CENTER FOR ADVANCED RESEARCH IN FINANCE
GRADUATE SCHOOL OF ECONOMICS, THE UNIVERSITY OF TOKYO

CARF Working Paper

CARF-F-616

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January 21, 2026

CARF is presently supported by Nomura Holdings, Inc., Mitsubishi UFJ Financial Group, Inc., Sumitomo Mitsui Banking Corporation., Mizuho Financial Group, Inc., Sumitomo Mitsui Trust Bank, Limited, The University of Tokyo Edge Capital Partners Co., Ltd., Brevan Howard Asset Management LLP, Ernst & Young ShinNihon LLC, JAPAN POST INSURANCE Co.,Ltd., SUMITOMO LIFE INSURANCE COMPANY and All Nippon Asset Management Co., Ltd.. This financial support enables us to issue CARF Working Papers.

Correcting COVID-19 Risk Misperceptions via Information Provision*

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Abstract

We conducted an information provision experiment in April 2023 in Japan to investigate how different types of information affect people's subjective assessment of COVID-19 related risks. The majority of respondents overestimate infection and fatality risks. Recent infection-related statistics lower risk perceptions if presented in percentage, but do not lower them if presented in levels. Providing pessimistic outlooks raises risk perceptions. We also find substantial heterogeneity in the response to information provision across various individual characteristics, such as age, gender, education, marital status, health status, COVID-19-related experiences, and vaccination status.

Keywords: COVID-19, Pandemic, Risk Communication, Risk Perception

*This experiment is registered in the AEA RCT Registry as AEARCTR-0017584. We obtained the ethics approval from the Ethics Review Board at the University of Tokyo (Approval No. 23-32). Taisuke Nakata is supported by JSPS Grant-in-Aid for Scientific Research (KAKENHI), Project Number 22H04927, the Research Institute of Science and Technology for Society at the Japan Science and Technology Agency, and COVID-19 AI and Simulation Project (Cabinet Secretariat). The authors declare no conflicts of interest.

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1 Introduction

The extent to which people engage in preventive behaviors—such as social distancing, mask wearing, and vaccination—depends importantly on how they perceive the associated risks. During the COVID-19 pandemic, governments provided various information to help the public accurately assess COVID-19-related risks. However, different kinds of information—such as absolute numbers, percentages, or qualitative statements—may shape people's subjective risk assessments in different ways. Understanding these effects is therefore crucial for designing effective risk-communication strategies.

In this paper, we examine how different types of information affect COVID-19 risk perceptions via an information provision experiment. We conducted our experiment in April 2023 in Japan near the end of the COVID-19 crisis. We consider two types of risk: infection risk and fatality risk. We consider three types of information provision. In the first, we provided a subset of the participants with the recent actual total new infection cases and deaths—which we call "level" information. In the second, we provided a subset of the participants with the recent actual probabilities of getting infected and dying from COVID-19 once infected—which we call "percentage" information. Finally, we provided a subset of the participants with a pessimistic outlook of infection without mentioning any specific numbers—which we call "qualitative" information. We compare risk perceptions of these three treatment groups with those of a control group that received no information to quantify the causal effect of information provision on risk perceptions. We also examine whether there is a significant association between the subjective risk and other attributes through multivariate logistic and multiple regression analysis.

We focus on these three types of information because they represent typical ways in which infection-related information was communicated to the public during the COVID-19 crisis. For example, the government frequently reported level information—such as the daily number of new infections, severe cases, or deaths (MHLW (2023))—which was probably the most frequent type of information for the public. Some communications relied on percentage information such as case fatality rates (Asahi (2022b); Asahi (2022a)). Qualitative information was also common in Japan: public health experts often expressed concerns about waves of infection without referring to specific data (Mainichi (2022)). Notably, qualitative information tended to highlight the risks of COVID-19 and was mostly pessimistic rather than optimistic.

We emphasize the following three results. First, regardless of whether participants are provided with information or not, they on average overestimate both infection and fatality risks. Across all groups, the median perception of infection risk is 4.05%, substantially higher than the actual infection risk of 0.23%. Across all groups, the median perception of fatality risk is 0.55%, substantially higher than the actual fatality risk of 0.24%.

Second, "percentage" and "qualitative" information led to lower and higher subjective risks, respectively, whereas "level" information did not alter risk perceptions in a statistically significant way. The median infection and fatality risks among those with "percentage" information are 1.25% and 0.13%, lower than 4.42% and 0.68% in the control group. The median infection and fatality risks among those with "qualitative" information are 6.44% and 0.97%, higher than 4.42% and 0.68% in the control group. These patterns remain robust when we utilize multiple regression analyses that control for various individual characteristics.

Third, there was substantial heterogeneity in both risk perceptions and responses to information provision. Infection risk tends to be overestimated more by females, people with chronic diseases, previously infected people, people who lost acquaintances because of COVID-19, and vaccinated people, but less by older people and college graduates. Fatality risk tends to be overestimated more by older people, those with chronic diseases, and those who lost acquaintances, but less by college graduates, married individuals, previously infected people, and the vaccinated. Responses to information provision also differ depending on individual characteristics: the effects of "percentage" and "qualitative" information on risk perceptions differ across age, gender, health status, COVID-19-related experiences, and vaccination status. Although level information has little effect on average, it affects certain groups—such as females, college graduates, and those who lost acquaintances—differently from their counterparts.

Our work contributes to the following three strands of the literature. First, it is related to the literature on the public's subjective assessments of COVID-19 risks. Many studies have identified factors associated with risk perceptions (Adachi et al., 2022; Cipolletta et al., 2022; Dryhurst et al., 2020; Dyer et al., 2022; Gollust et al., 2020; Huynh, 2020; Vai et al., 2020; Wise et al., 2020), while a few have compared perceived and actual risks (Chiba et al., 2024; Graso, 2022). Others have examined the relationship between COVID-19 subjective risk and prevention behaviors (Bundorf et al., 2025; Bruine De Bruin and Bennett, 2020; Garfin et al., 2021; Sato et al., 2022; Savadori and Lauriola, 2022). We differ from these studies because we conduct an information provision experiment to investigate its effect on COVID-19 subjective risks whereas they did not involve any experiments.

