42] and may interact with messages differently from our participants. Future research should examine how to most effectively communicate with underserved minority populations hardest hit by the pandemic.

Our results add to a growing body of research investigating the impact of social media platforms for public health communication. The majority of Twitter users cite it as a news source,[1] presenting an opportunity for health professionals to capitalize on this channel as an adjunct for reaching a broader segment of the public. Physicians, scientists, and health providers have played an increasing role on Twitter, using it to share personal communications[43] and engage with the public on health issues.[44] Relevant to a pandemic, Twitter has been identified as a tool for efficient information dissemination during emergency events[5] and in public health crises to communicate recommendations.[45] Our findings support the increased use of Twitter by healthcare professionals as a platform to communicate directly to the public.

While government mandated public activity restrictions and social distancing recommendations play a key role in preventing the spread of COVID-19, these interventions will be ineffective if the public is not willing to adhere to them. Social media based public messaging may help to improve the public's perception of these measures and thus adherence to health guidelines. However, during the pandemic, several U.S. healthcare institutions urged physicians not to make public appeals.[46–49] Our findings bolster policies that protect social media use by scientists and health providers to share public health communications directly to the public.

Limitations

This study has several limitations. First, the experimental design used a simulated Twitter message in the context of an online survey. Federal officials may be restricted on what they can communicate on social media using their official titles, but pilot data for this experiment showed most participants found the Twitter stimuli believable. It is possible that participants would react differently if they encountered these messages on the actual social media platform. However, participant likelihood to share a post has been shown to correlate highly with action in real life.[26] Furthermore, while the effects of user comments on social media were beyond the scope of this study, prior research has shown that user comments may have an additive effect on messaging impact,[50,51] though whether it will change reader behavior is unknown. Although we observed an increased willingness to share certain messages, we did not find differences in pledging to stay home nor writing a letter to the governor to maintain restrictions. It remains unclear if the impact of the messages would translate into real-life changes in compliance with social distancing measures. Second, though the participant pool matches U.S. demographics in most regards, our participants had higher educational attainment and lower proportion of Hispanic origin (approximately 15.4% of U.S. population with access to internet versus 11% in our study)[18] We weighted our sample to account for educational differences and still did not observe an appreciable impact on treatment effects (**eTable 3**). Further supporting generalizability, Lucid participants have exhibited behavioral experimental results similar to U.S. national probability samples.[17] Third, the high levels of reported anxiety created a likely ceiling effect for our outcomes. For PME, almost half of participants rated the message at 6 or above on a 7-point scale. Ceiling effects may have reduced sensitivity to determining differences by treatment, biasing results towards null. Lastly, we selected white males for the physician and federal official in the study, the most common demographic for both groups. It is possible that other race and genders of the Twitter messenger could have influenced subpopulations of this study differently than white males, however prior patient satisfaction simulation studies did not find differences by physician race or gender.[52]

CONCLUSION

Using a rigorous randomized experiment of a simulated Twitter message, we found that an emergency physician's Twitter message of a personal story and recommendation related to COVID-19 increased the attitudinal, emotional and willingness to share measures of impact compared to a federal official sharing impersonal guidance. These results underscore the advocacy role for physicians on social media in promoting public health recommendations. We did not find an impact on letter writing to their governor to support COVID-19 restrictions nor pledging to stay home. Future directions should explore the real-world impact of emergency physician public health tweets on measures of behavior change.

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Figure 1. Simulated Twitter Messages for COVID-19 Public Health Messaging

Simulated Twitter posts showing a sample of the federal official/ impersonal treatment arm on the left, and the physician/ personal arm on the right. The text was copied in larger font on the online survey. Two additional posts were created with the texts reversed.

