Investigating the Accuracy of US Citizens' Beliefs About the COVID-19 Pandemic: A Longitudinal Study With Educational Intervention

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Abstract

Background: The COVID-19 'infodemic', a surge of misinformation, has sparked worry about the public's perception of the novel coronavirus and Coronavirus Disease (COVID-19). Misinformation can lead to belief in false information, as well as reduce the accurate interpretation of true information. Such incorrect beliefs about the COVID-19 pandemic might lead to behavior that puts people at risk of both contracting and spreading the virus.

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Methods: We conducted a four-week longitudinal study among US citizens, starting April 27, 2020, just after daily COVID-19 deaths in the US had peaked. Each week, we measured participants' belief accuracy related to the coronavirus and COVID-19 by asking them to indicate to what extent they believed a number of true and false statements (split 50/50). Furthermore, each new survey wave included both the original statements and four new statements (2 false, 2 true). Half of the participants were exposed to an intervention aimed at increasing belief accuracy. The intervention consisted of a short infographic that set out three steps to verify information by searching for and verifying a scientific consensus.

Results: A total of 1202 US citizens, balanced on age, sex, and ethnicity to approximate the US general public, completed the baseline wave. Retention rate for the follow-up waves was high (minimum was 85.02%). Mean scores of belief accuracy were high at all waves, with scores reflecting low belief in false statements and high belief in true statements (scale of -1 to 1, with -1 indicating completely inaccurate beliefs and 1 indicating completely accurate beliefs; mean baseline=0.75, mean follow-up1=0.78, mean follow-up2=0.77, mean follow-up3=0.75). Accurate beliefs were correlated with self-reported behavior aimed at preventing the coronavirus from spreading (e.g., social distancing; r at all waves between 0.26 and 0.29, all Ps<.001), and were associated with trust in scientists (higher trust associated with more accurate beliefs), political orientation (liberal/Democratic participants held more accurate beliefs than conservative/Republican participants) and the primary news source (participants reporting CNN or Fox News as main news source held less accurate beliefs than others). The intervention did not significantly improve belief accuracy.

Conclusions: The supposed infodemic was not reflected in US citizens' beliefs about the COVID-19 pandemic. Most people were quite able to figure out the facts in these relatively early days of the crisis, calling into question the prevalence of misinformation and the public's susceptibility to misinformation.

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Conclusions: The supposed infodemic was not reflected in US citizens' beliefs about the COVID-19 pandemic. Most people were quite able to figure out the facts in these relatively early days of the crisis, calling into question the prevalence of misinformation and the public's susceptibility to misinformation.

Keywords: infodemic; misinformation; COVID-19 pandemic; belief accuracy; facts; educational intervention; trust in scientists; political orientation; media use

Introduction

Public health crises tend to go hand in hand with information crises. The COVID-19 pandemic, which is taking many lives and is hospitalizing hundreds of thousands of people globally, is no exception. In the wake of the COVID-19 pandemic, we are seeing signs of a misinformation pandemic. Around the first peak of the coronavirus outbreak in the US, the country with the highest COVID-19 death toll [1], about two-thirds of Americans said they had been exposed to at least some made-up news and information related to the virus [2]. Misinformation about the pandemic seems to have proliferated quickly, especially on social media [3]. The World Health Organization (WHO) has labelled this surge of misinformation about the COVID-19 pandemic an ‘infodemic’ [4].

Countries and social media platforms are trying to tackle this infodemic in a number of ways. Several social media platforms, including Facebook and Twitter, have implemented new procedures to remove or label false and misleading content [5,6]. However, with the vast number of posts made to these platforms every day and the platforms’ fear of infringing on free speech, the success of these procedures is limited [e.g., 7]. A second strategy consists of surfacing trusted content, for instance by referring people with questions to the WHO or national health agencies, such as the Centers for Disease Control and Prevention (CDC) in the US and the National Epidemiology Center (CENEPI) in Brazil. This approach might be hindered by government officials, including US president Donald Trump and Brazilian president Jair Bolsonaro, actually contributing to the spread of misinformation [e.g., 8,9]. Considering this apparent infodemic, are people able to distinguish facts from fiction? And what correlates might enable or disable them in forming accurate beliefs?

One promising approach to limiting the effects of misinformation was already on the rise before the COVID-19 pandemic: increasing misinformation resistance through educational interventions. A substantial number of countries have implemented educational interventions, primarily focused on ‘media literacy’ [10], which can be understood as the ability to access, analyze, evaluate and communicate messages in a variety of forms [11]. The Swedish Civil Contingencies Agency, for instance, has included a section about misinformation in its public emergency preparedness brochure, advising Swedes to be aware of the aim of information and check the source of information, amongst others [12]. Similarly, Facebook tries to help its users recognize misinformation by providing 10 tips [13]. A focus on media literacy has the advantage of being able to prevent problems with misinformation, instead of having to correct false beliefs after they have taken hold. Being able to identify and process misinformation critically is a useful skill, especially in times of crisis. Can these types of interventions, focusing on empowerment of media consumers, help individuals deal with the supposed COVID-19 infodemic?

The current research had two main goals. One involved an exploratory (not preregistered) investigation to gain insight into the effects of the supposed infodemic on individuals’ belief accuracy in times of crisis, and to investigate potential correlates of belief accuracy. The second goal was a preregistered test of an educational intervention aimed at increasing belief accuracy. Accordingly, we hypothesized our intervention to lead to more accurate beliefs about the COVID-19 pandemic than no intervention (the complete preregistration can be found on the Open Science Framework (OSF)[14]. The research was conducted online, recruiting a balanced sample of the US population. We decided to focus on the US, because this is arguably the country worst hit by the COVID-19 pandemic. Using a longitudinal design, measuring beliefs about the pandemic over four weeks, allowed us to investigate and intervene on belief formation in the relatively early days of the pandemic. All data and material are available on the project page on the OSF [15].

Methods

Recruitment

We used online crowdsourcing platform Prolific to collect data from US citizens over a four-week period. Recruitment was balanced on age, sex, and ethnicity to approximate the US general public (via census data). Recruitment for the initial baseline wave started on April 27, about two weeks after the daily confirmed COVID-19 deaths had peaked at over 4000 (see Figure 1). A total of 1212 individuals participated in the study at baseline (T0). A total of 1089 individuals participated in the first follow-up wave (T1), 1070 individuals participated in the second follow-up wave (T2), and 1028 individuals participated in the final wave (T3; see Table 1 for total sample size, exclusions, and final sample size per wave). Each of the waves was separated by approximately one week ($mean_{T0-T1}$=6.98 days, SD_{T0-T1}=14.92 hours; $mean_{T1-T2}$=7.01 days, SD_{T1-T2}=12.72 hours; $mean_{T2-T3}$=7.06 days, SD_{T2-T3}=13.18 hours). The sample size was determined by the available resources.

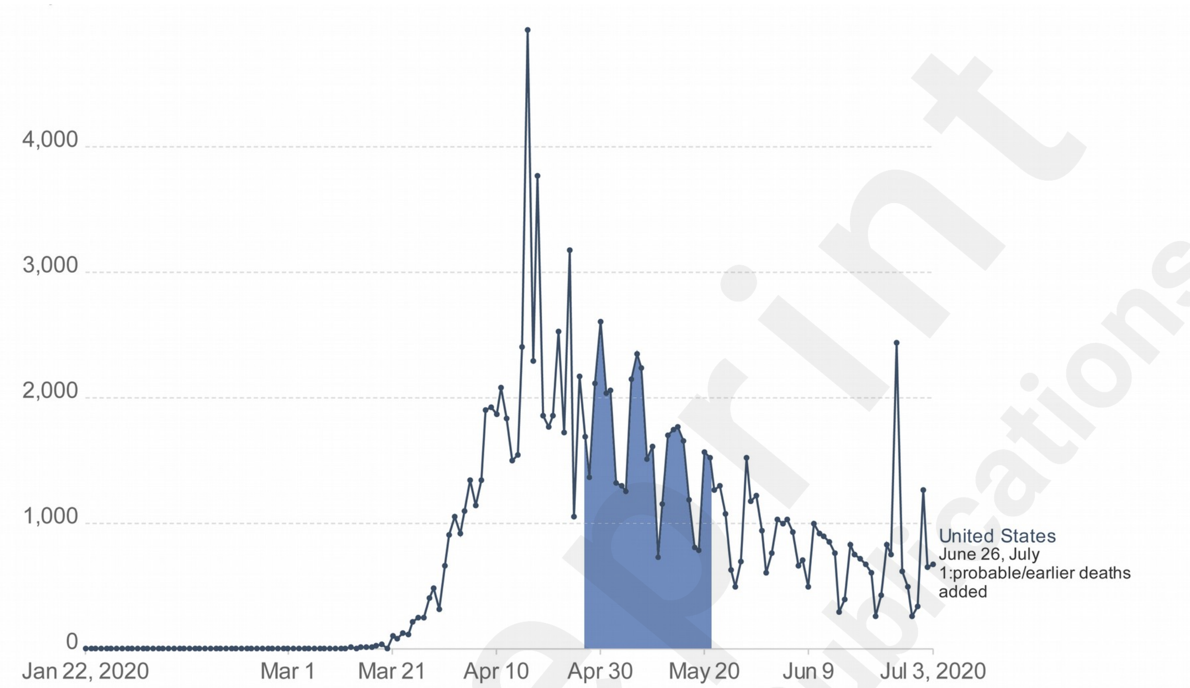

Figure 1. Daily confirmed COVID-19 deaths in the US. The blue area indicates the time period in which data were collected. Image provided by Our World in Data. Source of the data: European CDC.