Second, our work is closely related to a few studies investigating how information provision affects COVID-19 risk perceptions and behaviors (Akesson et al., 2022; Abel et al., 2021; Sinclair et al., 2021). Our work differs from theirs in that, while they focused on statistical information about actual risk, we consider other types of information that were commonly communicated to the public during the COVID-19 pandemic and analyze how the treatment effect varies based on different representations of information.

Third, our work contributes to the broad literature from various fields examining how information provision affects risk assessments. Examples include Greenaway and Fielding (2020), Hall and Madsen (2022), Komatsu et al. (2022), Linciano et al. (2018), Oviedo-Trespalacios et al. (2019), Wang et al. (2012), among many others. These studies analyze the perception of risk across a wide range of areas—from recycled water and disposable plastics to health diseases, traffic crashes, and financial products. We contribute to this literature by focusing on the assessment of COVID-19 infection and fatality risks, thereby providing novel implications for risk communication in public health.

The structure of the paper is as follows. Section 2 describes the survey and methodology. Section 3 presents the summary statistics and the main results of our analyses. Section 4 examines heterogeneity in responses to information provision. Section 5 provides some discussion of our results. Section 6 concludes.

2 Experimental Design

We conducted a large-scale online survey of adults between age 20 and 79 nationwide from April 25th to April 27th, 2023, in collaboration with Cross Marketing Inc. The target sample size was approximately 10,000 individuals. To ensure the representativeness of our sample, the proportions of gender (Male, Female), age cohort (20s-30s, 40s-50s, $\geq$60s), and geographic residence (Prefectures) were stratified to match the demographic distribution reported in the 2020 Population Census.[1] Respondents received redeemable "points" as compensation for their participation. A total of 10,008 valid responses were collected. Detailed summary statistics regarding individual attributes are presented in Table 1.

In the survey, we asked our participants about their perceptions of COVID-19 infection or fatality risks and their individual characteristics. For infection or fatality risks we asked participants about their subjective probability related COVID-19 within the next one month. Specifically, we asked the probability of being infected COVID-19 within the next one month and the probability of dying if infected with COVID-19. For both infection and fatality rates, we presented the following response options to choose from: (1)

[1] There might be concerns that online users of the marketing company may differ from the general population. However, matching our sample's age, gender, and residence distributions to those in the population census helps mitigate this potential selection bias.

Table 1: Summary Statistics

	No Info.	Level	Percentage	Qualitative	Total
Age					
20-59 years	1,644	1,644	1,644	1,644	6,756 (65.7%)
Over 60 years	858	858	858	858	3,432 (34.3%)
Gender					
Male	1,236	1,236	1,236	1,236	4,944 (49.4%)
Female	1,266	1,266	1,266	1,266	5,064 (50.6%)
Education Level					
Non-College Graduate	1,278	1,256	1,287	1,333	5,154 (51.5%)
College Graduate	1,224	1,246	1,215	1,169	4,854 (48.5%)
Marital Status					
Unmarried	1,025	1,064	1,069	1,040	4,198 (42.0%)
Married	1,477	1,438	1,433	1,462	5,810 (58.1%)
Vaccination					
Unvaccinated	319	356	371	323	1,369 (13.7%)
Vaccinated	2,183	2,146	2,131	2,179	8,639 (86.3%)
Chronic Diseases					
Yes	385	441	433	434	1,693 (16.9%)
No	2,117	2,061	2,069	2,068	8,315 (83.1%)
Infected with COVID-19					
Yes	502	511	527	526	2,066 (20.6%)
No	2,000	1,991	1,975	1,976	7,942 (79.4%)
Acq. Died from COVID-19					
Yes	178	165	157	164	664 (6.6%)
No	2,324	2,337	2,345	2,338	9,344 (93.4%)
N					10,008

less than 0.001%, (2) 0.001%-0.01%, (3) 0.01%-0.1%, (4) 0.1%-1%, (5) 1%-5%, (6) 5%-10%, (7) 10%-20%, (8) 20%-50%, (9) 50% or higher.[2]

For individual characteristics, we collected participants' information to examine the association with the subjective risks. From the survey company, we obtained participants' registered data, such as age, gender, prefecture of residence, and marital status. We also asked about the following:

- Education level: elementary/junior high school, high school, associate's degree, bachelor's degree, master's degree, or Ph.D.
- Medical history of chronic diseases: malignant neoplasms, cerebrovascular disease, respiratory system diseases, cardiovascular disease, gastrointestinal diseases, endocrine system diseases, kidney diseases, hematological diseases, or none
- Primary media source: television, newspaper, the Internet, SNS, radio, or others
- COVID-19-related experiences: vaccination status, number of past infections, and acquaintance's COVID-19-related deaths

When we provided an information about COVID-19, we divided participants into four groups (each consisting of 2,502 respondents). We did not provide one group with any information, which we call "the control group." We provided one group with information about the recent dynamics of new infections in level ("level" information). We provided one group with information about the recent dynamics of new infections as a percentage of the total population in Japan levels ("percentage" information). We provided one group with qualitative information about a possible future path of new infection ("qualitative" information). The exact wording for these three types of information are as follows:

"Level" information

> *"From mid-March 2023 to mid-April 2023 in Japan, total infected cases are 226,007. From April 2022 to March 2023 in Japan, the total deaths are 45,727."*

"Percentage" information

> *"From mid-March 2023 to mid-April 2023 in Japan, the actual infection rate is 0.18%. From April 2022 to March 2023 in Japan, the actual fatality rate is 0.17%."*

[2] We adopted the same response options in our previous work (Chiba et al., 2024) that examined COVID-19 risk perceptions without conducting information provision experiments.

"Qualitative" information

> *"The number of new cases has been gradually increasing, and there is concern about the spread of infection after the holidays in May. On April 19, the expert group mentioned the possibility of a 9th wave, which would be larger than the 8th wave. Compared to the 6th and 7th waves (January-April 2022 and July-September 2022), the 8th wave (November 2022-February 2023) showed an increase in fatality rate."*

We obtained the specific numbers in the level and percentage information from (i) population in Japan published from the Statistics Bureau of Japan (MIAC (2023)) and (ii) daily data on the newly confirmed cases and death cases published from the Ministry of Health, Labor and Welfare (MHLW (2023)).

In Table 2, we examine whether randomization in our samples successfully balances respondents' characteristics across groups using a balance test. The first four columns report the mean values of individual characteristics for each group, while the next three columns show the p-values from t-tests comparing each treatment group with the control group. In most cases, the p-values are above 0.1, suggesting that our sample is well balanced across groups.