Table 1. Participant Demographics and Baseline Characteristics

	No.(%) of participants by treatment arm				
	Federal Impersonal	Federal Personal	Physician Impersonal	Physician Personal	Overall
	(n=499)	(n=505)	(n=505)	(n=498)	2007
Patient Demographics					
Female	246 (49.3)	247 (48.9)	271 (53.7)	267 (53.6)	1034 (51.4)
Age Group					
18-24	59 (12.4)	70 (14.3)	67 (13.8)	61 (12.7)	257 (13.3)
25-44	187 (39.3)	163 (33.4)	189 (38.9)	178 (36.9)	720 (37.2)
45-64	148 (31.1)	178 (36.5)	152 (31.3)	157 (32.6)	635 (32.8)
65+	82 (17.2)	77 (15.8)	78 (16.0)	86 (17.8)	323 (16.7)
Region (%)					
Midwest	90 (18.0)	107 (21.2)	94 (18.6)	96 (19.3)	388 (19.3)
Northeast	100 (20.0)	115 (22.8)	96 (19.0)	103 (20.7)	414 (20.6)

South	189 (37.9)	184 (36.4)	209 (41.4)	189 (38.0)	772 (38.4)
West	120 (24.0)	99 (19.6)	106 (21.0)	110 (22.1)	436 (21.7)
Race/Ethnicity					
American Indian or Alaskan Native	5 (1.0)	4 (0.8)	4 (0.8)	3 (0.6)	16 (0.8)
Asian	25 (5.0)	27 (5.3)	30 (5.9)	27 (5.4)	110 (5.5)
Black	53 (10.6)	51 (10.1)	59 (11.7)	51 (10.2)	214 (10.6)
Hispanic	57 (11.4)	60 (11.9)	62 (12.3)	55 (11.0)	234 (11.6)
Other	15 (3.0)	16 (3.2)	18 (3.6)	12 (2.4)	61 (3.0)
White	344 (68.9)	347 (68.7)	332 (65.7)	350 (70.3)	1375 (68.4)
Education					
College Grad	291 (58.6)	261 (51.9)	270 (53.6)	299 (60.0)	1122 (56.0)
High School Grad	107 (21.5)	123 (24.5)	115 (22.8)	84 (16.9)	430 (21.4)
No Diploma	12 (2.4)	12 (2.4)	13 (2.6)	10 (2.0)	47 (2.3)
Some College	87 (17.5)	107 (21.3)	106 (21.0)	105 (21.1)	406 (20.2)
Income					
Missing	14 (2.8)	15 (3.0)	21 (4.2)	13 (2.6)	63 (3.1)
<25k	134 (26.9)	117 (23.2)	140 (27.7)	106 (21.3)	498 (24.8)
>99k	108 (21.6)	97 (19.2)	82 (16.2)	114 (22.9)	401 (20.0)
25k-49k	110 (22.0)	118 (23.4)	130 (25.7)	102 (20.5)	461 (22.9)
50k-74k	69 (13.8)	95 (18.8)	83 (16.4)	95 (19.1)	343 (17.1)
75k-99k	64 (12.8)	63 (12.5)	49 (9.7)	68 (13.7)	244 (12.1)
Marital Status					

Married	227 (45.5)	233 (46.1)	233 (46.1)	245 (49.2)	938 (46.7)
Other	130 (26.1)	127 (25.1)	134 (26.5)	121 (24.3)	512 (25.5)
Single	142 (28.5)	145 (28.7)	138 (27.3)	132 (26.5)	557 (27.8)
Health Status					
Missing	6 (1.2)	6 (1.2)	7 (1.4)	6 (1.2)	28 (1.4)
Excellent	67 (13.4)	64 (12.7)	62 (12.3)	75 (15.1)	268 (13.3)
Fair	78 (15.6)	66 (13.1)	76 (15.0)	69 (13.9)	289 (14.4)
Good	189 (37.9)	202 (40.0)	182 (36.0)	191 (38.4)	764 (38.0)
Poor	16 (3.2)	9 (1.8)	15 (3.0)	13 (2.6)	53 (2.6)
Very good	143 (28.7)	158 (31.3)	163 (32.3)	144 (28.9)	608 (30.2)
Baseline Characteristics					
News Frequency					
Frequently	140 (28.1)	156 (30.9)	154 (30.5)	145 (29.1)	595 (29.6)
Other	97 (19.4)	93 (18.4)	92 (18.2)	80 (16.1)	362 (18.0)
Very frequently	262 (52.5)	256 (50.7)	259 (51.3)	273 (54.8)	1050 (52.3)
Prioritize public health over economy	394 (79.1)	396 (78.9)	414 (82.8)	407 (82.1)	1611 (80.7)
Political Party					
Dem	237 (47.5)	229 (45.3)	229 (45.3)	209 (42.0)	905 (45.0)
Ind	60 (12.0)	62 (12.3)	76 (15.0)	69 (13.9)	268 (13.3)
Rep	202 (40.5)	214 (42.4)	200 (39.6)	220 (44.2)	837 (41.6)
Political Ideology					
Missing	6 (1.2)	9 (1.8)	9 (1.8)	6 (1.2)	33 (1.6)