Table 1. Total sample size, exclusions, and final sample size per wave.[ab]

Wave	Sample	N
T0: April 27 – April 29		
	Total sample	1212
	Excluded	10
	Final sample	1202
T1: May 4 – May 7		
	Total sample	1089
	Excluded	11
	Final sample	1078 (RT = 89.68%)
T2: May 11 – May 14		

	Total sample	1070
	Excluded	3
	Final sample	1067 (RT = 88.77%)
T3: May 18 – May 21		
	Total sample	1028
	Excluded	6
	Final sample	1022 (RT = 85.02%)

[a]RT = Retention rate, based on final samples of T0 and respective wave. Total sample sizes of follow up waves counted excluding two participants who should have been excluded but had been allowed to participate in the follow-up waves due to a technical error.
[b]More details on exclusions can be found in Statistical Analysis: Data exclusion, below.

Procedure

At the start of the first survey, the participants were randomly assigned to either receive the intervention (the 'boost' condition; see Material and Measures) or no intervention (control condition). All surveys started with the measure of belief accuracy, for which participants were presented with 10 (T0), 14 (T1), 18 (T2), or 22 (T3) statements about the coronavirus and COVID-19. Participants indicated to what extent they believed each statement to be true. An attention check was included among these statements (see Multimedia Appendix 1). Subsequently, participants reported their behavior aimed at preventing the spread of the coronavirus. This was followed by measures of i) trust in scientists as a source of information about the coronavirus, and ii) participants' self-perceived knowledgeability. At T0, we asked participants to report their main source of news about the coronavirus. In all other waves, participants were asked about their exposure to and search for coronavirus information. Additionally, at T3, participants completed a manipulation check. The boosting intervention was included at the end of T0, T1, and T2, during which only participants in the boost condition were presented with an infographic, allowing them to apply their boosted consensus reasoning skill in the week leading up to the next wave. At T0, all participants then entered demographic information and completed a seriousness check (see Multimedia Appendix 1). In all waves participants were debriefed, while only in T0, T1, and T2 participants were made aware that there would be a follow-up survey.

Materials and Measures

Belief accuracy

The key dependent variable was the accuracy of participants' beliefs related to the COVID-19 pandemic. This variable consisted of responses to a number of statements about the pandemic, which were sourced from preprints of early research on public perceptions of COVID-19 [e.g., 16], public health agencies and medical institutes (e.g., WHO), media tracking organizations (e.g., NewsGuard), and expert reports in established media (e.g., CNBC; comprehensive list available in Multimedia Appendix 2). Only statements based on scientific claims were included, to make sure that there was compelling evidence that the claims were either true or false.

At baseline, participants were exposed to 10 statements, of which five were scientifically accurate (e.g., 'Fever is one of the symptoms of COVID-19') and five were at odds with the best available evidence (e.g., 'Radiation from 5G cell towers is helping spread the coronavirus'). Participants responded by indicating a statement was either false, probably false, they did not know, probably true or true. In each subsequent wave, four new statements were added to the list of statements (two accurate ones and two inaccurate ones). This allowed us to keep the belief accuracy measure current, reflecting contemporary insights and discussion points. A belief accuracy score was calculated by converting the response to each statement to a number reflecting how accurate the response was, counting a correct judgment as 1, an incorrect judgment as -1. A less certain but correct ‘probably true’ or ‘probably false’ counted as 0.5, an incorrect one as -0.5. Finally, a ‘Don’t know’ was counted as 0. Average scores were calculated per wave per participant, resulting in a repeated measure of belief accuracy. Internal consistency was acceptable to good across the four waves (McDonald’s ω_t between 0.75 and 0.87 in all waves).

Coronavirus-related behavior

Coronavirus-related behavior aimed at preventing the coronavirus from spreading was measured by asking participants to indicate their agreement with three statements. The statements were “To prevent the coronavirus from spreading…” i) “I wash my hands frequently”, ii) “I try to stay at home / limit the times I go out”, and iii) “I practice social distancing (also referred to as 'physical distancing') in case I go out,” all measured on a scale from 1 (strongly disagree) to 7 (strongly agree). Scores were averaged per wave per participant. Internal consistency was acceptable to good across the four waves (McDonald’s ω_t between 0.77 and 0.83 in all waves).

Additional measures

Trust in scientists and perceived knowledgeability were measured in all four waves with responses to the statements “I trust scientists as a source of information about the coronavirus” and “I am knowledgeable about the coronavirus”, respectively. Participants responded on a 7-point scale ranging from “Strongly disagree” to “Strongly agree”.

Participants’ primary news source for information about the COVID-19 pandemic was identified by asking them what their main source of news about the coronavirus was at T0. Participants could choose one option from a list of 11 news sources, based on data from the Pew Research Center on Americans’ news habits [17].

General coronavirus information exposure was measured with two statements: “To what degree were you exposed to (news or social media) messages about the coronavirus?” and “To what degree did you try to find information on the coronavirus?”. Exposure to information about scientific consensus related to the coronavirus was only measured in the boost condition. It was measured with two statements: “To what degree did you look for information about the scientific consensus related to the coronavirus?” and “To what degree did you actually process (e.g. read, view, hear) information about the scientific consensus?”. Participants responded to these statements on a 7-point scale ranging from “Not at all” to “Very much”.

Finally, we included a manipulation check at T3. This consisted of asking participants how they evaluated the truthfulness of the statements about the coronavirus and coronavirus disease in the study over the past weeks. We asked them to name the steps that they took to evaluate the claims in three open text boxes, of which at least one had to be used. These answers were coded by the first author to indicate whether they mention consensus (or something similar) or not. A second coder coded a random subset of 120 (10%) answers, with Krippendorff’s alpha indicating good (α=0.85) inter-rater reliability. Therefore, the complete coding from the first author was used in the analyses.

Intervention

The educational intervention that was included at the end of T0, T1, and T2 consisted of a short infographic that was aimed at empowering participants to use the scientific consensus when evaluating claims related to the COVID-19 pandemic. The infographic set out three steps that can be used to evaluate a claim: i) searching for a statement indicating consensus among scientists, ii) checking the source of this consensus statement, and iii) evaluating the expertise of the consensus. The infographic can be found in Multimedia Appendix 3. Participants in the control condition were not exposed to the infographic. The current strategy is considered a 'boosting' approach, as it focuses on improving people's decision making skills [18].

Demographics

Demographics political orientation, age, sex, ethnicity, and education were asked at T0. Political orientation was measured by combining political identity (Strong Democrat, Democrat, Independent Lean Democrat, Independent, Independent Lean Republican, Republican, or Strong Republican) and political ideology (Very Liberal, Liberal, Moderate, Conservative, or Very Conservative), into one standardized measure, based on [19].

Statistical Analysis

Data Exclusion

First, we removed one of two duplicate responses at T1 and excluded all responses of one participant with three varying responses at T3.

As preregistered, participants who failed the attention check at T0 were excluded and replaced (n =8; including two who had been allowed to participate in the follow-up waves due to a technical error). If a participant failed one of the attention checks in the subsequent waves, data from that wave was not included in the analyses (n_{t1}=5, n_{t2}=2, n_{t3}=5), but other surveys in which the attention check was not failed were retained. Participants who indicated at the seriousness check at T0 that their data should not be used were excluded from further participation, their data was not used, but they were not replaced (n=2). No participants completed T0 in less than one minute, but if a participant completed a subsequent wave in less than one minute, data from that survey was not included in the analyses (n_{t1}=6, n_{t2}=1, n_{t3}=0). Other waves in which the one-minute threshold was passed were retained.

Exploratory (not preregistered) analyses

The relationship between belief accuracy and coronavirus-related behavior was explored with correlations for each wave. The relationship of belief accuracy with trust in scientists, political orientation, and primary news source was explored using mixed modeling, controlling for wave, age, sex, education, and ethnicity, with the lme4 package [20] in R [21]. We included the measure of trust in scientists from T0. Moreover, the interaction between trust and political orientation was included in the model. The five most chosen news sources (CNN, Fox News, NPR, social media sites, and The New York Times, excluding the option "Other sources") were included as dummy coded variables. The dependent variable was the repeated measure of belief accuracy (at T0, T1, T2, and T3). A random intercept and a random slope for wave were included per participant. The model was examined using likelihood ratio tests (LRT), using the package lmerTest [22].