Table 2: Balance test

	Mean values				*P-values (t-test)*		
	No Info.	Level	Percentage	Qualitative	Level	Percentage	Qualitative
Age	50.898	50.828	50.997	50.881	0.877	0.827	0.970
Female	0.506	0.506	0.506	0.506	1.000	1.000	1.000
College Graduate	0.489	0.498	0.486	0.467	0.534	0.799	0.120
Married	0.590	0.575	0.573	0.584	0.264	0.207	0.667
Chronic Diseases	0.154	0.176	0.173	0.173	0.033	0.067	0.061
Infected with COVID-19	0.201	0.204	0.211	0.210	0.752	0.382	0.401
Acq. Died from COVID-19	0.071	0.066	0.063	0.066	0.467	0.235	0.433
Vaccinated	0.873	0.858	0.852	0.871	0.126	0.033	0.866

3 Results

We first compare the mean, median, and the proportion of overestimation and underestimation in perceived risks between the control group and the three treatment groups. To compute the mean, we converted participants' Likert scale responses for infection and fatality risks into numerical values using the midpoint of each category. For example, participants choosing "(1) less than 0.001%" were assigned a subjective risk of 0.0005%. We calculate the median assuming a uniform distribution of subjective risk within each category. We define participants with subjective risk higher than 5% as overestimation and lower than 0.01% as underestimation.

Figure 1 shows the results for infection risks. Panels (a) and (b) show, respectively, the median and mean values of infection risks, represented by the black dots. Vertical bar shows confidence intervals. The dashed red horizontal line represents the actual infection risk. Across all four groups, respondents tend to overestimate the actual infection risk: the median perceived infection risks are 4.42, 4.31, 1.25, and 6.44% for these four groups versus the actual infection risk of 0.23%.[3] A similar pattern is observed when comparing the mean values with the actual risk.[4]

Turning to the effect of information provision, "level" information does not alter the risk perception by much, while "percentage" and "qualitative" information decrease and increase the risk perception, respectively. The median and mean perceived infection risks are 1.25% and 8.24% with "percentage" information, much lower than 4.42% and 11.27% with no information provision. In contrast, the median and mean perceived infection risks are 6.44% and 14.25% with "qualitative" information, much higher than those with no information provision.

Panels (c) and (d) present the proportions of respondents who overestimated (i.e., perceived it as 5% or higher) and underestimated (i.e., perceived it as less than 0.01%) the COVID-19 infection risks. There are no significant differences in the proportions of overestimation or underestimation between the "no information" and "level" groups, with 46.8% and 46.4% (17.4% and 16.5%) of respondents overestimating (underestimating) the infection risk, respectively. The proportion of respondents who overestimated the infection risk is lowest in the "percentage" group (32.6%) and highest in the "qualitative" group (54.9%). In contrast, the proportion of respondents who underestimated the infection risk is highest in the "percentage" group (21.6%) and lowest in the "qualitative" group (14.1%). These results—the similar trend in overestimation (as observed in the mean and median comparisons) and the opposite trend in underestimation—support the earlier findings that "level" information has minimal impact on risk perception, whereas "percentage" information mitigates overestimation of infection risks and "qualitative" information exacerbates it.

Figure 2 presents the mean and median values of fatality risks (panels (a) and (b)), as well as the proportions of fatality risk overestimation and underestimation (panels (c) and

[3] We estimated the actual risk about infection risk (April 9 – May 8, 2023) was 0.23%, and fatality risk (November 1, 2022 – February 28, 2023) was 0.24%.

[4] The values for the no-information group in Figures 1 and 2 are consistent with those in Chiba et al., 2024 which examined the COVID-19 related risk perceptions without conducting information provision experiments.

