Appendices

Mede, N. G., Rauchfleisch, A., Metag, J., & Schäfer, M. S. (2024). The interplay of knowledge overestimation, social media use, and populist ideas: Cross-sectional and experimental evidence from Germany and Taiwan. *Communication Research.* Advance online publication. https://doi.org/10.1177/00936502241230203

Appendix 1: Preregistration

All studies presented in this article were preregistered at the Open Science Framework (OSF), i.e. hypotheses and research questions, study design, questionnaires and stimulus material, data collection procedures, power analyses, analysis plan, and R code for power analyses and our knowledge overestimation measure (see below). Preregistrations and additional materials of the main study can be accessed at: https://osf.io/32xnp (preregistration) and https://osf.io/yrm8w (materials). Preregistrations and additional materials of the experiment can be accessed at: https://osf.io/5dx3u (preregistration) and https://osf.io/czvf7/ (materials).

All procedures followed the preregistrations exactly – with one slight deviation: Different to the preregistered analysis plan, we tested H1a, H1b, and H6 in single regression models for Taiwan and Germany instead of three separate models for each country. This is arguably a more reasonable approach because separate models would not have controlled for correlations of SNS exposure (H1a), IM exposure (H1b), and science-related populist attitudes (H6). If tested in single models, H1a and H1b test would yield significant results. See also our argument in the conclusion. Two of our preregistered hypotheses are not explicitly discussed in the main paper. We report them in Appendix 8.

We also preregistered and conducted a second experiment, which was implemented in the same questionnaire as the first one (respondents only participated in one of the two experiments). This experiment examined if participants differ in their evaluations of the policy presented in the Facebook post/message depending on who recommends this policy. The preregistration and additional materials can be accessed at: https://osf.io/cgp63 (preregistration) and https://osf.io/e3xmd/ (materials). In this manuscript, we present the main study and the experiment that manipulated the publicness of the stimulus message (private vs. public visibility) and do not focus on the second experiment.

Appendix 2: Overview of Variables, Questions, and Items

Table A1

All variables used for the analysis

Variable	Question	Taiwan		Germany	
		M (*SD*)	*n*	*M* (*SD*)	*n*
COVID-19 knowledge overestimation		0.00 (1.37)	1,295	0.00 (1.25)	1,587
Actual COVID-19 knowledge (12 items)	See Table A2	7.01 (1.83)	1,295	7.39 (1.85)	1,587
Perceived COVID-19 knowledge (4 items, α_{TWN} = 0.91, α_{GER} = 0.91; ωt_{TWN} = 0.91, ω_{tGER} = 0.91)	(1 = “I do not agree at all”, 7 = “strongly agree”)	4.16 (1.17)	1,295	3.69 (1.30)	1,587
	I know a lot about the novel coronavirus.	4.42 (1.25)	1,295	4.15 (1.40)	1,587
	I know a lot about how scientists work to study the novel coronavirus.	4.32 (1.29)	1,295	3.49 (1.51)	1,587
	I know a lot about viruses in general.	4.17 (1.29)	1,295	3.66 (1.45)	1,587
	I know a lot about the way scientists work who study viruses in general.	3.71 (1.41)	1,295	3.46 (1.50)	1,587
Science-related populist attitudes (SciPop Score)	(1 = “I do not agree at all”, 5 = “strongly agree”)	2.10 (0.78)	1,207	1.74 (0.86)	1,493
	What unites the ordinary people is that they trust their common sense in everyday life.	3.63 (0.95)	1,251	3.11 (1.19)	1,492
	Ordinary people are of good and honest character.	3.43 (1.02)	1,262	2.91 (1.20)	1,474
	Scientists are only after their own advantage.	2.55 (0.97)	1,195	2.09 (1.10)	1,514
	Scientists are in cahoots with politics and business.	3.02 (1.00)	1,135	2.45 (1.28)	1,489
	The people should have influence on the work of scientists.	2.79 (1.11)	1,220	2.22 (1.22)	1,494
	People like me should be involved in decisions about the topics scientists research.	2.28 (1.09)	1,209	2.25 (1.16)	1,499