Preregistered analysis

The hypothesis that our intervention would lead to more accurate beliefs than control was also tested using linear mixed modeling. The experimental condition (intervention vs. control) and wave, and the interaction between condition and wave, were included as predictors in the model. Political orientation was included as a covariate, because beliefs about the COVID-19 pandemic are related to political ideology [23]. Just as in the exploratory models, a random intercept and a random slope for wave were included per participant. The hypothesis was tested by comparing the full model, with the interaction between condition and wave, to a model without this interaction effect. We used the mixed function from package afex [24] that calls the PBmodcomp function from package pbkrtest [25] for parametric bootstrapping (10,000 simulations).

Results

Belief Accuracy

Mean scores of belief accuracy were very high at all waves, with scores reflecting low belief in false statements and high belief in true statements in general. There was substantial variation in the accuracy of responses between statements, although none of the statements was ever interpreted with less than 0.25 accuracy on average (see Multimedia Appendix 4 for a complete overview of scores per statement per wave).

There was a modest increase in belief accuracy over time, looking at each set of statements separately (first 10: estimate=0.02, se<0.01; $t_{3202.59}$=13.82, *P*<.001; T1 set: estimate=0.01, se<0.01; $t_{2041.94}$=4.80, *P*<.001; T2 set: estimate=0.02, se<0.01; $t_{1003.22}$=3.40, *P*<.001). This increase was positive for all three sets of statements that were asked more than once (see Figure 2), indicating that participants became more accurate in their interpretation of the statements over time.

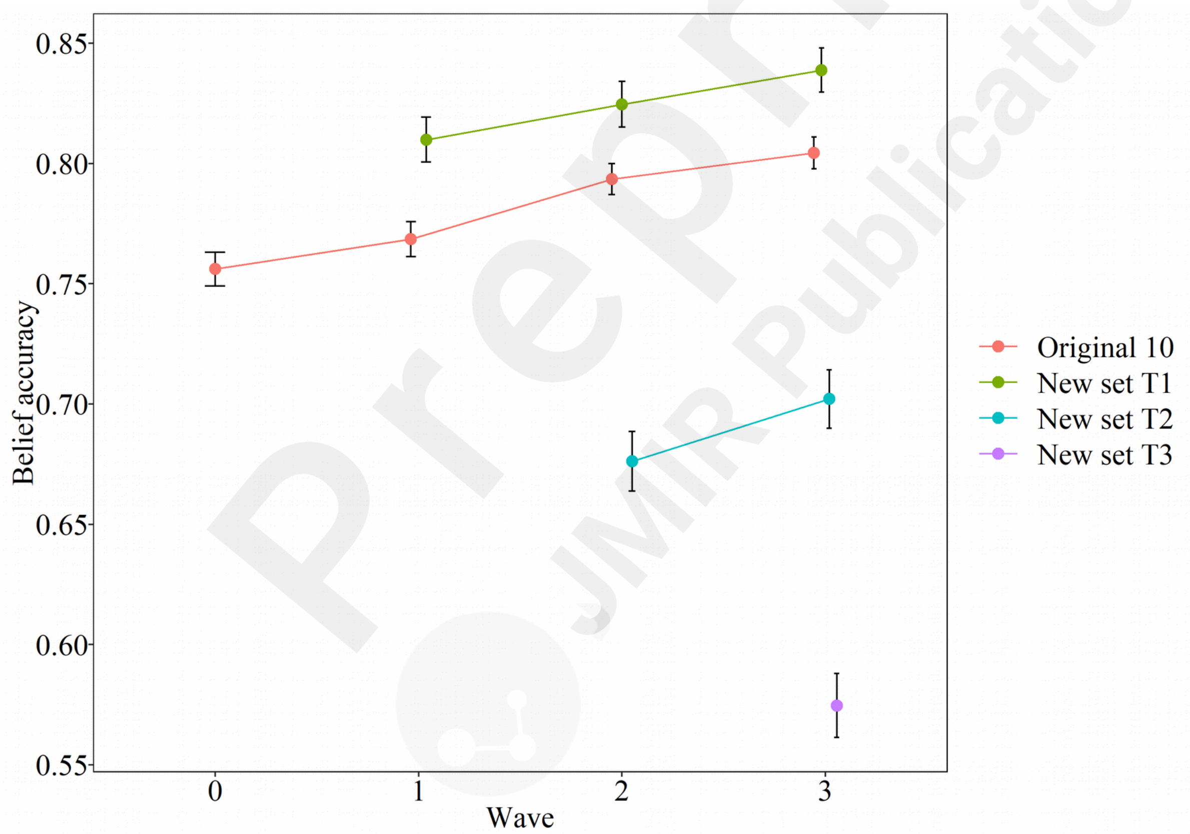

Figure 2. Belief accuracy per set of statements over time. The new set at T3 was included for completeness. Focusing on within subject change, dots represent normed means, error bars indicate 95% confidence intervals (CI) of the within-subject standard error [26], calculated using the summarySEwithin function from the Rmisc package [27].

Coronavirus-related behavior

Accurate beliefs were correlated with self-reported behavior aimed at preventing the coronavirus from spreading (*r* at all waves between 0.26 and 0.29, all *P*s<.001). This small, but robust correlation suggests that accurate beliefs are important for corona-proof behavior. We explored potential evidence of any causal effects in the data using a random intercept cross-lagged panel model (RI-CLPM). This yielded a tentative indication that accurate beliefs might be predictive of behavior, with belief accuracy at T2 predicting coronavirus-related behavior at T3. However, with all other paths showing no sign of significant predictive effects, the results are largely inconclusive (see Multimedia Appendix 5).

Associations with belief accuracy

We explored the relationship of trust in scientists (at T0), political orientation, and the primary news source with belief accuracy. The mixed model yielded a significant positive relation between belief accuracy and trust (estimate=0.07, se<0.01; $t_{1200.23}$=16.44, *P*<.001), and a significant negative correlation with political orientation (estimate=-0.02, se<0.01; $t_{1199.62}$=-6.78, *P*<.001). These main effects indicated that participants with higher trust in scientists scored higher on the measure of belief accuracy and that liberal/Democratic participants held more accurate beliefs than conservative/Republican participants. Moreover, these main effects were partially qualified by an interaction effect among trust and political orientation (estimate=-0.01, se<0.01; $t_{1195.05}$=-3.62, *P*<.001). Plotting of this interaction effect demonstrated that trust in scientists had a stronger relationship with belief accuracy for liberal/Democratic participants than it had for conservative/Republican participants (see Figure 3).

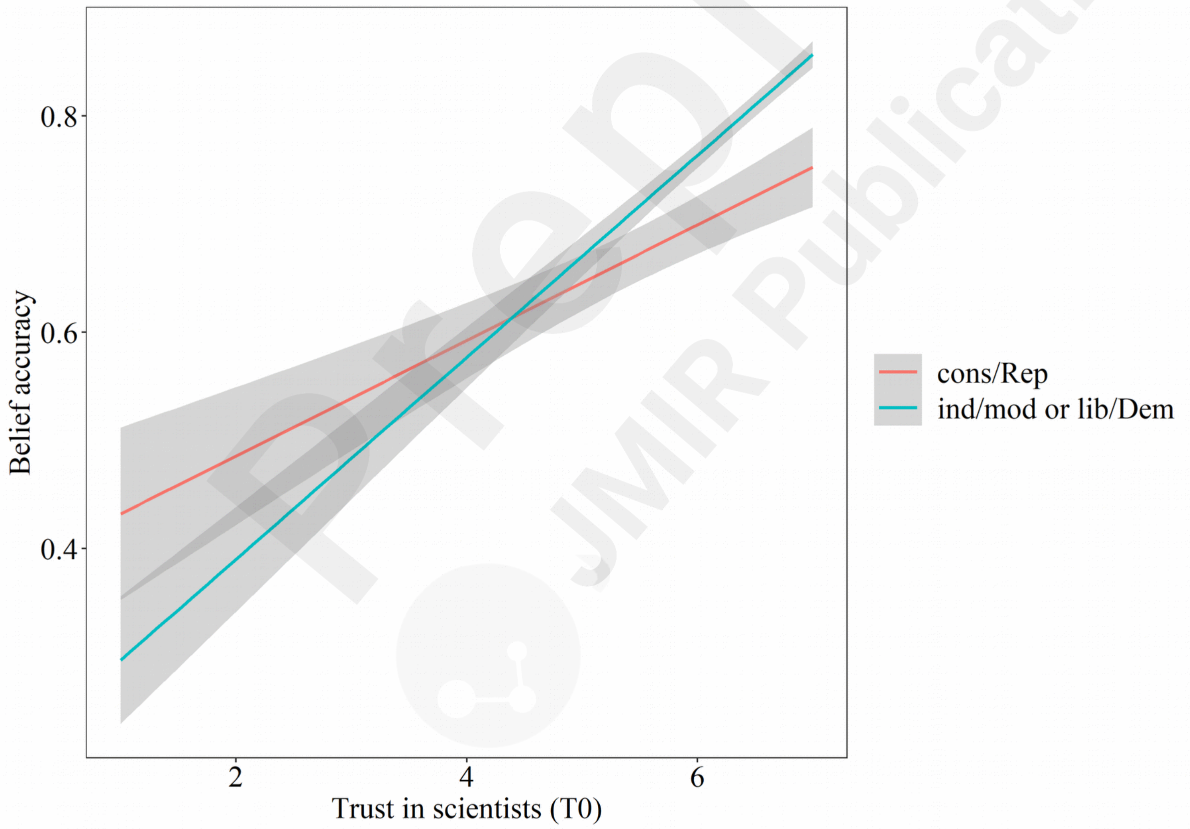

Figure 3. Linear relationship between belief accuracy (averaged over wave for plotting) by trust in scientists at T0, split by political orientation (dichotomized for plotting). The grey area represents the 95% CI.