Figure 1: Perceived Infection Risks in the Control Group and Treatment Groups

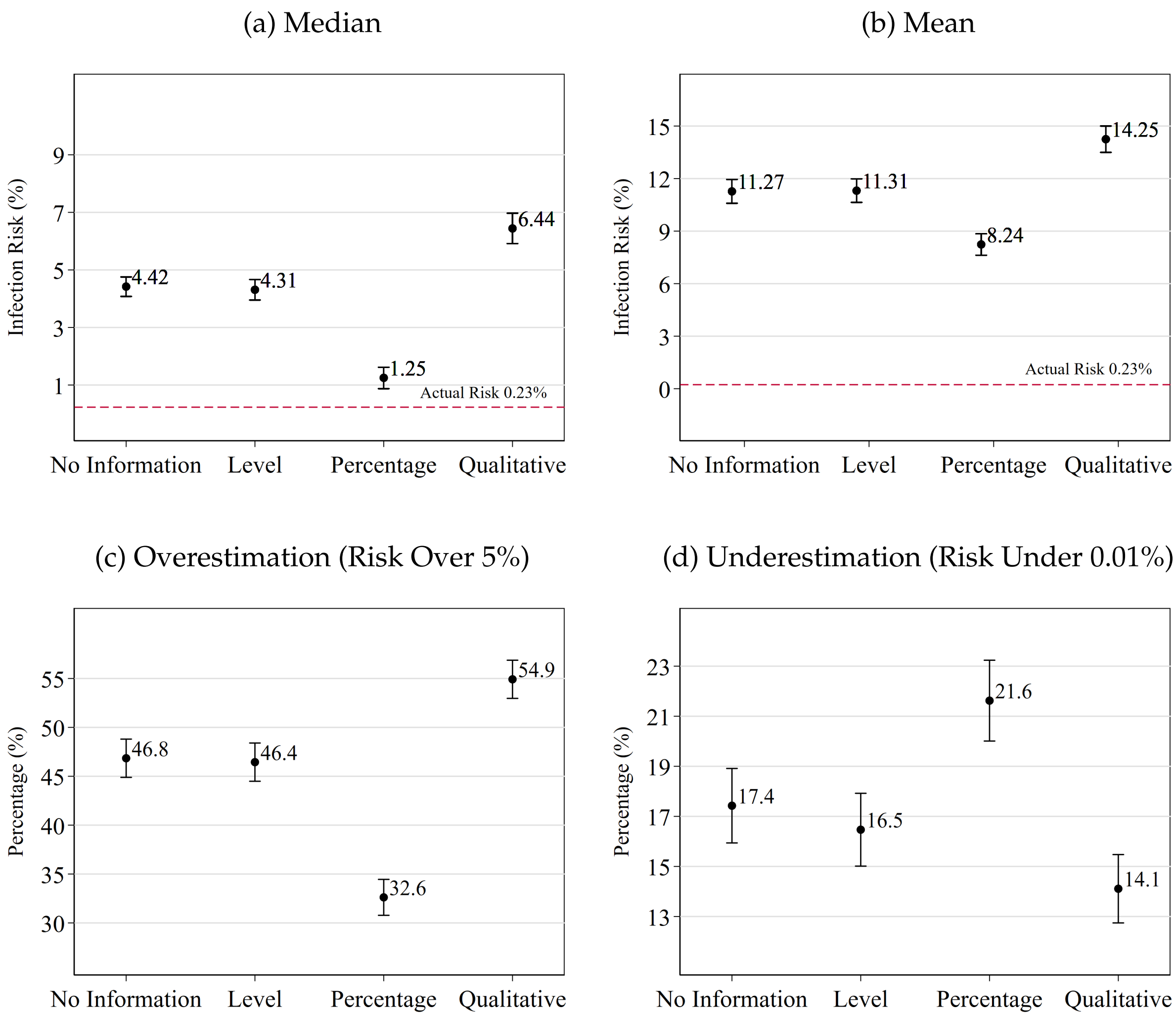
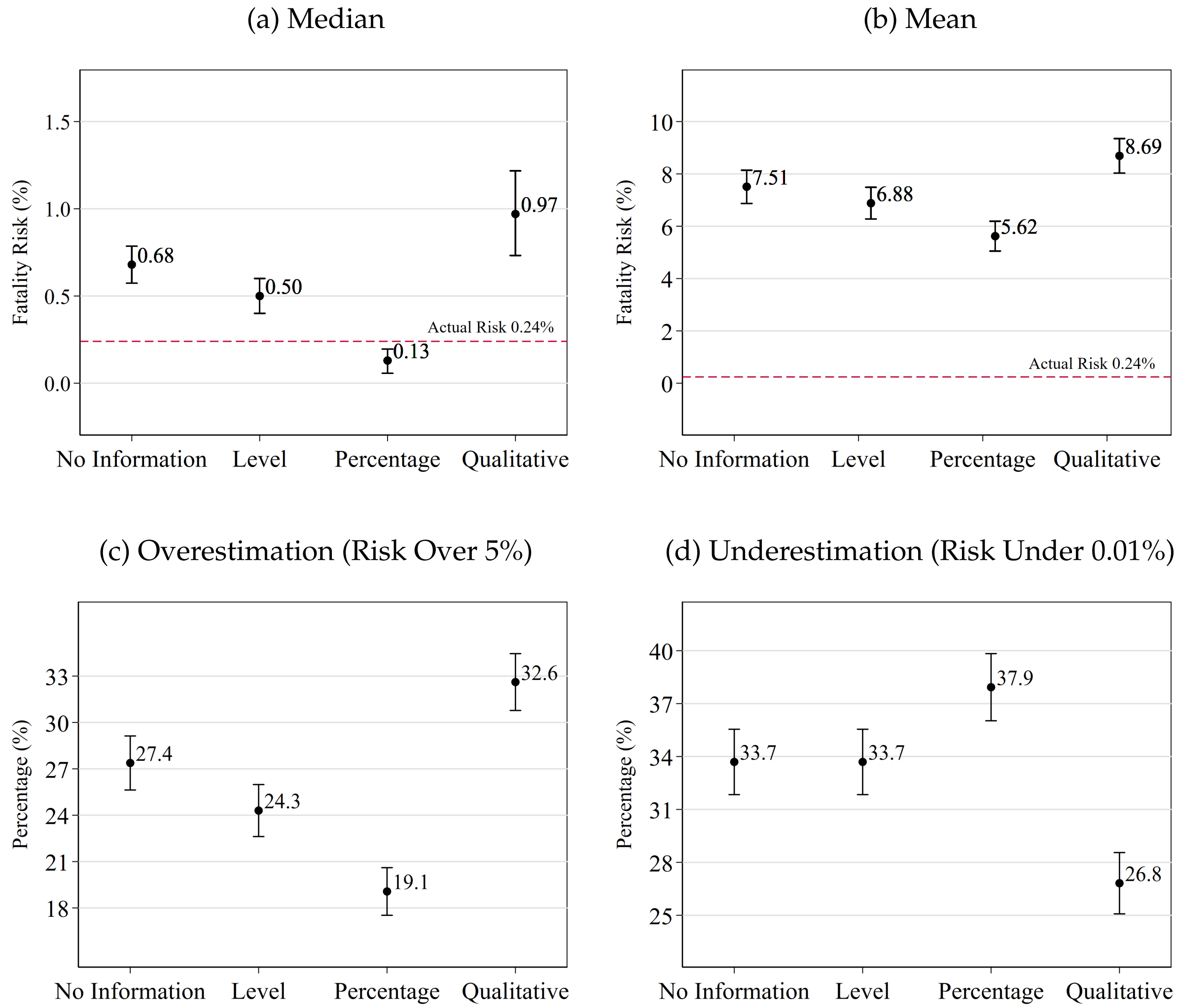


Figure 2: Perceived Fatality Risks in the Control Group and Treatment Groups



(d)) for the control and three treatment groups. Panels (a) and (b) indicate that respondents in all four groups tend to overestimate the actual fatality risk of 0.24%. Providing "level" information has little effect on the perception of fatality risks, whereas "percentage" information reduces such risk perception, and "qualitative" information increases it. Specifically, the median (mean) perceived fatality risks are 0.68% (7.51%) with "no information", 0.50% (6.88%) with "level" information, 0.13% (5.62%) with "percentage" information, and 0.97% (8.69%) with "qualitative" information.

Panels (c) and (d) show the proportions of respondents who overestimated or underestimated the fatality risk. The proportion of fatality risk overestimation was lowest in the "percentage" group (19.1%) and highest in the "qualitative" group (32.6%), while the proportion of underestimation follows the opposite pattern. Overall, these results reinforce our findings that percentage information helps correct the overestimation of COVID-19 risks, while qualitative information tends to amplify them.

