A global test of message framing on behavioural intentions, policy support, information seeking, and experienced anxiety during the COVID-19 pandemic

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Abstract

The COVID-19 pandemic presents a critical need to identify best practices for communicating health information to the global public. It also provides an opportunity to test theories about risk communication. As part of a larger Psychological Science Accelerator COVID-19 Rapid Project, a global consortium of researchers will experimentally test competing hypotheses regarding the effects of framing messages in terms of losses versus gains. We will examine effects on three primary outcomes: intentions to adhere to policies designed to prevent the spread of COVID-19, opinions about such policies, and the likelihood that participants seek additional policy information. Whereas research on negativity bias and loss aversion predicts that loss-framing will have greater impact, research on encouraging the adoption of protective health behaviour suggests the opposite (i.e., gain-framing will be more persuasive). We will also assess effects on experienced anxiety. Given the potentially low cost and the scalable nature of framing interventions, results could be valuable to health organizations, policymakers, and news sources globally.

In the course of the COVID-19 pandemic, individuals around the world will witness two realities: implementation of policies designed to reduce the spread of COVID-19 (e.g., social distancing) and a simultaneous explosion of infections and deaths. For example, in New York City on March 22, 2020, the order from Governor Cuomo to close all nonessential businesses coincided with a 33% daily increase in reported COVID-19 cases[1, 2]. Similar examples abound around the globe. The simultaneous imposition of new restrictions and reporting of new infections may lead citizens to wonder whether these rules are effective and/or necessary. At worst, such simultaneous occurrences could lead individuals to abandon the rules altogether[3, 4]. It is thus critical to understand how best to communicate factual information to the global public in the context of a rapidly moving pandemic[5, 6].

As part of a larger Psychological Science Accelerator (PSA) COVID-19 Rapid Project , a global consortium of researchers will experimentally test the effects of framing messages in terms of losses versus gains. We will examine effects on three primary outcomes: intentions to adhere to policies to prevent the spread of COVID-19, opinions about such policies, and the likelihood that participants seek additional policy information. Given the potentially low cost and scalable nature of framing interventions, results could be leveraged by health organizations, policymakers, and news sources globally. Currently, the World Health Organization website (i.e., as of April 16, 2020) uses both gain and loss framing (emphasis added below), a practice that the results from this study can refine with scientifically-derived and reliable information:

<u>Gain frame:</u> "Follow advice given by your healthcare provider, your national and local

public health authority or your employer on how to *protect yourself and others from COVID-19*."

Loss frame: "These measures can *reduce working days lost due to illness and stop or slow the spread of COVID-19* if it arrives at one of your workplaces."

Notably, a recent influential review of using social and behavioural science to support COVID-19 pandemic response by Van Bavel and colleagues[7] concluded that "research is needed to determine whether a more positive [versus negative] frame could educate the public and relieve negative emotions while increasing public health behaviors." The present study aims to fill this gap.

Results will address not only the immediate policy question of how best to communicate health information during the COVID-19 pandemic but also a theoretical tension between competing perspectives. On the one hand, prior research has documented advantages of gain-framed messages (vs. loss-framed messages) on people's interest in, and performance of, behaviours that promote health and prevent the onset of disease[8-10]. When individuals perceive preventive behaviours as affording safe and certain outcomes, gain-framed messages have been more effective than loss-framed messages because the message frame fits how an individual perceived the decision[11-17]. Indeed, because loss-framed messages could trigger anxiety, some research implies they could actually fail to motivate health behaviour and information seeking if they do not concurrently trigger a sense of self-efficacy[18].

On the other hand, given the unusual risks posed by COVID-19 and the ubiquitous warning of its dangers, one might hypothesize the opposite pattern of effects—i.e., that loss framing is superior. As noted, prior research supporting the effectiveness of gain frames focused on preventive health behaviours that offered safe and relatively certain outcomes. In the present pandemic, individuals may not perceive preventive behaviours as affording such outcomes, especially given the simultaneous occurrence of restrictions and new infections (described above). Indeed, prior research has also identified a generalized negativity bias wherein negative information exerts greater impact than positive information[19]. In particular, research on prospect theory[20, 21] has revealed that individuals tend to give more weight to losses than to equivalent gains. Given this, one could expect that a loss-framed health message would be more effective than a gain-framed message.