Some of the five most chosen primary news sources were associated with a worse understanding of the facts regarding the COVID-19 pandemic than others (see Figure 4). Participants who reported CNN (estimate=-0.03, se=0.01; $t_{1194.49}$=-2.33, *P*=.02) or Fox News (estimate=-0.05, se=0.02; $t_{1202.49}$=-3.05, *P*=.002) as their main news source scored below average on belief accuracy.

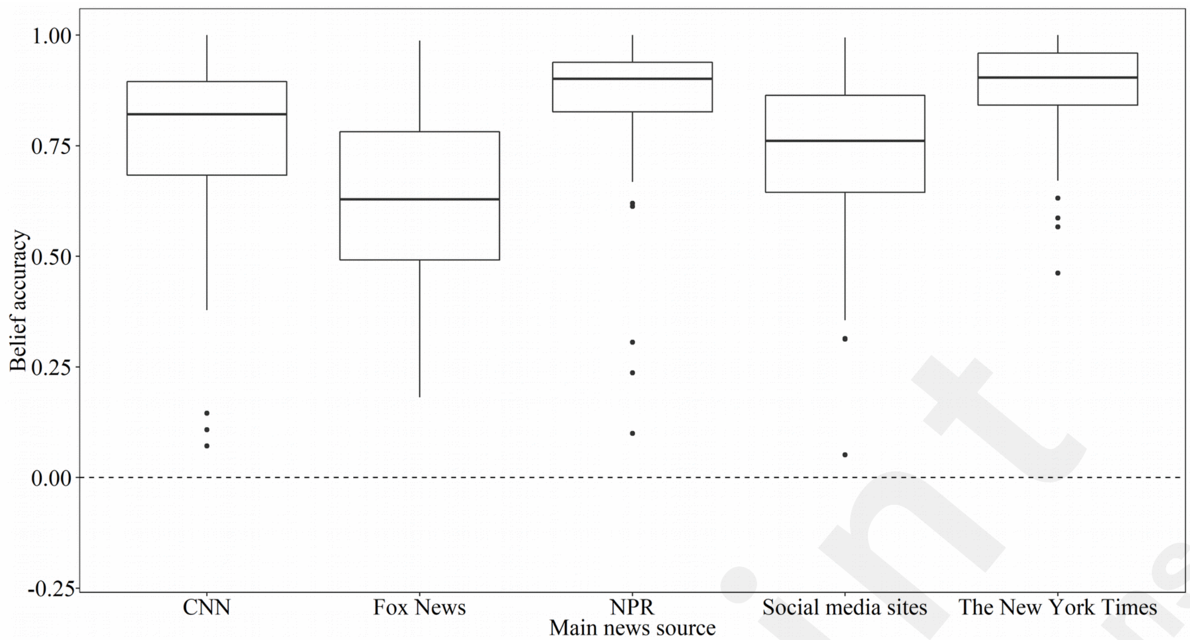

Figure 4. Boxplot of raw (unadjusted) scores of belief accuracy (averaged over wave for plotting) by main news source.

Intervention

We conducted a manipulation check and, as expected, when asked how they evaluated claims, participants in the boost condition mentioned consensus (or something similar) more often (22.67%) than participants in the control condition (4.32%; $\chi^2(1, N=1202)=85.18$, P<.001).

We hypothesized that our boosting intervention would lead to more accurate beliefs about the COVID-19 pandemic than control. However, the interaction effect between condition and wave on belief accuracy was not significant (estimate<0.01, se<0.01; $t_{1074.36}=0.22$, *P*=.83). This means that the boosting intervention did not significantly alter belief accuracy of participants over time, compared to control (see Figure 5). This was also the case when we explored effects of the intervention on inaccurate statements only (*P*=.48), accurate statements only (*P*=.49), only the original 10 statements that were included in all waves (*P*=.61), and only included participants who scored relatively low on belief accuracy at T0 (belief $\text{accuracy}_{T0}<0.76$; *P*=.32).

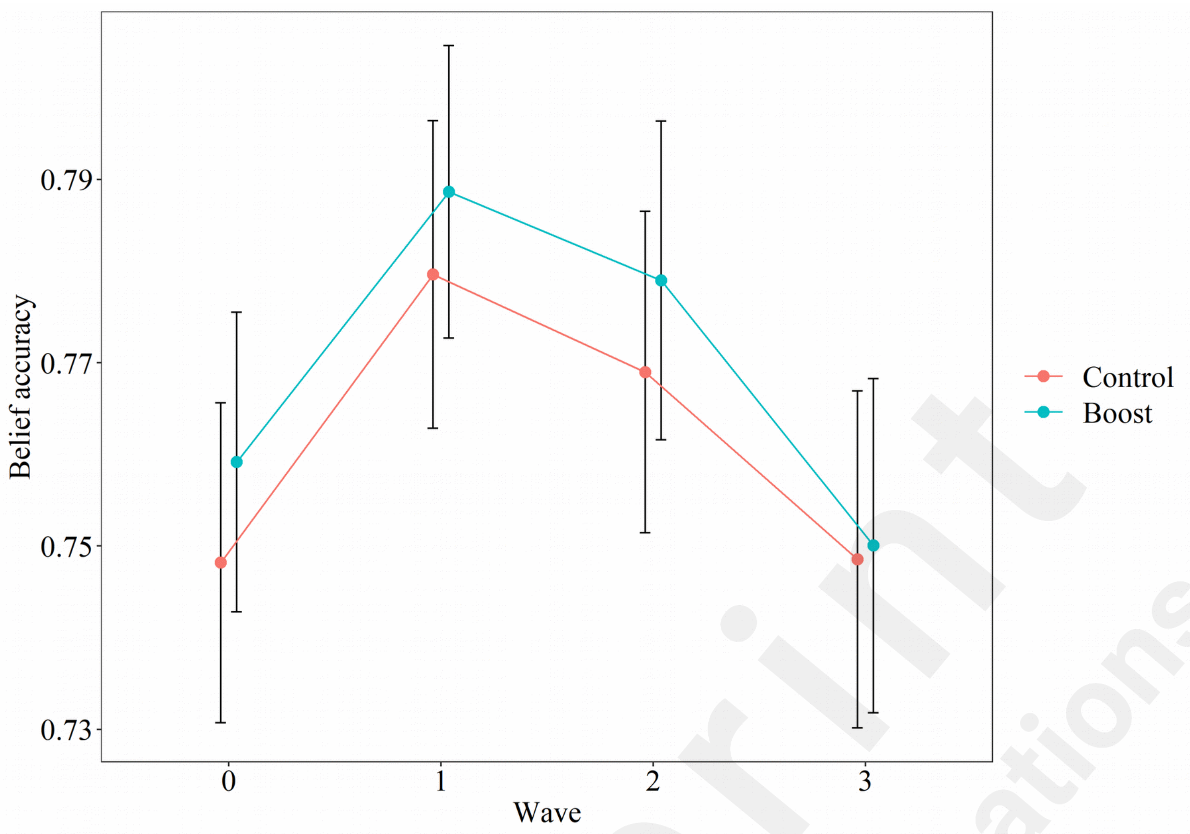

Figure 5. Belief accuracy per condition over time. Error bars indicate 95% CI focusing on the comparison between experimental conditions, not adjusted for within-subject variability.

We explored the effect of the boosting intervention on trust in scientists as a source of information about the coronavirus. The mixed effects model, similar to the hypothesis test but with the repeated measure of trust as the dependent variable, yielded a significant interaction between condition and wave (estimate=0.04, se=0.02; $t_{1089.10}$=2.37, *P*=.02). Trust in scientists was very high in all four waves (means between 6.11 and 6.19), but investigation of the simple slopes of the interaction effect indicated a significant decline over time in trust in scientists in the control condition (estimate=-0.04, se=0.01; $t_{559.17}$=-3.49, *P*=.001), while there was no significant effect of wave in the boost condition (*P*=0.69; see Figure 6). This suggests that the boosting intervention inhibited a decline of trust in scientists as a source of information about the coronavirus.