	In case of doubt, one should rather trust the life experience of ordinary people than the estimations of scientists.	2.6 (1.02)	1,256	2.08 (1.12)	1,515
	We should rely more on common sense and less on scientific studies.	2.82 (1.16)	1,250	2.39 (1.21)	1,544
SNS exposure to COVID-19 information	How often did you get in contact with information about the novel coronavirus through the following media during the past months? (1 = “never”, 7 = “very often”)				
	Social networking sites (e.g., Facebook, Twitter, or Instagram)	4.58 (1.83)	1,295	3.00 (2.27)	1,587
IM exposure to COVID-19 information	How often did you get in contact with information about the novel coronavirus through the following media during the past months? (1 = “never”, 7 = “very often”)	4.34 (1.86)	1,295	2.40 (1.90)	1,587
	Instant messengers (e.g., WhatsApp, Facebook Messenger, or Telegram)				
Legacy media exposure to COVID-19 information (3 items, α_{TWN} = 0.64, α_{GER} = 0.68; ω_{tTWN} = 0.66, ω_{tGER} = 0.68)	How often did you get in contact with information about the novel coronavirus through the following media during the past months? (1 = “never”, 7 = “very often”)	4.12 (1.40)	1,295	4.7 (1.68)	1,587
	Television, without online media libraries	5.47 (1.66)	1,295	5.64 (1.96)	1,587
	Radio	3.16 (1.89)	1,295	4.50 (2.19)	1,587
	Printed daily newspapers, weekly newspapers or magazines	3.74 (1.96)	1,295	3.96 (2.27)	1,587
SNS engagement with COVID-19 content (3 items, α_{TWN} = 0.89, α_{GER} = 0.91; ω_{tTWN} = 0.89, ω_{tGER} = 0.91)	How often do you do the following? (1 = “never”, 7 = “very often”)	2.59 (1.65)	1,295	1.83 (1.34)	1,587
	Post or share information or opinions about the novel coronavirus in social media	2.36 (1.77)	1,295	1.8 (1.43)	1,587
	Like or favor information or	3.07 (1.98)	1,295	1.92 (1.52)	1,587

	opinions about the novel coronavirus in social media				
	Comment on information or opinions about the novel coronavirus in social media.	2.35 (1.72)	1,295	1.78 (1.41)	1,587
IM engagement with COVID-19 content	How often do you do the following? (1 = “never”, 7 = “very often”)				
	Post or share information or opinions about the novel coronavirus in messengers.	2.42 (1.76)	1,295	1.72 (1.33)	1,587
Age	(in years)	39.27 (11.25)	1,295	51.41 (14.06)	1,587
Gender	(1 = male)	0.49	1,295	0.54	1,587
Education	(1 = Master degree of higher)	0.22	1,295	0.19	1,587
Income	(GER: 1 = “under 500 Euro”, 11 = “5000 Euro or more”; TWN: 1 = “under 10k NTD”, 11 = “more than 100k NTD”)	8.00 (2.86)	1,295	5.84 (2.69)	1,587
Political orientation	(GER:1 = “left”, 7 = “right”; TWN: 1 = “left (progressive)”, 7 = “right (conservative)”)	3.86 (1.11)	1,295	3.77 (1.13)	1,587
Trust in scientists	(1 = “not at all trustworthy”, 7 = “very trustworthy”)	4.93 (1.14)	1,295	5.19 (1.35)	1,587
Affected by COVID-19	(1 = tested/risk group)	0.11	1,295	0.50	1,587
Attitudes toward COVID-19 (6 items, α_{TWN} = 0.79, α_{GER} = 0.87; ω_{tTWN} = 0.81, ωt_{GER} = 0.87)	(1 = “I do not agree at all”, 7 = “very strongly agree”)	0.83 (0.16)	1,295	0.82 (0.22)	1,587
	I often think about the novel coronavirus.	4.45 (1.47)	1,295	4.46 (1.71)	1,587
	I am interested in the novel coronavirus.	3.84 (1.47)	1,295	4.69 (1.67)	1,587
	I am afraid of the novel coronavirus.	5.09 (1.47)	1,295	4.1 (1.87)	1,587
	The novel coronavirus worries me.	5.22 (1.42)	1,295	4.79 (1.77)	1,587
	I avoid crowded public places to avoid being infected with the	5.38 (1.33)	1,295	5.36 (1.76)	1,587