The competing hypotheses for three primary outcomes are summarized in Table 1. Taken together, the present study is poised to make both practical and theoretical contributions regardless of which hypothesis receives support. Even if neither frame is superior to the other, that information itself is useful for health organizations, policy makers, and news sources globally.

Primary outcomes	**Prediction from negativity bias/loss aversion literature**	**Prediction from health preventive behaviour literature**
Behavioural intentions to adhere to policies designed to prevent the spread of COVID-19.	Framing messages as *losses* will increase behavioural intentions compared to framing messages as *gains*.	Framing messages as *gains* will increase behavioural intentions compared to framing messages as *losses*.

Support for policies designed to prevent the spread of COVID-19.	Framing messages as *losses* will increase policy support compared to framing messages as *gains*.	Framing messages as *gains* will increase policy support compared to framing messages as *losses*.
Likelihood that participants seek additional information about policies designed to prevent the spread of COVID-19.	Framing messages as *losses* will increase information seeking compared to framing messages as *gains*.	Framing messages as *gains* will increase information seeking compared to framing messages as *losses*.

Table 1. Competing hypotheses for three primary outcomes. Whereas research on negativity bias and loss aversion predict that loss-framed messages will be more effective, research on preventive health behaviour predicts that gain-framed messages will be more effective. Experienced anxiety will be analyzed as a secondary, exploratory outcome variable.

Method

Study Overview

We test competing hypotheses regarding message framing during the COVID-19 pandemic by drawing directly on common COVID-19 recommendations (e.g., social distancing) while varying the message frame (loss vs. gain). We measure three primary outcome variables: behavioural intentions to follow anti-infection recommendations, support for anti-infection policies, and information seeking. We also measure experienced anxiety as a secondary outcome variable. We chose behavioural intentions and policy support because these variables provide ready tools to "flatten the curve" of the current pandemic[22]. We chose information seeking because individuals may be either too high (compulsively overconsuming news) or too low (avoiding news all together). Finally, as a secondary variable, we chose to measure experienced anxiety, in line with Van Bavel and colleague's call to examine how to effectively communicate information while relieving negative emotions[7].

PSA COVID-19 Rapid Project

This study is being conducted as part of a larger PSA COVID-19 Rapid Project, which involves three studies related to COVID-19. The current study will be bundled with another study into a single data collection link, with the two studies presented in random order. At the end of the study bundle, participants will also complete a general survey that includes questions about beliefs and behaviours related to COVID-19. The other two studies and the general survey responses will be reported elsewhere. A comprehensive summary of the PSA COVID-19 Rapid Project—including descriptions of the study selection procedure, the other selected studies, the internal peer review process, and implementation plans—can be found at https://psyarxiv.com/x976j.

Design

Independent Variable

Upon entering the study, participants will be randomly assigned to view gain-framed or loss-framed versions of four messages related to common COVID-19 policies. These messages relate to: (1) staying home (unless absolutely necessary), (2) avoiding all shops other than necessary ones (such as for food), (3) wearing a mouth and nose covering in public at all times, and (4) completely isolating yourself if you think you have been exposed to COVID-19. While all participants will see the same four recommendations, participants will be randomly assigned to one of two between-subjects experimental conditions (Framing: gain, loss). In the *gain condition*, participants will be told: "There is so much to gain. You can stay healthy and protect others by practicing the four steps below." In the *loss condition*, participants will be told: "There is so much to lose. You can avoid losing your health and avoid endangering others by practicing the four steps below." The same four recommendations will be displayed for all participants, but the manipulation will vary by condition. The manipulation will appear at the top of the page and will be repeated with each recommendation. The manipulation will also appear in the instructions introducing each dependent variable, as described below.

At the end of the survey, participants will complete a manipulation check. Participants will be asked which of the following phrases, if any, they recalled reading during the survey. The options will include: (a) There is so much to gain. You can stay healthy and protect others by…; (b) There is so much to lose. You can avoid losing your health and avoid endangering others by…"; (c) neither. This will allow us to later estimate the "intent-to-treat" impact of being assigned to the gain or loss condition as well as the impact of "treatment on the treated" (using a two-stage least-squares approach) for those who are confirmed to have read the manipulations.

Dependent Variables

After reading the four recommendations (with message framing varied by condition), participants will complete three self-report questionnaires (behavioural intentions to adhere to anti-infection recommendations, support for anti-infection policies, and anxiety). Then, they will identify whether they would be interested in learning more information about safe practices regarding COVID-19. The order of the dependent variables will be held constant.