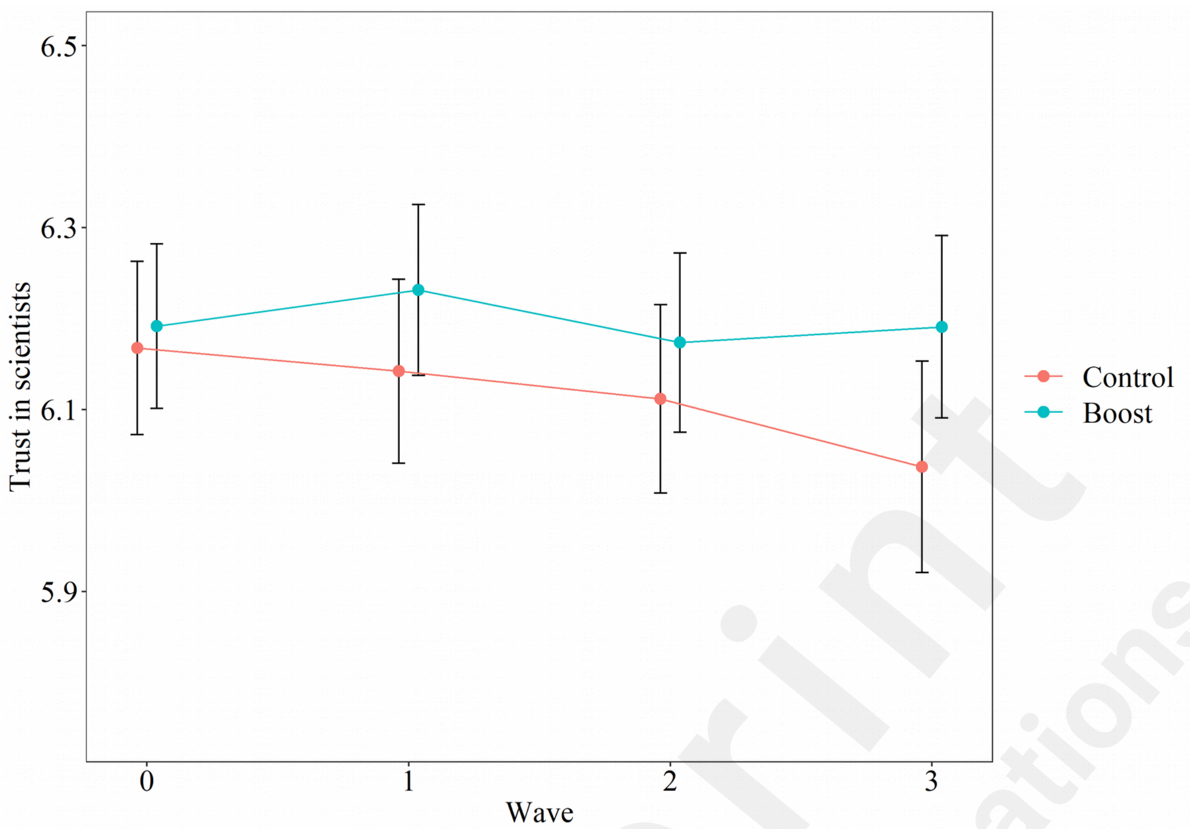

Figure 6. Trust in scientists as a source of information about the coronavirus per condition over time. Error bars indicate 95% CI focusing on the comparison between experimental conditions, not adjusted for within-subject variability.

Discussion

Principal Results

The aims of the current research were to gain insight into the beliefs of the US public about the COVID-19 pandemic and to investigate whether an educational intervention could improve people's belief accuracy. Interestingly, the average scores on belief accuracy over the surveyed four-week period were quite high, indicating low belief in false statements and high belief in true statements. Looking at each set of statements, we found a small but significant increase in belief accuracy over time. This indicates that the general public already is quite able to figure out what is true and what is not in times of crisis. Moreover, a small, but robust correlation suggests that accurate beliefs about the pandemic are important for corona-proof behavior. Associations with belief accuracy suggest that the processes of belief formation and correction might be affected by individuals' trust in scientists and political orientation, as well as their news habits. Finally, the educational intervention yielded no significant increase in belief accuracy over control, demonstrating that the boosting infographic was not successful in helping people figure out what is true and what is false. Exploratory analyses suggested that the intervention did, however, inhibit a decline in trust in scientists as a source of information about the coronavirus.

Comparison with Prior Work

There is a great deal of worry about the prevalence of misinformation in the current pandemic, which is reflected in popular media [e.g., 28,29], as well as among scientists [e.g., 30,31] and public health agencies [e.g., 4,32]. The supposed COVID-19 infodemic is not reflected in US citizens' beliefs. The finding that most Americans hold quite accurate beliefs about the COVID-19 pandemic is in line with emerging work on perceptions of the pandemic that shows that belief in COVID-19 misperceptions and conspiracy theories is quite low [33–35]. Consequently, this calls into question the prevalence of misinformation or the public's susceptibility to misinformation.

A convincing body of empirical work on the prevalence of misinformation surrounding the COVID-19 pandemic is not yet available. However, research from before the COVID-19 pandemic indicates that the prevalence of misinformation might be lower than many believe [36–38]. Although it is likely that the current pandemic has led to an increase in misinformation compared to the information landscape from before the pandemic, we should consider the possibility that COVID-19 misinformation is not as widespread as expected.

The second possibility is that we are indeed facing a COVID-19 infodemic, but that the public is not very susceptible to it. Misinformation campaigns regarding other topics, such as climate change and the health effects of tobacco [39,40], have demonstrated that misinformation can contribute to misperceptions about important matters in the general public. In these cases however, misinformation campaigns have been carefully organized and executed, continually misinforming the public for decades. In contrast, the COVID-19 pandemic is a novel issue and, at least in the relatively early months that we investigated, did not yield many such coordinated misinformation campaigns. Moreover, the COVID-19 pandemic originated in a very different media landscape than the climate and tobacco misinformation campaigns. Fake news, misinformation, and disinformation have been discussed widely and frequently in popular media since the 2016 US presidential election and the 2016 United Kingdom European Union membership referendum. This might have resulted in the public being more aware of campaigns targeted at misinforming them. Perhaps the widespread discussion of misinformation in popular media has worked as a large scale media literacy intervention, putting people 'on guard' against false information. In support of this idea, recent research has demonstrated that simply asking one to consider the accuracy of a claim improved subsequent choices about what COVID-19 news to share on social media [41].

A third possibility that should be considered is that the public is more careful in forming beliefs in times of crisis, especially in the relatively early days of a crisis, making a well-informed public not unique to the COVID-19 pandemic. In times of crisis, people are likely to increase news consumption [e.g., 42]. This was also the case in the US during the first months of the COVID-19 pandemic, with people reporting increased news consumption [43]. This increase in news consumption may lead to a better understanding of the crisis situation, including more accurate beliefs.

Turning to the finding that political orientation is associated with individuals' belief accuracy, we see that this is in line with other emerging work [33]. There is likely a multitude of explanations for this emerging partisan divide [44] on perceptions about the pandemic, such as political party cues in the news affecting opinion formation [45], the difficulty of correcting false beliefs for the ideological group most likely to hold those misperceptions [46], as well as the differences in news consumption that are reflected in the current study. A second variable that is even more strongly related to belief accuracy is trust in scientists as a source of information about the coronavirus, demonstrating that higher trust is related to more accurate beliefs. Interestingly, the associations of political orientation and trust with accurate beliefs were partially explained by an interaction effect among political orientations and trust. The stronger association of trust with belief accuracy for liberal/Democratic individuals might mean that they rely more on scientists' perceptions in forming beliefs, while conservative/Republican individuals might rely more on other cues.

In addition, the current work demonstrates that some news sources might be doing a worse job of informing their consumers about the COVID-19 pandemic than others, or perhaps that better informed news consumers turn to different news sources than less well-informed consumers (again in line with other emerging work [33]). Most likely, a combination of both selection and influence [e.g., 47] explain the differences in belief accuracy found in the current study. Interestingly, considering the role of social media in the spread of misinformation [e.g., 48], with about 26-42% of tweets in the data collection period containing unreliable facts [49], participants who reported social media sites as their main source of news about the coronavirus did not display significantly worse belief accuracy than others. However, it is possible that participants who reported social media sites as their main source followed major news outlets via the social media site, thereby being exposed to similar news content as the other participants.

Finally, the current work demonstrates the difficulty of crafting media literacy interventions aimed at increasing belief accuracy. Recent work demonstrates that simple, short media literacy interventions can work [50,51], while other work highlights the difficulties of crafting these interventions [52]. We argue that the divergent findings can be explained by the fact that in the former work the interventions were paired with corrections, while in the current work participants had to put their new skill to use outside of the study context. Considering that cues signaling the existence of consensus in relevant news content are very rare [53], participants likely had to search for information about scientific consensus themselves. The results from the manipulation check indicated that only a relatively small portion of participants actually applied this strategy.