	novel coronavirus.				
	I wash my hands regularly to prevent infection with the novel coronavirus.	5.77 (1.18)	1,295	5.97 (1.40)	1,587
Attention to COVID-19 information in legacy media	Now it is all about the media coverage of the novel coronavirus. How closely do you follow them? (1 = “not attentive at all”, 7 = “very attentive”)	5.22 (1.18)	1,295	5.17 (1.58)	1,587
Attention to COVID-19 information on SNSs/IMs	This is about information on the novel coronavirus, which can be obtained on the Internet or in messenger apps. How much attention do you pay to such information? (1 = “not attentive at all”, 7 = “very attentive”)	5.36 (1.17)	1,295	4.46 (1.96)	1,587
Trust in government	(1 = “not at all trustworthy”, 7 = “very trustworthy”)	3.83 (1.39)	698	4.24 (1.75)	993
Negative commenting intentions	(1 = “very unlikely”, 7 = “very likely”)	2.81 (1.63)	698	1.93 (1.65)	993
Positive commenting intentions	(1 = “very unlikely”, 7 = “very likely”)	3.08 (1.80)	698	2.22 (1.86)	993

Table A2

Overview of knowledge questions

Question	Taiwan		Germany	
	correct	*n*	correct	*N*
The new type of coronavirus can be transmitted via droplets through coughing, sneezing or close contact (droplet infection). (T)	97%	1,295	97%	1,587
In Taiwan [Germany], more than 400 [150,000] people tested positive for the novel coronavirus. (T)	69%	1,295	78%	1,587
The scientific name for the novel coronavirus is COVID-19. (F)	4%	1,295	9%	1,587
A coronavirus test with a false positive rate of 1% only shows a wrong result in 1% of all people tested. (F)	52%	1,295	33%	1,587
The development of an approved vaccine against the novel coronavirus takes a total of about 4 weeks. (F)	50%	1,295	88%	1,587

Animal experiments are also used to research the novel coronavirus. (T)	91%	1,295	42%	1,587
Vaccines can cure sick people. (F)	43%	1,295	69%	1,587
A virus that does not cause symptoms in all people can spread unnoticed. (T)	87%	1,295	95%	1,587
Cells that are infected by viruses are called virions. (F)	11%	1,295	27%	1,587
Sometimes scientists publish studies on the Internet that have not yet been reviewed by other scientists. (T)	71%	1,295	71%	1,587
Epidemiologists mainly work on the development of vaccines. (F)	36%	1,295	43%	1,587
Scientists use statistical models to predict how pandemics will spread. (T)	90%	1,295	85%	1,587

Note. F = false. T = true.

Appendix 3: Stimulus Material

Figures A1-A4 show the original stimulus material. The message translates to: “The federal government invested [EUR 45 million] [NT$ 1.56 billion] from COVID-19 emergency budget in the healthcare system – and has thus burdened the wallets of [Germans / Taiwanese]. Because of the measure, taxes will probably have to be raised.”

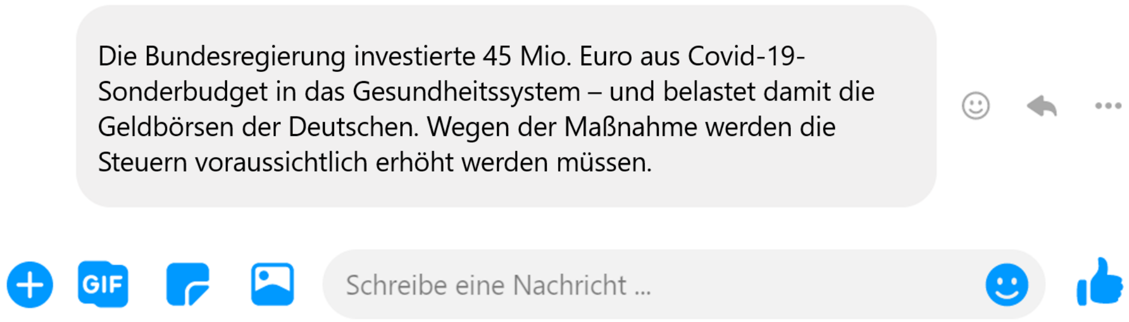

Figure A1. Stimulus: private Facebook message (Germany).