To quantify the effects of information provision in an alternative way, we now estimate the following equation:

$$y_i = \alpha + \sum_{j=1}^{3} \beta_j D_{ji} + \mathbf{x}_i' \gamma + \epsilon_i \tag{1}$$

where the dependent variable (y_i) is the subjective infection or fatality risks, defined as the midpoints of each response category. The independent variables (D_{1i},D_{2i},D_{3i}) are dummy variables for "level", "percentage", and "qualitative" information group, respectively. The set of control variables ($\mathbf{x}_i$) include dummy variables for information group, age, gender, education, marital status, chronic diseases, infection history (0 or $\geq$1), acquaintance's COVID-19-related deaths, and vaccination status. We also control for prefecture fixed effects and for the primary type of media respondents used to obtain information about COVID-19, considering that participants were under different measures and situations of COVID-19 across prefectures and under different accuracy and accessibility to information across media. However, in all tables presenting regression results, the coefficients on media types and prefectures are omitted for simplicity.

Table 3 shows the results of this regression analysis. Two-sided p-values <0.05 were considered to indicate statistical significance. For each group dummy variable included in the regression, if the estimated coefficient is positive (negative), participants in that group perceive the risk to be higher (or lower) than those in the benchmark group. The coefficient on "level" information is negative for fatality risk, though only weakly statistically significant, and the magnitude of the effect is small. Meanwhile, the coefficients on "percentage" and "qualitative" information are large and statistically significant in both infection risk and fatality risk regressions.

Overall, this evidence is consistent with the unconditional analyses in Figures 1 and 2. That is, "level" information does not alter the risk perception by much, while "percentage" and "qualitative" information substantially decrease and increase the risk perception, respectively.

Table 3 reveals heterogeneity in risk perception across various individual characteristics. For infection risk, older people and college graduates tend to overestimate the risk by less, while females, people with chronic diseases, people with COVID-19 infection experience, people who knew their close friends or relatives who died from COVID-19, and vaccinated people tend to overestimate the risk by more. For fatality risk, older people, people with chronic diseases, and people who knew their close friends or relatives who died from COVID-19 tend to overestimate the risk by more, while college graduates, mar-

Table 3: Perceived Risks in the Control Group and Treatment Groups: Multiple Regression Analysis

	(1) Infection Risk	(2) Fatality Risk
Info.: Level	0.026	−0.747*
	(0.486)	(0.441)
Info.: Percentage	−2.995***	−2.027***
	(0.467)	(0.431)
Info.: Qualitative	2.877***	1.002**
	(0.510)	(0.456)
Age Over 60 years	−4.648***	1.070***
	(0.386)	(0.366)
Female	1.101***	0.276
	(0.363)	(0.327)
College Graduate	−1.302***	−2.171***
	(0.363)	(0.325)
Married	−0.576	−1.555***
	(0.381)	(0.344)
Chronic Diseases	2.381***	6.238***
	(0.501)	(0.545)
Infected with COVID-19	1.397***	−2.174***
	(0.445)	(0.341)
Acq. Died from COVID-19	3.738***	2.432***
	(0.797)	(0.717)
Vaccination	1.611***	−1.698***
	(0.563)	(0.552)
Constant	10.866***	8.729***
	(1.072)	(0.974)
Observations	10,008	10,008
R-squared	0.046	0.051

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Misperceptions of Risks in the Control Group and Treatment Groups: Multivariate Logistic Regression - Odd Ratios

(a) Infection Risk

	(1) Risk Under 0.01%	(2) Risk Over 5%
Info.: Level	0.915	0.987
	(0.071)	(0.057)
Info.: Percentage	1.272***	0.544***
	(0.094)	(0.033)
Info.: Qualitative	0.761***	1.396***
	(0.061)	(0.081)
Age Over 60 years	1.488***	0.590***
	(0.093)	(0.029)
Female	0.809***	1.330***
	(0.046)	(0.058)
College Graduate	0.808***	0.988
	(0.046)	(0.043)
Married	1.026	0.943
	(0.060)	(0.042)
Chronic Diseases	0.760***	1.263***
	(0.059)	(0.072)
Infected with COVID-19	0.599***	1.335***
	(0.047)	(0.069)
Acq. Died from COVID-19	0.544***	1.532***
	(0.072)	(0.127)
Vaccination	0.372***	1.738***
	(0.026)	(0.113)
Constant	0.471***	0.509***
	(0.075)	(0.062)
Observations	10,008	10,008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

ried people, people with COVID-19 infection experience, and vaccinated people tend to overestimate the risk by less. The results regarding education, gender, and chronic diseases are consistent with Akesson et al. (2022). The results on those who knew someone who died from COVID-19 are consistent with Abel et al. (2021).

As a robustness check, we employ multivariate logistic regressions in which the dependent variables are dummy variables for risk overestimation or underestimation (subjective risk higher than 5% or subjective risk lower than 0.1%). We use the same set of independent and control variables as in our multiple regression analyses. As shown in Table 4, the logistic regression results indicate that our findings are robust to alternative model specifications.

(b) Fatality Risk

	(1) Risk Under 0.01%	(2) Risk Over 5%
Info.: Level	1.002	0.825***
	(0.061)	(0.054)
Info.: Percentage	1.194***	0.606***
	(0.072)	(0.042)
Info.: Qualitative	0.717***	1.271***
	(0.045)	(0.080)
Age Over 60 years	0.832***	1.183***
	(0.043)	(0.063)
Female	0.866***	1.123**
	(0.039)	(0.055)
College Graduate	1.022	0.758***
	(0.047)	(0.038)
Married	1.214***	0.795***
	(0.057)	(0.040)
Chronic Diseases	0.597***	2.005***
	(0.038)	(0.120)
Infected with COVID-19	1.214***	0.663***
	(0.065)	(0.042)
Acq. Died from COVID-19	0.773***	1.447***
	(0.071)	(0.130)
Vaccination	0.608***	0.999
	(0.038)	(0.071)
Constant	0.792*	0.366***
	(0.100)	(0.050)
Observations	10,008	10,008

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4 Heterogeneous Responses to Information Provision

In the last part of the previous section, we discussed heterogeneity in the risk perception across respondents' demographic/socio-economic characteristics and their COVID-19 experiences. In this section, we examine heterogeneity in the response of risk perception to information provision across these individual characteristics. For that purpose, we estimate the following equation:

$$y_i = \alpha + \sum_{j=1}^{3} \beta_j D_{ji} + \sum_{j=1}^{3} \eta_j D_{ji} \times H_i + \delta H_i + \mathbf{x}_i' \boldsymbol{\gamma} + \epsilon_i \tag{2}$$

For this analysis, we added to our baseline regressions in (1) (presented in Table 3) the interaction terms between the information group dummy variables and each characteristic of interest (H_i)—age, gender, education, marital status, health condition, COVID-19-related experiences, and vaccination status. Panels (a) and (b) of Table 5 present the estimation results for infection risk and fatality risk, respectively. For brevity, the coefficients for the control variables are omitted from the panels.