Limitations

There are two notable limitations to the current work. First, our belief accuracy measure consisted only of science-based statements. We incorporated only science-based claims in our study to ensure that there was sufficient, empirical evidence either stating a claim was true or false. However, this decision did exclude some coronavirus-related claims that were not based on science (e.g., “Bill Gates patented the coronavirus”) or unresolved at the time (e.g., “A vaccine will be available before the end of the year”). It should have been harder for participants to figure out whether such unresolved issues were true or not, yielding different responses from participants for such a measure reflecting non-science based, unresolved issues about the pandemic.

A second limitation is the fact that the recruitment platform that we used, Prolific, is known as a platform for research. Although participants on the platform receive financial incentives for completing studies, they might be more interested in scientific research than the average US citizen. This could lead to them also having a higher trust in science than the general population, even though our sample was balanced on age, sex, and ethnicity. As trust in science was highly related to belief accuracy, it could be possible that this lead to an inflated belief accuracy score.

Conclusions

Our work demonstrates that most people are quite able to figure out the facts in this time of crisis, but also that it is difficult to intervene on these beliefs. However, in cases where people do not immediately have a clear understanding of the facts, they are capable of figuring them out over time. There are some factors that might make it easier or harder for one to figure out the facts. We found that the accuracy of participants’ beliefs was related to political orientation, as well as the primary news source. This suggests that, even in the relatively early days of the pandemic, political polarization and media diet had a grip on US citizens’ factual beliefs, leading to polarization along party lines. Another factor strongly related to accurate beliefs about the pandemic was trust in scientists. It is unclear whether an already high trust lead to accurate beliefs or that being able to figure out the facts increased trust in scientists, but the importance of expert communication is underlined by these findings.

Although a small but robust correlation suggests that accurate beliefs about the pandemic are important for corona-proof behavior, the role of misinformation in the pandemic seems to be relatively small, either because it is rare or because it is unable to persuade. However, we note that even if misinformation is not widespread and only believed by a small portion of the receivers, it can still be dangerous. To illustrate, we found that almost all participants in this study disregarded the statement that injecting or ingesting bleach is a safe way to kill the coronavirus, but this false claim is reported to have cost at least one life [54].

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Conflicts of Interest

None declared.

Abbreviations

COVID-19: coronavirus disease 2019
WHO: World Health Organization
CDC: Centers for Disease Control and Prevention
OSF: Open Science Framework
CI: confidence intervals
RI-CLPM: random intercept cross-lagged panel model

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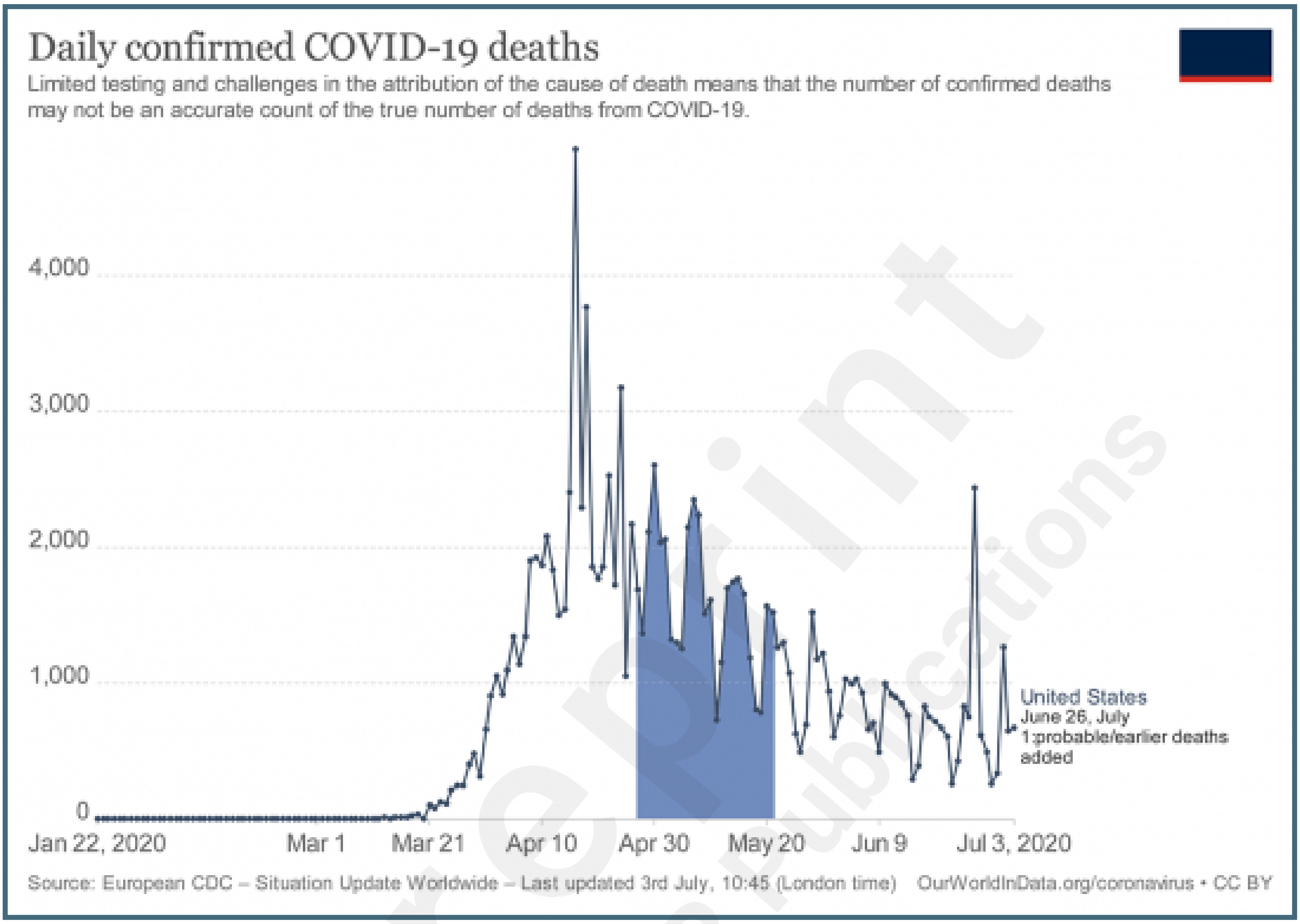
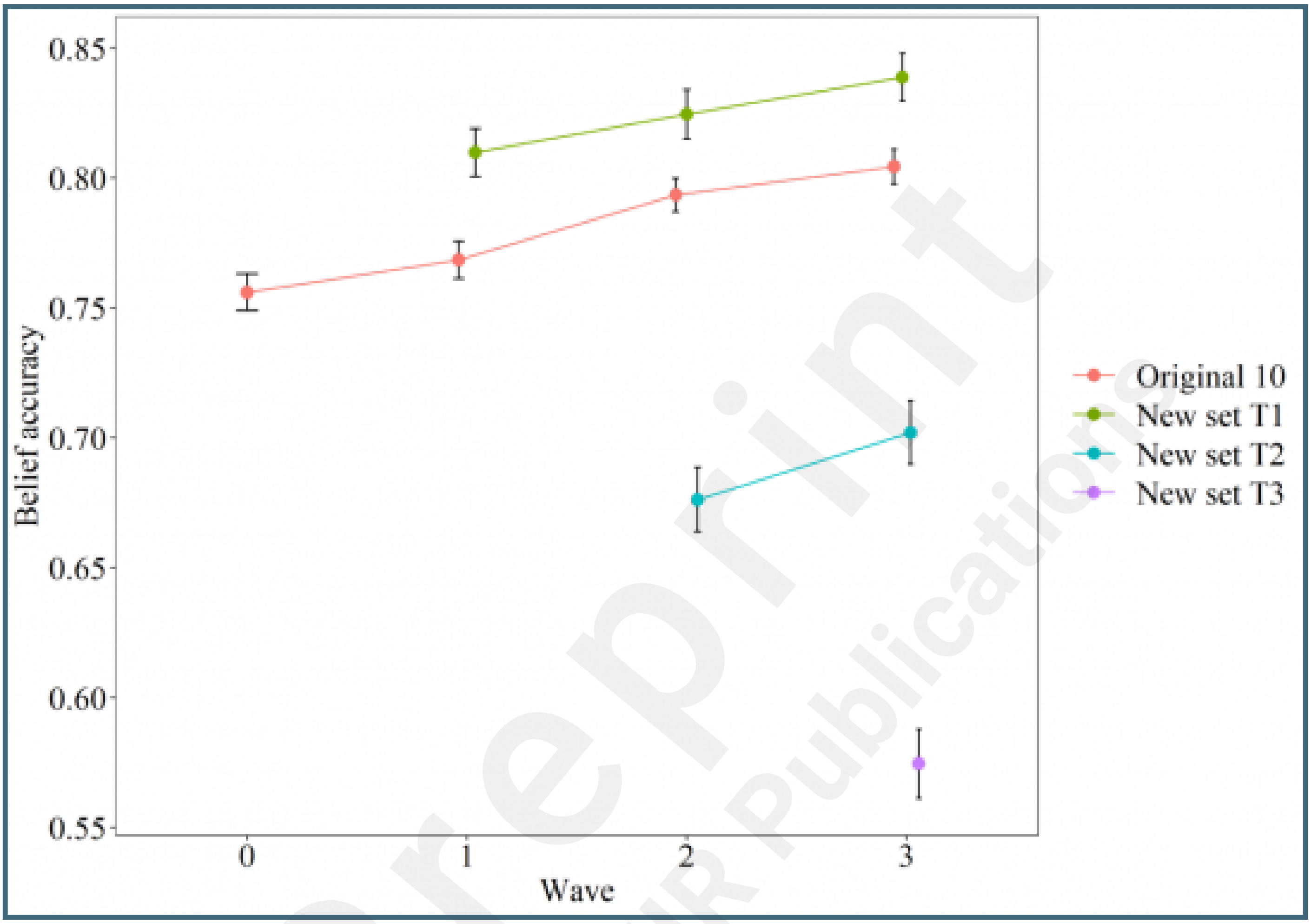
Supplementary Files