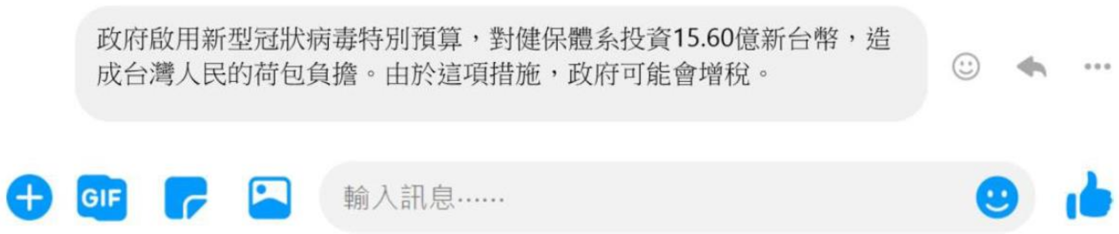

Figure A2. Stimulus: private Facebook message (Taiwan).

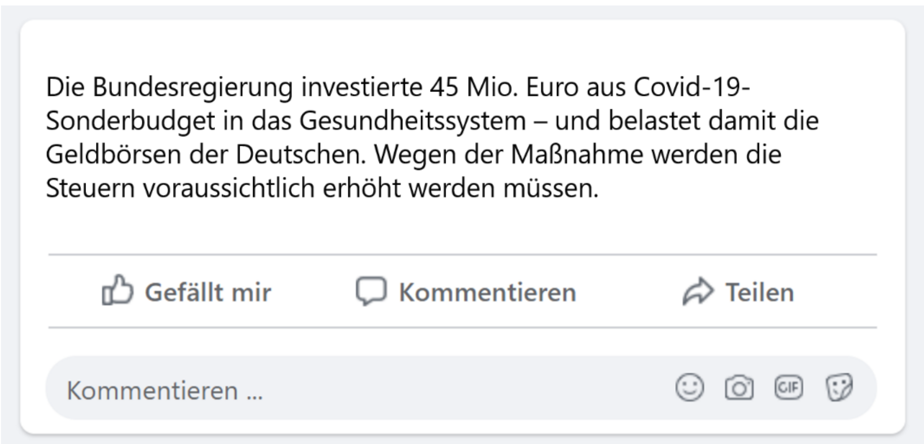

Figure A3. Stimulus: public Facebook posting (Germany).

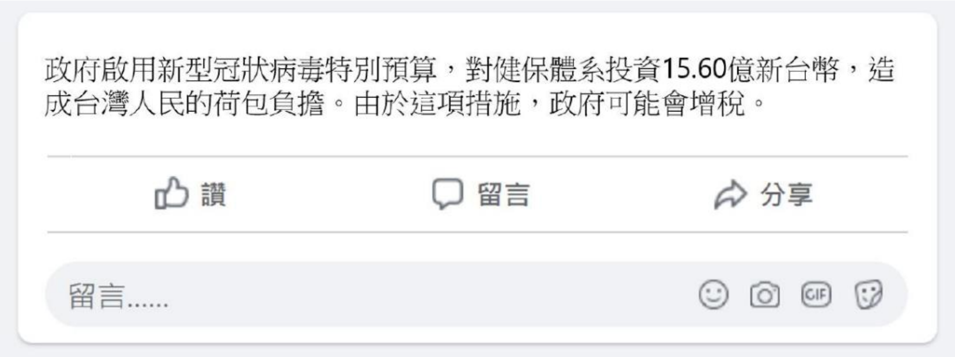

Figure A4. Stimulus: public Facebook posting (Taiwan).