Starting with panel (a), the coefficients on "level" information are statistically insignificant, whereas those on "percentage" ("qualitative") information are negative (positive) and statistically significant across almost all model specifications. These results reaffirm the average effects of information provision observed in Figure 1 and Table 3. That is, "level" information does not significantly affect the perceptions of infection risk, while "percentage" and "qualitative" information lead to lower and higher infection risk perceptions, respectively.

The next row reports the coefficients on "H," which capture the heterogeneity in risk perception across individual characteristics. Older people and college graduates are less likely to overestimate the infection risk, while females, people with chronic diseases, and people who had acquaintances who died from the virus are more likely to overestimate the risk. These results are consistent with the empirical evidence reported in Table 3.

Table 5: Heterogeneous Effects of Information Provision

(a) Infection Risk

	(1) Age H=Old	(2) Gender H=Female	(3) Education H=College Graduate	(4) Marital Status H=Married	(5) Health H=Chronic Diseases	(6) Infection H=Infected	(7) Acq. Death H= Acq. Died	(8) Vaccination H=Vaccinated
Info.: Level	0.464	1.069	−0.923	−0.09	−0.008	0.023	0.423	−0.265
	(0.635)	(0.681)	(0.71)	(0.785)	(0.523)	(0.549)	(0.495)	(1.551)
Info.: Percentage	−2.599***	−1.793***	−2.891***	−2.706***	−2.799***	−3.294***	−2.641***	−2.381
	(0.621)	(0.653)	(0.698)	(0.776)	(0.507)	(0.52)	(0.473)	(1.506)
Info.: Qualitative	3.614***	2.741***	3.226***	2.280***	2.790***	2.103***	3.133***	−0.994
	(0.661)	(0.699)	(0.756)	(0.825)	(0.553)	(0.565)	(0.519)	(1.49)
H	−3.497***	2.144***	−1.539**	−0.754	2.504**	0.055	7.286***	0.657
	(0.714)	(0.697)	(0.704)	(0.727)	(1.008)	(0.86)	(1.803)	(1.219)
H*Info: Level	−1.278	−2.059**	1.904**	0.199	0.174	0.045	−5.740**	0.324
	(0.960)	(0.970)	(0.971)	(0.999)	(1.377)	(1.163)	(2.269)	(1.630)
H*Info: Percentage	−1.155	−2.370**	−0.217	−0.511	−1.145	1.485	−5.161**	−0.745
	(0.901)	(0.928)	(0.929)	(0.962)	(1.299)	(1.175)	(2.279)	(1.579)
H*Info: Qualitative	−2.152**	0.272	−0.758	1.018	0.489	3.740***	−3.615	4.444***
	(1.020)	(1.020)	(1.015)	(1.049)	(1.445)	(1.303)	(2.433)	(1.583)
Constant	10.510***	10.337***	11.000***	10.954***	10.857***	11.129***	10.549***	11.672***
	(1.098)	(1.111)	(1.111)	(1.150)	(1.081)	(1.080)	(1.075)	(1.451)
Observations	10,008	10,008	10,008	10,008	10,008	10,008	10,008	10,008
R-squared	0.046	0.047	0.046	0.046	0.047	0.047	0.047	0.046

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column separately examines the heterogeneous effects with respect to an individual characteristic. **H** is a dummy variable equal to one for people with the characteristic listed at the top of each column and zero otherwise (e.g., **H** equals one for older people in column (1), females in column (2), and so on).

(b) Fatality Risk

	(1) Age H=Old	(2) Gender H=Female	(3) Education H=College Graduate	(4) Marital Status H=Married	(5) Health H=Chronic Diseases	(6) Infection H=Infected	(7) Acq. Death H= Acq. Died	(8) Vaccination H=Vaccinated
Info: Level	−0.839*	−0.143	−1.338**	−0.730	−0.667	−0.840	−0.472	−1.937
	(0.495)	(0.623)	(0.678)	(0.709)	(0.434)	(0.517)	(0.449)	(1.532)
Info: Percentage	−1.133**	−1.347**	−2.295***	−1.693**	−1.514***	−2.463***	−1.769***	−3.171**
	(0.511)	(0.604)	(0.665)	(0.715)	(0.431)	(0.499)	(0.438)	(1.501)
Info: Qualitative	1.520***	0.611	1.239*	0.667	0.924**	0.739	1.215***	−1.413
	(0.535)	(0.626)	(0.696)	(0.740)	(0.459)	(0.530)	(0.465)	(1.534)
H	2.036***	0.717	−2.476***	−1.546**	7.074***	−3.158***	5.058***	−3.066**
	(0.715)	(0.640)	(0.644)	(0.665)	(1.154)	(0.687)	(1.581)	(1.231)
H*Info: Level	0.266	−1.192	1.188	−0.028	−0.567	0.475	−3.971*	1.365
	(0.992)	(0.879)	(0.878)	(0.899)	(1.564)	(0.912)	(2.083)	(1.596)
H*Info: Percentage	−2.612***	−1.339	0.548	−0.584	−3.052**	2.114**	−3.746*	1.309
	(0.934)	(0.855)	(0.853)	(0.888)	(1.499)	(0.938)	(2.017)	(1.563)
H*Info: Qualitative	−1.509	0.776	−0.522	0.573	0.359	1.296	−3.029	2.772*
	(0.999)	(0.914)	(0.907)	(0.939)	(1.588)	(1.004)	(2.144)	(1.605)
Constant	8.415***	8.497***	8.887***	8.712***	8.631***	8.933***	8.495***	9.912***
	(0.980)	(1.012)	(1.031)	(1.020)	(0.970)	(0.992)	(0.972)	(1.368)
Observations	10,008	10,008	10,008	10,008	10,008	10,008	10,008	10,008
R-squared	0.052	0.051	0.051	0.051	0.052	0.051	0.051	0.051

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column separately examines the heterogeneous effects with respect to an individual characteristic. **H** is a dummy variable equal to one for people with the characteristic listed at the top of each column and zero otherwise (e.g., **H** equals one for older people in column (1), females in column (2), and so on).