Figures

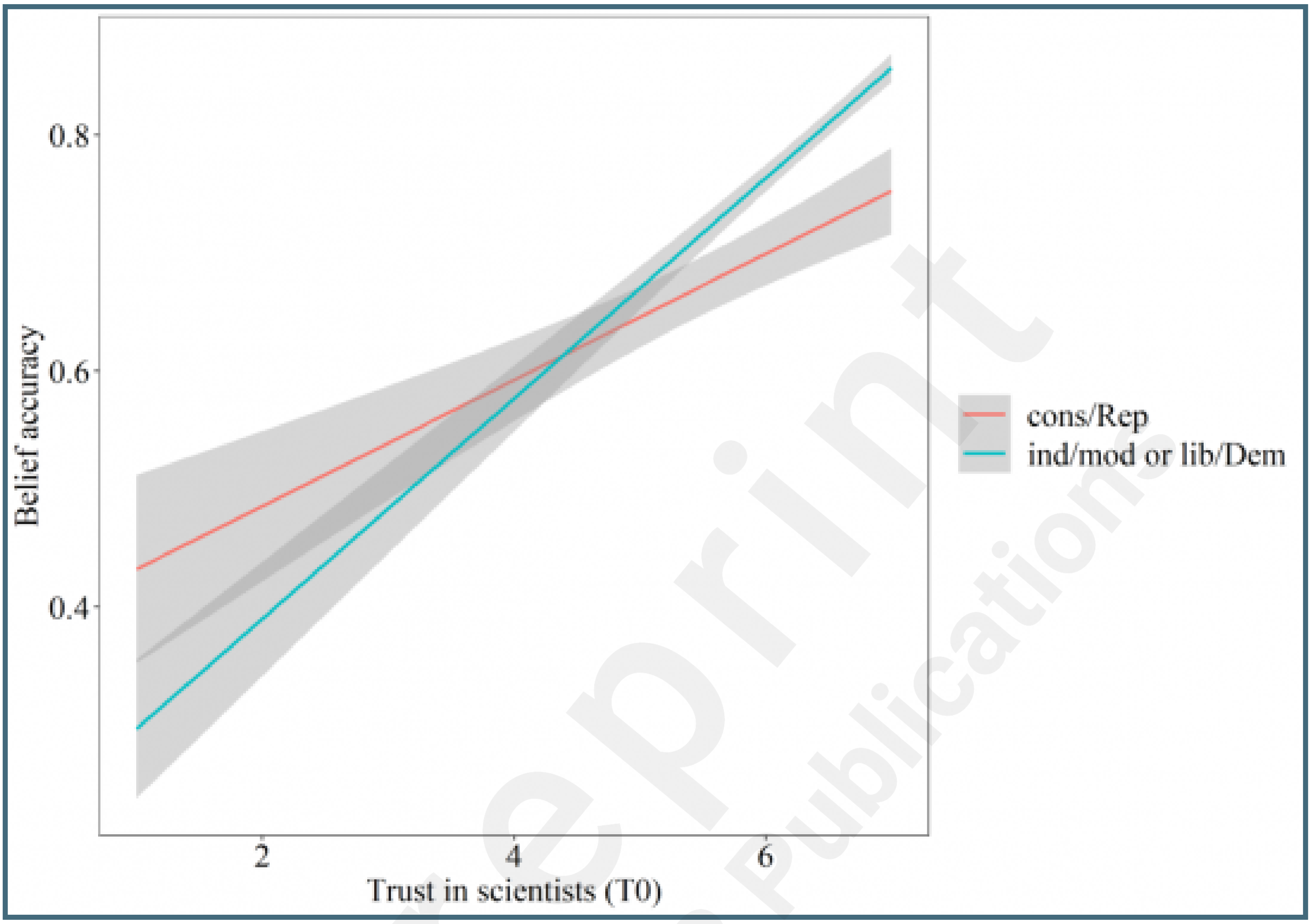
Daily confirmed COVID-19 deaths in the US. The blue area indicates the time period in which data were collected. Image provided by Our World in Data. Source of the data: European CDC.



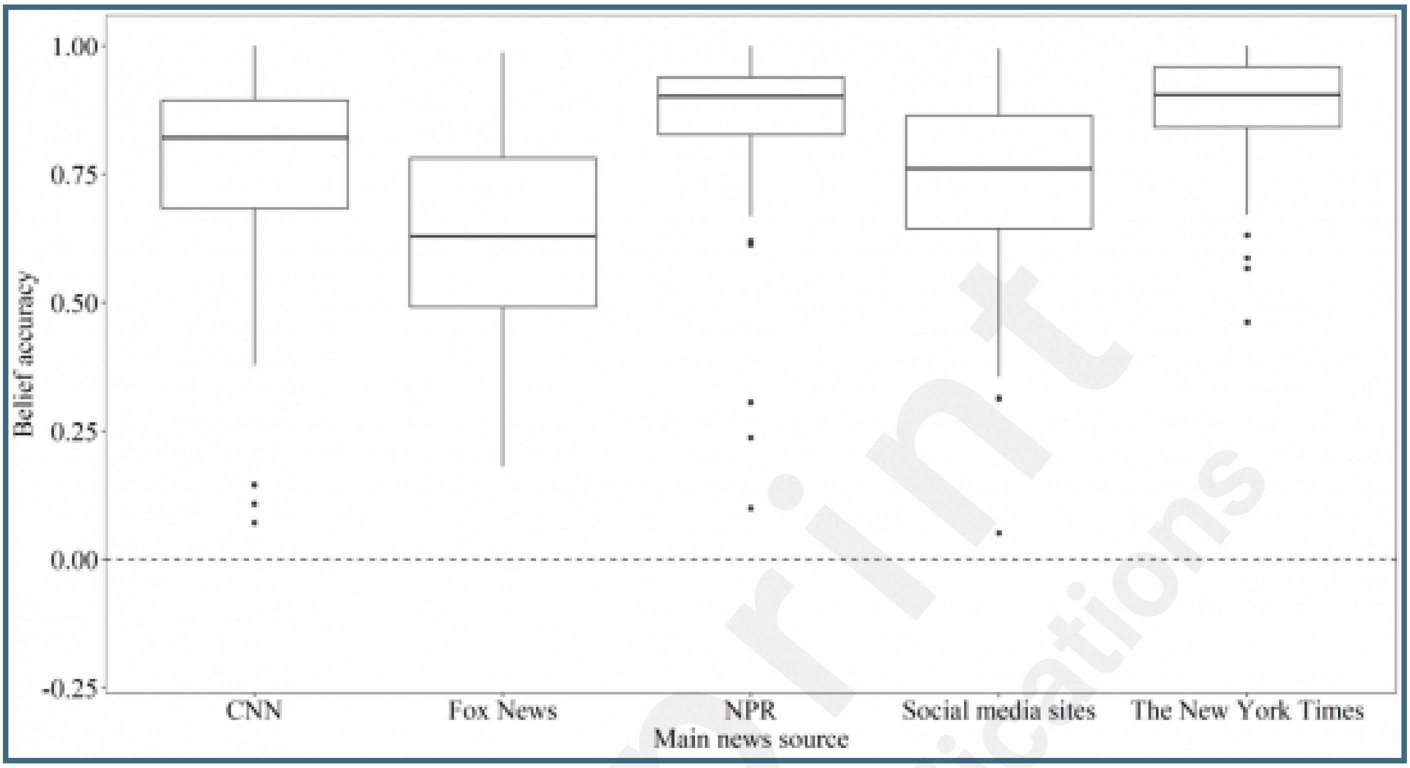
Belief accuracy per set of statements over time. The new set at T3 was included for completeness. Focusing on within subject change, dots represent normed means, error bars indicate 95% confidence intervals (CI) of the within-subject standard error [26], calculated using the summarySEwithin function from the Rmisc package [27].