First, participants will be asked about their behavioural intentions in the coming week. While the questions themselves are identical across conditions, participants will receive different instructions depending on their randomly-assigned condition. As described above, at the top of the page, participants in the *gain condition* will see text saying: "Stay healthy and protect others. There is so much to gain." Participants in the *loss condition* will see text saying: "Avoid losing your health and avoid endangering others. There is so much to lose." Below this header—which will be present on the top of the screen for all dependent variables—all participants will be told that "People around the world respond in different ways to the current situation." Participants in the *gain condition* will then read the following instructions: "We are interested in how you yourself will respond in the coming week in order to stay healthy and protect others." Participants in the *loss condition* will read a different set of instructions: "We are interested in how you yourself will respond in the coming week in order to avoid losing your health and avoid endangering others." Then, participants in all conditions will indicate how likely they are to: (1) stay at home at all times unless absolutely necessary, (2) avoid all shops other than necessary ones (such as for food), (3) wear a mouth and nose covering (such as a mask) in public at all times, and (4) completely isolate yourself if you think you have been exposed to COVID-19. The four questions will be presented in a randomized order and all responses will be on a 7-point Likert scale (1 = Extremely unlikely to 7 = Extremely likely).

On the following page, we will ask participants about their support for anti-infection policies in response to the COVID-19 pandemic. The policy items focus on trade-offs between individual rights and collective security. Specifically, participants will indicate to what extent they agree with five policy statements. Two statements will emphasize individual rights and autonomy (e.g., "Individuals, not governments, should decide how best to act during the COVID-19 pandemic"), whereas the other three statements will emphasize collective security (e.g., "Government health officials should do everything in their power to address the spread of COVID-19, even if it severely limits daily activities for citizens"). The five questions will be presented in a randomized order and all responses will be on a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). Answers to the two statements emphasizing individual rights and autonomy will be reverse-coded.

Next, participants will answer questions regarding experienced anxiety. In the *gain condition*, participants will be given the following instructions: "We are interested in how you feel when considering the COVID-19 recommendations for staying healthy and protecting others." Participants in the *loss condition* will read: "We are interested in how you feel when considering COVID-19 recommendations for avoiding losing your health and avoiding endangering others." Participants will then be asked three questions: "To what extent do you feel anxious (afraid, fearful) when considering these recommendations?" The three questions will be presented in a randomized order and all responses will be on 5-point Likert scales (1 = Not at all to 5 = Extremely).

Finally, participants will be given the option to learn more information about COVID-19. Specifically, participants will be given the opportunity to be directed to the World Health Organization website at the end of the study. The dependent variable will be assessed as a binary variable (yes, no). Materials will be translated into 45 languages using back-translation procedures[23]. A copy of all materials can be downloaded at https://osf.io/m6q8f/.

Participants

Sample size will primarily be determined by the availability of resources amongst members of the PSA[24]. At the time of Stage 1 submission, 194 research groups from 55 countries speaking 42 languages have signed up to collect data as part of the PSA COVID-19 Rapid Project. Data collection will take place between April 20th and June 1st, 2020. We expect 25,448 participants to complete the current study. Out of these 25,448 participants, 4,050 will be recruited through semi-representative paneling (based on sex, age, and sometimes ethnicity) from the following countries: Egypt, Kenya, Nigeria, South Africa, Mexico, United States, Austria, Romania, Russia, Sweden, Switzerland, United Kingdom, China, Japan, and South Korea (270 participants per country). The remaining participants will mostly be convenience samples recruited by the 194 research groups.

Due to the nested structure of our data (participant responses nested within countries), data will be analyzed using linear mixed-effects modeling with random intercepts and slopes. We conducted a simulation to estimate power for a variety of potential effects sizes ($|d|$ = 0.10, 0.20, 0.30), number of countries ($n_{country}$ = 40, 45, 50, 55, 60), within-country sample sizes (n = 100, 300, 500), by-country intercept variances ($\sigma^2_{intercept}$ = 0.10, 0.60, 1.10, 1.60, 2.10, 2.60), and by-country slope variances (σ^2_{slope} = .02, .03, .04) at α = .05. We conducted 1,000 simulations for each set of simulation parameters using the R simr package[25] using computing power harnessed through the Open Science Grid[26, 27].