Looking at the interaction terms, the results suggest that individual characteristics play a role in shaping how people respond to information provision. "Percentage" information reduces the perception of infection risks more for females and people who have lost acquaintances due to COVID-19 than for their counterparts. "Qualitative" information increases risk perception more for people under 60, vaccinated people, and those who have contracted COVID-19. For "level" information, although it generally does not alter infection risk perception, females, college graduates, and people who have lost acquaintances due to COVID-19 tend to respond differently to this type of information compared to their counterparts.

Turning to panel (b) on fatality risk, we find results consistent with those in Figure 2 and Table 3. In particular, "percentage" information reduces perceived fatality risk, whereas "qualitative" information increases it. There is also heterogeneity in fatality risk perceptions across individual characteristics—older people, those with chronic diseases, and those who had acquaintances who died from COVID-19 are more likely to overestimate the fatality risk, while college graduates, married people, people infected with COVID-19, and vaccinated people are less likely to overestimate it.

The interaction terms show that "percentage" information reduces fatality risk perception more for older people, those with chronic diseases, those who have not contracted COVID-19, and those who have lost acquaintances due to COVID-19 than for their counterparts. Meanwhile, "qualitative" information increases risk perception more for vaccinated people. Unlike infection risk, "percentage" information does not reduce fatality risk perception more for females, nor does "qualitative" information increase it more for younger people or previously infected people. Moreover, while "level" information affects fatality risk perception differently between those who have lost acquaintances to COVID-19 and their counterparts, it also affects infection risk perception differently between females, college graduates, and their counterparts.

Taken together, the empirical evidence suggests that individual characteristics play an important role in shaping how people respond to information provision. The results remain robust when we examine the heterogeneous effects through subsample comparisons of the median infection and fatality risks (not shown for the sake of brevity).

5 Discussion

In this study, we conducted an information provision experiment to examine how different types of information affect the perceptions of COVID-19 risks. We first compared perceived risks with actual risks and found that the majority of respondents overestimated the infection and fatality risks. We found that "percentage" information and "qualitative" information tend to reduce and increase perceived risks, respectively, while "level" information shows little effect. These results indicate that different types of information can affect risk perceptions in opposite directions, suggesting that the government should carefully consider how information is presented when communicating risks to the public.

More specifically, level information and pessimistic qualitative information were common ways of risk communication through the pandemic. Our results suggest that they are either ineffective or counterproductive in mitigating people's risk overestimation. Level information—such as the daily number of new infections, severe cases, or deaths—can appear large even when the actual risk is low, thus limiting its ability to correct misperceptions of risks. Qualitative information—such as pessimistic warnings of the government or experts about new waves of infection or serious situations—can increase pessimism and further raise the perceived risks. In contrast, percentage information makes it easier for people to evaluate the magnitude of the threat relative to the total population, helping align perceptions more closely with actual risks. Taken together, our results suggest that the government may want to adopt risk communication that relies more on % information than the other two types.

We found that there was heterogeneity in risk perceptions across individual characteristics. For example, our results suggest that unvaccinated people, older people, and people without chronic diseases tend to perceive lower subjective infection risks than their counterparts. Because vaccination status could be closely related to preventive behaviors, it seems natural that unvaccinated people are likely to underestimate COVID-19 infection risk. Meanwhile, age and health status may affect risk perceptions through normalcy bias—a cognitive tendency to underestimate the likelihood or potential impact of a threat. For instance, older people may perceive their infection risk as lower based on past experiences with infectious disease outbreaks in which they were not infected, while healthy individuals may believe they are less likely to be infected because of confidence in their own health.

There is also substantial heterogeneity in responses to information provision across individual characteristics. For example, "percentage" information reduces infection risk perceptions more for females and people who have lost acquaintances due to COVID-19, while "qualitative" information increases risk perceptions more for younger people, vaccinated people, and those who have contracted COVID-19. This result suggests that people with different backgrounds, experiences, and beliefs may interpret the same information differently. The government may consider adopting group-specific risk communication to correct risk misperceptions more effectively.

Let us conclude our discussion by pointing out the two possible limitations of our study. First, because we rely on an internet survey, our sample may not be representative. In particular, 6.6% of our respondents had acquaintances who died from COVID-19. By the time of our survey, the number of cumulative deaths was about 75,000, less than 0.1% of the total population in Japan. Thus, our sample is likely to overrepresent those who emotionally suffered from the COVID-19 pandemic. If their risk perceptions respond to information provision differently from the risk perceptions of an average citizen—which the seventh column of the panel (a) in Table 5 indicates is true—our results might be biased.

Second, we did not conduct the follow-up survey to investigate how persistent the effects of information provision on risk perceptions are. In thinking about the government communication policy, it is useful to know how persistently information provision affects the public's risk perceptions. We leave such an investigation to future research.

6 Conclusion

We conducted an experiment in April 2023 in Japan to investigate how different types of information affect people's subjective assessment of COVID-19 infection and fatality risks. We find that, regardless of whether participants are provided with information or not, the majority of respondents overestimate both infection and fatality risks. We also find that "percentage" and "qualitative" information lowers and raises subjective risks, respectively, whereas "level" information does not significantly alter risk perceptions. Finally, we found that there was substantial heterogeneity in both risk perceptions and responses to information provision across individual characteristics, namely, age, gender, education, marital status, health status, COVID-19-related experiences, and vaccination status. We hope that our results are useful for policymakers in refining their risk communication strategies in future pandemics.

References

Abel, M., T. Byker, and J. Carpenter (2021). Socially optimal mistakes? debiasing COVID-19 mortality risk perceptions and prosocial behavior. *Journal of Economic Behavior & Organization 183*, 456–480.