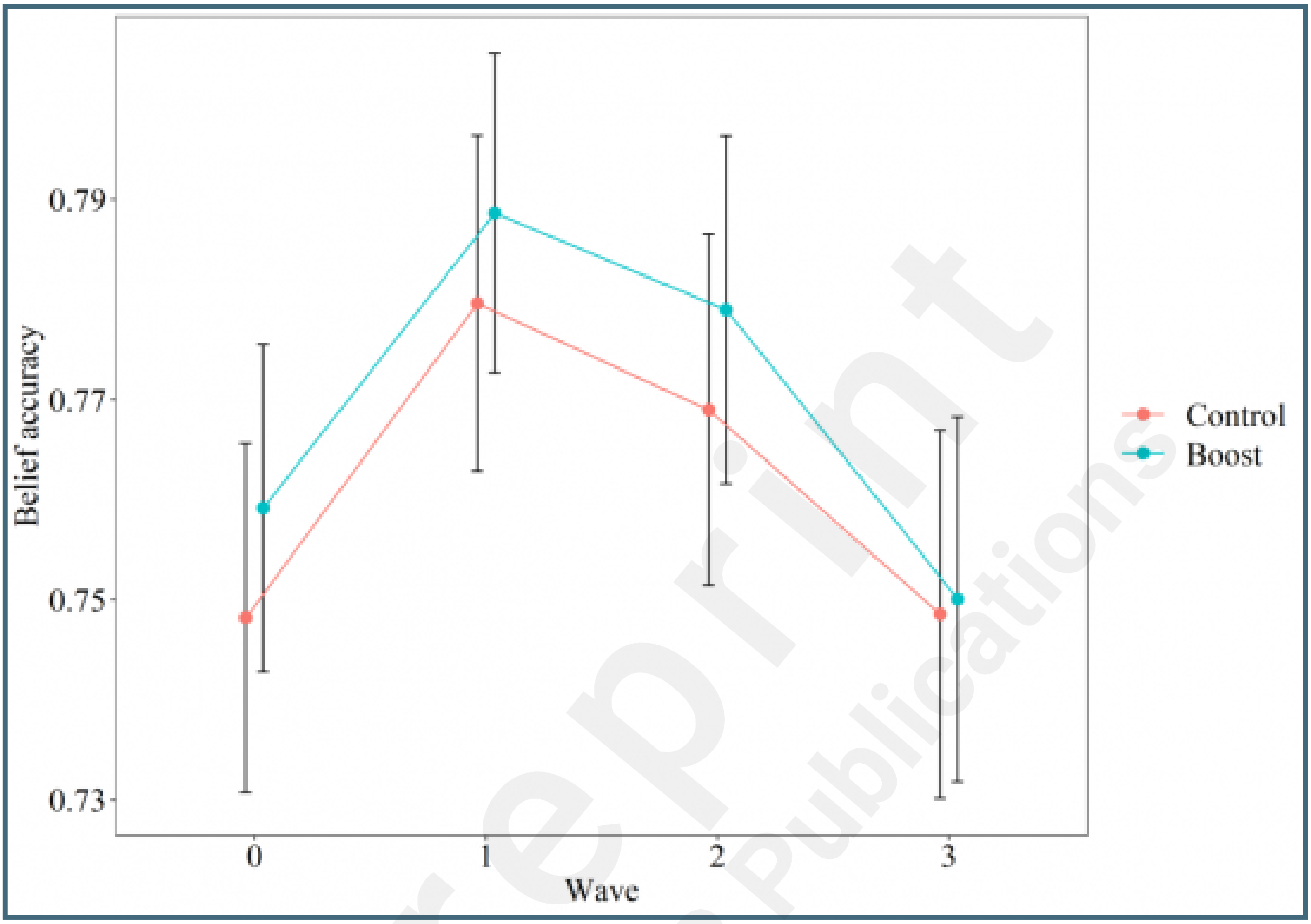
Linear relationship between belief accuracy (averaged over wave for plotting) by trust in scientists at T0, split by political orientation (dichotomized for plotting). The grey area represents the 95% CI.



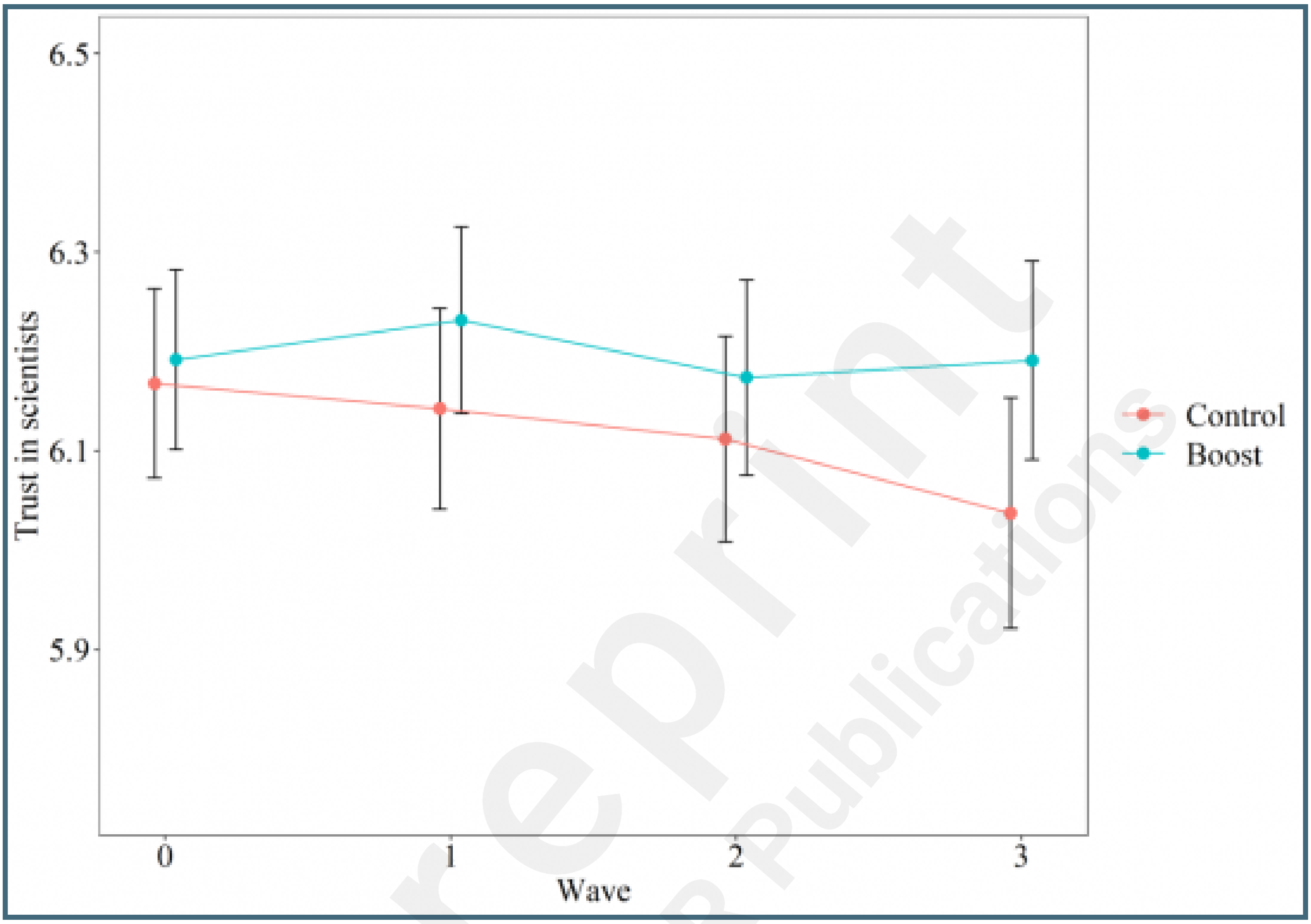
Boxplot of raw (unadjusted) scores of belief accuracy (averaged over wave for plotting) by main news source.



Belief accuracy per condition over time. Error bars indicate 95% CI focusing on the comparison between experimental conditions, not adjusted for within-subject variability.



Trust in scientists as a source of information about the coronavirus per condition over time. Error bars indicate 95% CI focusing on the comparison between experimental conditions, not adjusted for within-subject variability.



Multimedia Appendixes

Attention and seriousness checks.
URL: https://asset.jmir.pub/assets/1360b5b4d1ab45dea945592f351c1e5c.docx

Resources used to collect COVID-19 pandemic belief statements.
URL: https://asset.jmir.pub/assets/ab53c3c6dbebf1e96a80df6a2979ad77.docx

Infographic used in the boosting intervention to empower participants to use the scientific consensus when evaluating claims related to the COVID-19 pandemic.
URL: https://asset.jmir.pub/assets/4d705a9007c5f1ef9c83f4163bf43a2c.png

Descriptive statistics of all statements per wave.
URL: https://asset.jmir.pub/assets/173535c1b4cf4f1f74b98037f341a1bc.docx

Random intercept cross-lagged panel model (RI-CLPM).
URL: https://asset.jmir.pub/assets/55f57ff02098ccd9a8d3b25b3930f736.docx