Conservative	101 (20.2)	99 (19.6)	110 (21.8)	101 (20.3)	411 (20.4)
Liberal	93 (18.6)	91 (18.0)	81 (16.0)	79 (15.9)	344 (17.1)
Moderate	191 (38.3)	193 (38.2)	196 (38.8)	197 (39.6)	777 (38.7)
Very conservative	75 (15.0)	72 (14.3)	79 (15.6)	73 (14.7)	299 (14.9)
Very liberal	33 (6.6)	41 (8.1)	30 (5.9)	42 (8.4)	146 (7.3)
Anxiety Level					
Missing	6 (1.2)	6 (1.2)	6 (1.2)	1 (0.2)	22 (1.1)
Not at all	110 (22.0)	94 (18.6)	116 (23.0)	109 (21.9)	429 (21.3)
More than half the days	91 (18.2)	103 (20.4)	97 (19.2)	98 (19.7)	389 (19.4)
Several days	162 (32.5)	185 (36.6)	166 (32.9)	172 (34.5)	685 (34.1)
Nearly every day	130 (26.1)	117 (23.2)	120 (23.8)	118 (23.7)	485 (24.1)

Figure 2. Estimated Treatment Effects on Primary Outcomes by Treatment Arm Compared to the Federal, Impersonal Condition

*Covariate-adjusted treatment effects from ordinary least squares regression with reference being the control group, federal impersonal message. Estimates are standardized using Cohen's D, which scales outcomes by the pooled standard deviation. A Cohen's D of 0.2 is considered a small effect and 0.5 a medium effect.[39] (**eTable 6** for tabular form). Points are bounded by 95% CIs. Regression adjusted by covariates: race/ ethnicity, marital (married, single, other), party, gender, anxiety about COVID-19, news frequency (very frequent, frequent, other), and economy versus public health trade-off.*

Figure 3. Casual Forest Assessment of Treatment Effect Heterogeneity on Perceived Message Effectiveness by Participant Characteristics

Treatment effect heterogeneity shown for perceived messaging effect outcome, ordered by predicted treatment effect size in Cohen's D standardized units. A Cohen's D of 0.2 is considered a small effect and 0.5 a medium effect.[39] *Omnibus test for heterogeneity*[53] *found no significant heterogeneity in the effect (p-value 0.26). Political ideology and age selected due to highest relative variable importance, though not statistically significant. Race/ethnicity and health status selected due to hypothesized importance, though visually and statistically no heterogeneity demonstrated.*