We show abbreviated results for our power simulations in Figure 1 and comprehensive results at https://osf.io/m6q8f/. At low slope and intercept variances, we estimate that 300 participants from 55 countries (total n = 16,500) would provide 98% power to detect an effect size of $|d|$ = 0.10. At very high by-country slope and intercept variances, we estimate that our projected sample (n = 25,448) would provide over 99% power to detect an effect size of $|d|$ = 0.20. Given that (a) Gallagher and Updegraff's[8] meta-analysis of 94 studies examining the effects of gain-framed messaging on preventive behaviours (such as sunscreen use, smoking cessation, and physical activity) suggested that overall effect sizes ranged from d = 0.16-0.23 and

(b) previous large-scale collaborations in psychology have yielded low estimates of between-lab heterogeneity[28], we anticipate that power in this study will be well above 95%.

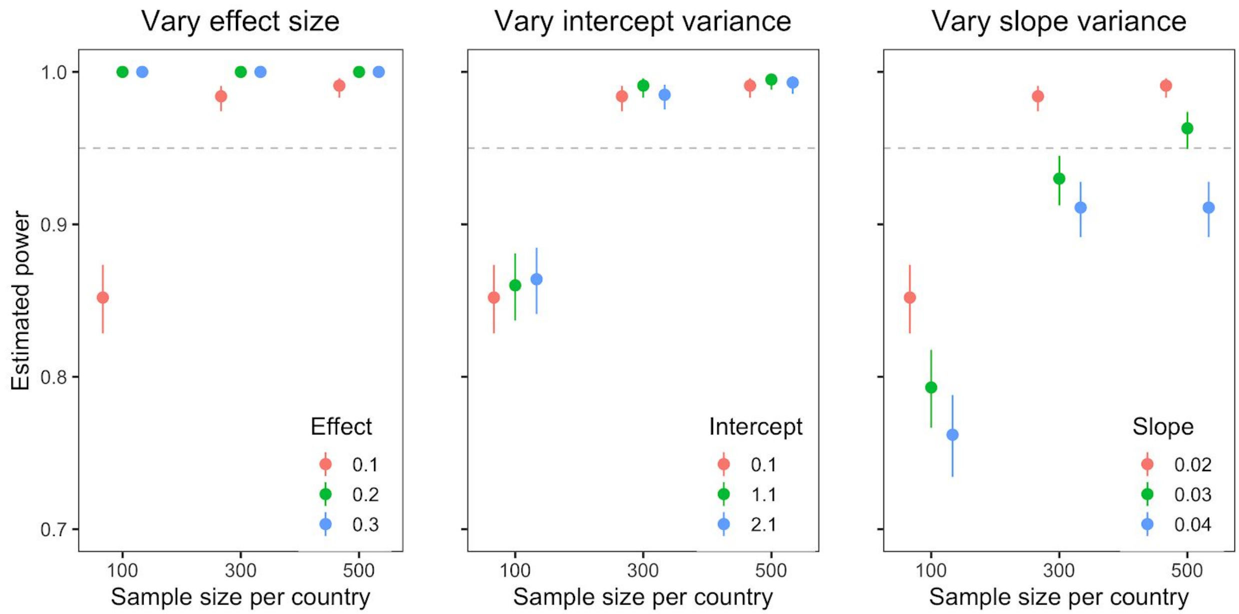

Figure 1. Abbreviated power simulation results. Points represent the estimated power across 1000 simulated datasets. Lines are Monte Carlo 95% confidence intervals. For all simulations, unless otherwise specified, the number of countries is fixed at 55, the target effect size is fixed at $d = 0.10$, the intercept variance is fixed at $\sigma^2_{intercept} = 0.10$, and the slope variance is fixed at $\sigma^2_{slope} = 0.02$. Comprehensive results are available at https://osf.io/m6q8f/.

Given the imprecise value regarding the costs and benefits of message framing in the current COVID-19 pandemic, we do not denote a precise smallest effect size of interest for this study. Although we anticipate that the costs of implementing a message framing intervention are low, the exact cost is difficult to precisely estimate without working closely with policy makers. Furthermore, potential benefits are difficult to precisely estimate given uncertainty regarding how responses in our survey will translate to actual behaviour (and how changes in actual behaviour will translate into lives actually saved). Thus, although costs are likely to be low and that even small impacts could be relevant given the large number of people who could be affected, we will interpret any possible effect sizes with caution.