Adachi, M., M. Murakami, D. Yoneoka, T. Kawashima, M. Hashizume, H. Sakamoto, A. Eguchi, C. Ghaznavi, S. Gilmour, S. Kaneko, H. Kunishima, K. Maruyama-Sakurai,

Y. Tanoue, Y. Yamamoto, H. Miyata, and S. Nomura (2022). Factors associated with the risk perception of COVID-19 infection and severe illness: A cross-sectional study in Japan. *SSM - Population Health 18*, 101105.

Akesson, J., S. Ashworth-Hayes, R. Hahn, R. Metcalfe, and I. Rasooly (2022). Fatalism, beliefs, and behaviors during the COVID-19 pandemic. *Journal of Risk and Uncertainty 64*(2), 147–190.

Asahi (2022a). Death rate from COVID-19 drops among seniors, ministry says. https://www.asahi.com/ajw/articles/14799310.

Asahi (2022b). Pandemic death toll in Osaka Prefecture defies easy explanation. https://www.asahi.com/ajw/articles/14565341.

Bruine De Bruin, W. and D. Bennett (2020). Relationships Between Initial COVID-19 Risk Perceptions and Protective Health Behaviors: A National Survey. *American Journal of Preventive Medicine 59*(2), 157–167.

Bundorf, M. K., J. DeMatteis, G. Miller, M. Polyakova, J. L. Streeter, and J. Wivagg (2025). Risk Perceptions and Private Protective Behaviors: Evidence from COVID-19 Pandemic. *Review of Economics and Statistics 107*(3), 728–740.

Chiba, A., T. Nakata, T. L. Nguyen, and R. Takaku (2024). COVID-19 risk perceptions in Japan: a cross-sectional study. *Scientific Reports 14*(1), 16862.

Cipolletta, S., G. Andreghetti, and G. Mioni (2022). Risk Perception towards COVID-19: A Systematic Review and Qualitative Synthesis. *International Journal of Environmental Research and Public Health 19*(8), 4649.

Dryhurst, S., C. R. Schneider, J. Kerr, A. L. J. Freeman, G. Recchia, A. M. Van Der Bles, D. Spiegelhalter, and S. Van Der Linden (2020). Risk perceptions of COVID-19 around the world. *Journal of Risk Research 23*(7-8), 994–1006.

Dyer, M. L., H. M. Sallis, J. N. Khouja, S. Dryhurst, and M. R. Munafò (2022). Associations between COVID-19 risk perceptions and mental health, wellbeing, and risk behaviours. *Journal of Risk Research 25*(11-12), 1372–1394.

Garfin, D. R., B. Fischhoff, E. A. Holman, and R. C. Silver (2021). Risk perceptions and health behaviors as COVID-19 emerged in the United States: Results from a probability-based nationally representative sample. *Journal of Experimental Psychology: Applied 27*(4), 584–598.

Gollust, S. E., R. I. Vogel, A. Rothman, M. Yzer, E. F. Fowler, and R. H. Nagler (2020). Americans' perceptions of disparities in COVID-19 mortality: Results from a nationally-representative survey. *Preventive Medicine 141*, 106278.

Graso, M. (2022). The new normal: Covid-19 risk perceptions and support for continuing restrictions past vaccinations. *PLOS ONE 17*(4), e0266602.

Greenaway, T. and K. S. Fielding (2020). Positive Affective Framing of Information Reduces Risk Perceptions and Increases Acceptance of Recycled Water. *Environmental Communication 14*(3), 391–402.

Hall, J. D. and J. M. Madsen (2022). Can behavioral interventions be too salient? Evidence from traffic safety messages. *Science 376*(6591), eabm3427.

Huynh, T. (2020). The COVID-19 risk perception: A survey on socioeconomics and media attention. *Economics Bulletin 40*(1), 758–764.

Komatsu, H., H. Kubota, N. Tanaka, M. Griffin, J. Link, G. Geher, and M. L. Fisher (2022). Cross-cultural comparison of nudging effects for environmental protection: A case-study of risk-averse attitudes toward disposable plastics. *PLOS ONE 17*(11), e0277183.

Linciano, N., C. Lucarelli, M. Gentile, and P. Soccorso (2018). How financial information disclosure affects risk perception. Evidence from Italian investors' behaviour. *The European Journal of Finance 24*(15), 1311–1332.

Mainichi (2022). Experts warn of 8th COVID wave as infections spread in Japan's chilly regions. https://mainichi.jp/english/articles/20221105/p2a/00m/0na/007000c.

MHLW (2023). Visualizing the data: information on COVID-19 infections. https://covid19.mhlw.go.jp/en/.

MIAC (2023). Population Estimates. https://www.stat.go.jp/data/jinsui/.

Oviedo-Trespalacios, O., V. Truelove, B. Watson, and J. A. Hinton (2019). The impact of road advertising signs on driver behaviour and implications for road safety: A critical systematic review. *Transportation Research Part A: Policy and Practice 122*, 85–98.

Sato, M., S. Kinoshita, and T. Ida (2022). Subjective Risk Valuation and Behavioral Change: Evidence From COVID-19 in the U.K. and Japan. *Graduate School of Economics Kyoto University Discussion Paper E-22-011*.

Savadori, L. and M. Lauriola (2022). Risk perceptions and COVID-19 protective behaviors: A two-wave longitudinal study of epidemic and post-epidemic periods. *Social Science & Medicine 301*, 114949.

Sinclair, A. H., S. Hakimi, M. L. Stanley, R. A. Adcock, and G. R. Samanez-Larkin (2021). Pairing facts with imagined consequences improves pandemic-related risk perception. *Proceedings of the National Academy of Sciences 118*(32), e2100970118.

Vai, B., S. Cazzetta, D. Ghiglino, L. Parenti, G. Saibene, M. Toti, C. Verga, A. Wykowska, and F. Benedetti (2020). Risk Perception and Media in Shaping Protective Behaviors: Insights From the Early Phase of COVID-19 Italian Outbreak. *Frontiers in Psychology 11*, 563426.

Wang, C., A. Sen, M. T. Ruffin, D. E. Nease, R. Gramling, L. S. Acheson, S. M. O'Neill, and W. S. Rubinstein (2012). Family History Assessment. *American Journal of Preventive Medicine 43*(4), 392–398.

Wise, T., T. D. Zbozinek, G. Michelini, C. C. Hagan, and D. Mobbs (2020). Changes in risk perception and self-reported protective behaviour during the first week of the COVID-19 pandemic in the United States. *Royal Society Open Science 7*(9), 200742.