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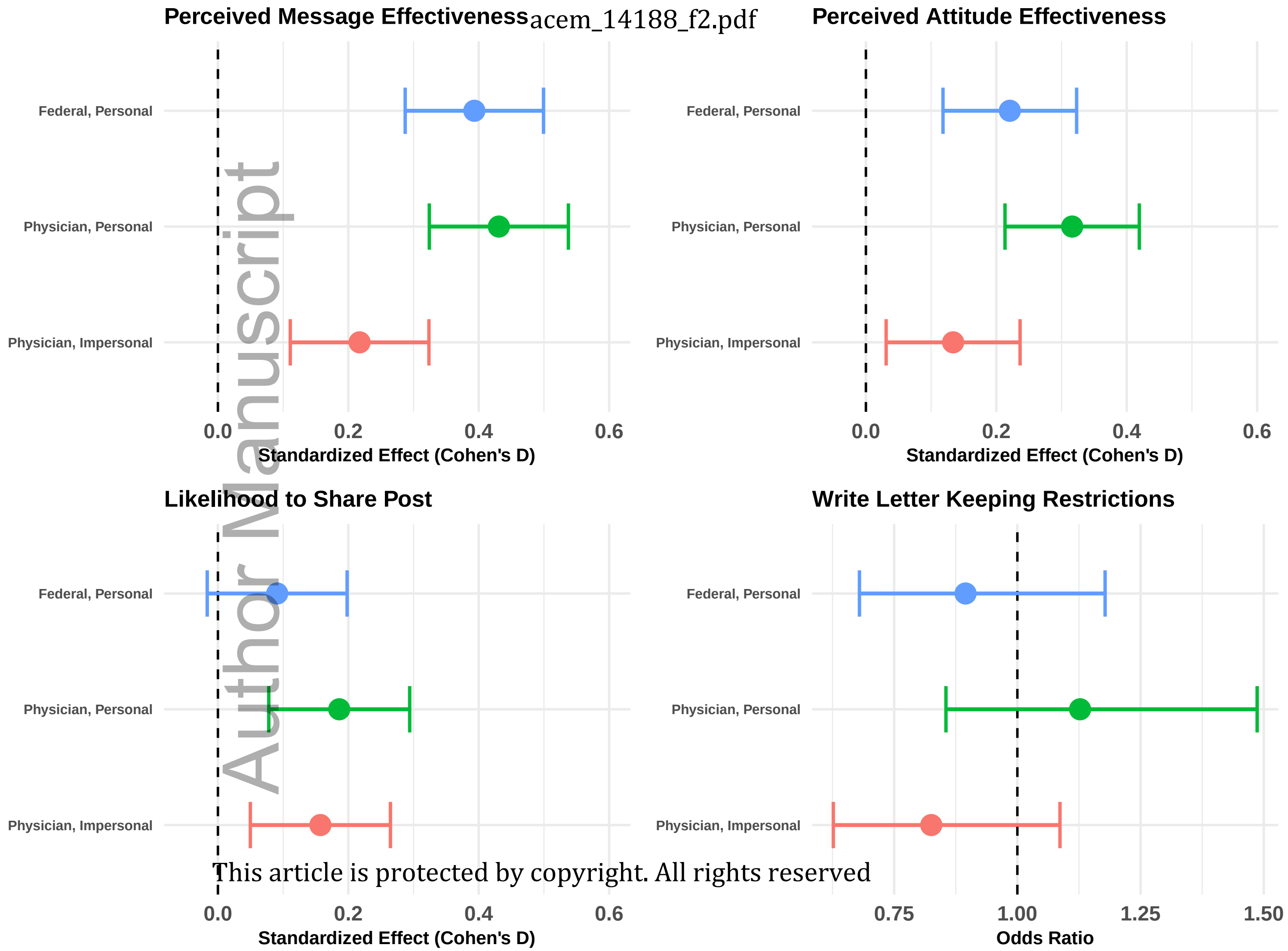
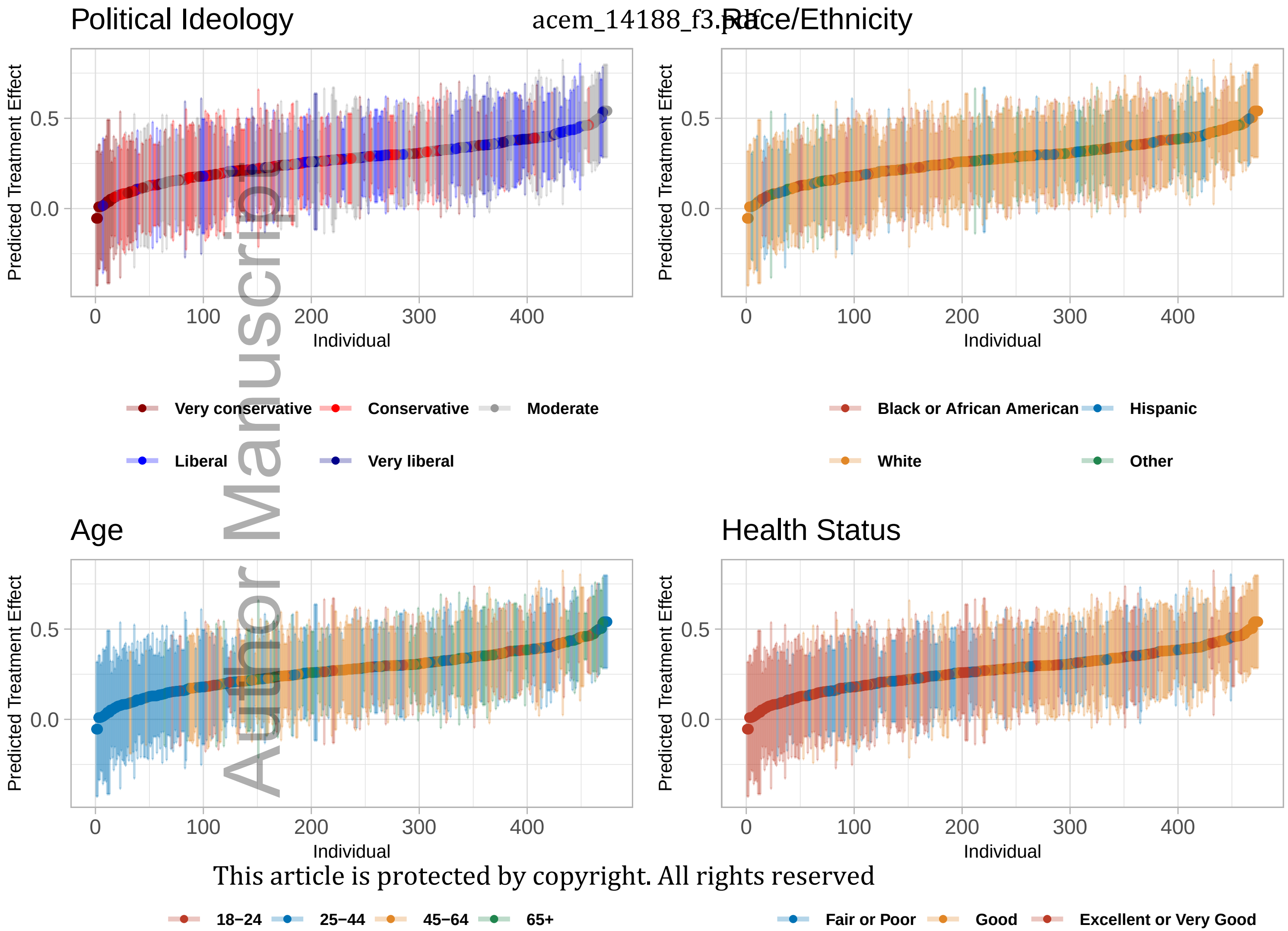
acem_14188_f1b.tif


Perceived Message Effectiveness
Federal, Personal
Physician, Personal
Physician, Impersonal
0.0
0.2
0.4
0.6
Standardized Effect (Cohen's D)
Perceived Attitude Effectiveness
Federal, Personal
Physician, Personal
Physician, Impersonal
0.0
0.2
0.4
0.6
Standardized Effect (Cohen's D)
Likelihood to Share Post
Federal, Personal
Physician, Personal
Physician, Impersonal
0.0
0.2
0.4
0.6
Standardized Effect (Cohen's D)
Write Letter Keeping Restrictions
Federal, Personal
Physician, Personal
Physician, Impersonal
0.75
1.00
1.25
1.50
Odds Ratio


Political Ideology
Predicted Treatment Effect
0.5
0.0
0
100
200
300
400
Individual
Very conservative
Conservative
Moderate
Liberal
Very liberal
Race/Ethnicity
Predicted Treatment Effect
Individual
Black or African American
Hispanic
White
Other
Age
Predicted Treatment Effect
Individual
18−24
25−44
45−64
65+
Health Status
Predicted Treatment Effect
Individual
Fair or Poor
Good
Excellent or Very Good