Analysis Plan

We have three primary dependent variables in our study: behavioural intentions to adhere to anti-infection recommendations, support for anti-infection policies, and information seeking. Given our competing hypotheses, the primary confirmatory hypothesis tests will be two-sided for each dependent variable. We will also use a two-sided test for our secondary, exploratory dependent variable: experienced anxiety.

Primary Analyses

We will use a similar analysis strategy for all three primary dependent variables. Since ratings will be nested within country, we will fit three separate multilevel models with framing as a dummy-coded factor, random slopes, and random intercepts. For continuous dependent variables (i.e., behavioural intentions and policy support), we will use linear mixed effects modeling. For the binary dependent variable (i.e., information seeking), we will use logistic mixed effects modeling.

Secondary Analyses

We specify below three sets of secondary analyses. First, we will analyze experienced anxiety using the same linear mixed effect model we specified for the other primary continuous dependent variables. Second, following an identical analytic plan laid out by Coles and colleagues[29], in order to be able to quantify the relative evidence between the null and alternative hypothesis, we will conduct the same analyses within a Bayesian framework[30] using the Bayes

Factor package in R[31]. To do so, we will refit our models using the *lmBF* function with Cuachy priors on the fixed effects. Third, we specify three key contingencies below that will influence both our frequentist and Bayesian analyses.

Contingency 1: Low reliability of self-report measures. For the self-report outcomes, we will assess the reliability of the measures before fitting the multilevel models. Behavioural intentions will be measured with four items, policy support will be measured with five items (including two reverse-coded items), and anxiety will be measured with three items. For each of the three outcome variables, if the average inter-item correlation is above .40, we will average scores on the items into a single combined index. If the average inter-item correlation is below .40, we will conduct an exploratory factor analysis with oblique rotation and maintain factors with an eigenvalue above 1.00. If no factors have an eigenvalue above 1, we will report results by item rather than as a composite.

Contingency 2: Order effects. The effect of message framing on our outcome variables may depend on whether the respondent completed the present study before or after the second non-focal study in the PSA COVID-19 Rapid Project survey bundle. To examine this, we will re-run our confirmatory analysis with order (0 = current study run first, 1 = current study run second) included as a dummy-coded factor and a framing condition by order interaction. If the order variable does not interact with condition, we will collapse all analyses across this variable.

If the framing condition by order interaction is significant, we will re-examine the simple effect of framing condition for each order. If the order variable interacts with condition but the effect of condition remains significant at both levels of order (1 and 0), we will analyze and report results at both levels separately. If the order variable interacts with condition and the effect of condition either is not significant or reverses in direction at either level of order, we will consider data from participants who completed the focal study first to be the best test of our hypothesis (but still report and examine participants who completed the focal study second).

Contingency 3: Panel vs. non-panel data. The effect of message framing on our outcome variables may depend on whether the respondent was recruited through a semi-representative panel or through convenience sampling. To examine this, we will re-run our confirmatory analyses with panel (0 = not recruited through panel, 1 = recruited through panel) included as a dummy-coded factor and a framing condition by panel interaction. If the panel variable does not interact with condition, we will collapse all analyses across this variable. If the framing condition by panel interaction is significant, we will re-examine the simple effect of framing condition for each level of the panel factor.

Ethics

All participating research groups are required to either obtain approval from their local Ethics Committee or IRB to conduct the study, explicitly indicate that their institution did not require approval to conduct this type of study, or explicitly indicate that the study is covered by a pre-existing approval. Although the specifics of the consent procedure will differ across research groups, all participants will provide informed consent.

At the time of submission, 101 research groups from 34 countries have ethics approvals to collect data from 10,625 participants. Other research groups are currently seeking ethics approval, and we anticipate that our final sample will include 194 research groups from 55 countries that will collect data from 25,448 participants. Given that (a) Gallagher and Updegraff's[8] meta-analysis of 94 studies examining the effects of gain-framed messaging on preventive behaviours (such as sunscreen use, smoking cessation, and physical activity) suggested that overall effect sizes ranged from *d* = 0.16-0.23 and (b) previous large-scale collaborations in psychology have yielded low estimates of between-lab heterogeneity[28], even 10,625 participants should provide over 95% power to detect a small effect of *d* = .20 (see Figure 1).

Data, Materials, and Code Availability

All data, materials, and analysis code (completed in R) will be made openly available at https://osf.io/m6q8f/.

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