Appendix 4: Development of the Knowledge Measurement in Pre-Studies

The knowledge measure, which we used to operationalize knowledge overestimation, was developed in pre-studies in May 2020. They contained a valid sample of *n* = 537 for Germany (GER) and *n* = 460 for Taiwan (TWN). Respondents were recruited from two online panels in Germany and Taiwan (polling companies: *Respondi* and *Rakuten Insight*, respectively). In the pre-study, we tested 24 questions that asked respondents if statements about the COVID-19 pandemic were “certainly true,” “rather true,” “rather wrong,” or “certainly wrong,” or if they do not know. Answers were counted as correct if respondents evaluated wrong statements as either “certainly wrong” or “rather wrong” and true statements as either “certainly true” or “rather true.” The 24 questions covered four different dimensions, i.e. factual knowledge about COVID-19, procedural knowledge about COVID-19, factual knowledge about virology/epidemiology, and procedural knowledge about virology/epidemiology (see Table A3). We adapted many of these questions from prior studies focusing on knowledge about epidemics (Balkhy et al., 2010; Betsch et al.; Lau et al., 2011), but half of them were specifically designed for this study, because previous studies had mainly focused on factual knowledge about a specific epidemic.

Table A3
Overview of all knowledge questions for the pre-study

Question number	Dimension	English translation	GER correct	TWN correct
1	COVID-19 factual knowledge	There is an approved vaccine against the novel coronavirus. (F)	94.6%	68.3%
2		Several studies show that an infection with the novel corona virus can be successfully treated with the HIV drug Kaletra. (F)	52.9%	37.0%
3*		The new type of corona virus can be transmitted via droplets through coughing, sneezing or close contact (droplet infection). (T)	97.6%	97.8%
4		Many infected people report losing their sense of taste and smell. (T)	86.8%	97.0%

5*		In Taiwan [Germany], more than 400 [150.000] people tested positive for the novel corona virus. (T)	76.9%	76.3%
6*		The scientific name for the novel corona virus is COVID-19. (F)	9.5%	3.3%
7	COVID-19 procedural knowledge	A test for the novel coronavirus can be negative even though you are infected. (T)	62.4%	95.4%
8		Based on throat swabs, the new type of coronavirus can be recognized without a doubt. (F)	15.3%	43.3%
9		Findings from previous pandemics can be transferred to the corona pandemic. (T)	64.6%	90.7%
10*		A corona virus test with a false positive rate of 1% only shows a wrong result in 1% of all people tested. (F)	24.6%	53.7%
11*		The development of an approved vaccine against the novel coronavirus takes a total of about 4 weeks. (F)	89.0%	60.9%
12*		Animal experiments are also used to research the novel corona virus. (T)	50.1%	86.7%
13*	Virology/ Epidemiology factual knowledge	Vaccines can cure sick people. (F)	61.3%	42.6%
14		Herd immunity can only be achieved by vaccination. (F)	43.2%	30.2%
15		The incubation period is the period from the first contact with a virus to the first symptoms of infection. (T)	91.1%	93.5%
16*		A virus that does not cause symptoms in all people can spread unnoticed. (T)	93.9%	88.5%
17		The reproduction number indicates how many people an infected person infects with a virus on average. (T)	89.6%	58.3%
18*		Cells that are infected by viruses are called virions. (F)	22.5%	8.3%
19	Virology/ Epidemiology procedural knowledge	The level of knowledge of epidemiology has not changed in the past 30 years. (F)	83.1%	59.1%
20*		Sometimes scientists publish studies on the Internet that have not yet been reviewed by other scientists. (T)	72.4%	75.9%
21*		Epidemiologists mainly work on the development of vaccines. (F)	36.7%	44.8%
22		When many virus or antibody tests are done in the population, it is easier for scientists to explain the spread of pandemics.	87.2%	89.8%
23*		Scientists use statistical models to predict how pandemics will spread. (T)	86.8%	91.7%
24		When doctors give a drug to 100 patients in an experiment and all patients are cured, this is clear and sufficient evidence of the effectiveness of the drug. (F)	42.8%	17.8%

Note. F = false. T = true. Germany *n* = 537, Taiwan *n* = 460.
*the 12 items we selected for our main study.

To develop a reliable and concise measure of knowledge we could later use to measure knowledge overestimation in the main study, we sought to identify 12 questions (three for each dimension) that have varying difficulty levels, help to discriminate between persons with different knowledge levels, and if possible, reduce so-called differential item functioning (DIF). DIF means that items "have different properties for persons belonging to different groups even if the persons have the same ability" (Bürkner, 2021, p. 8).

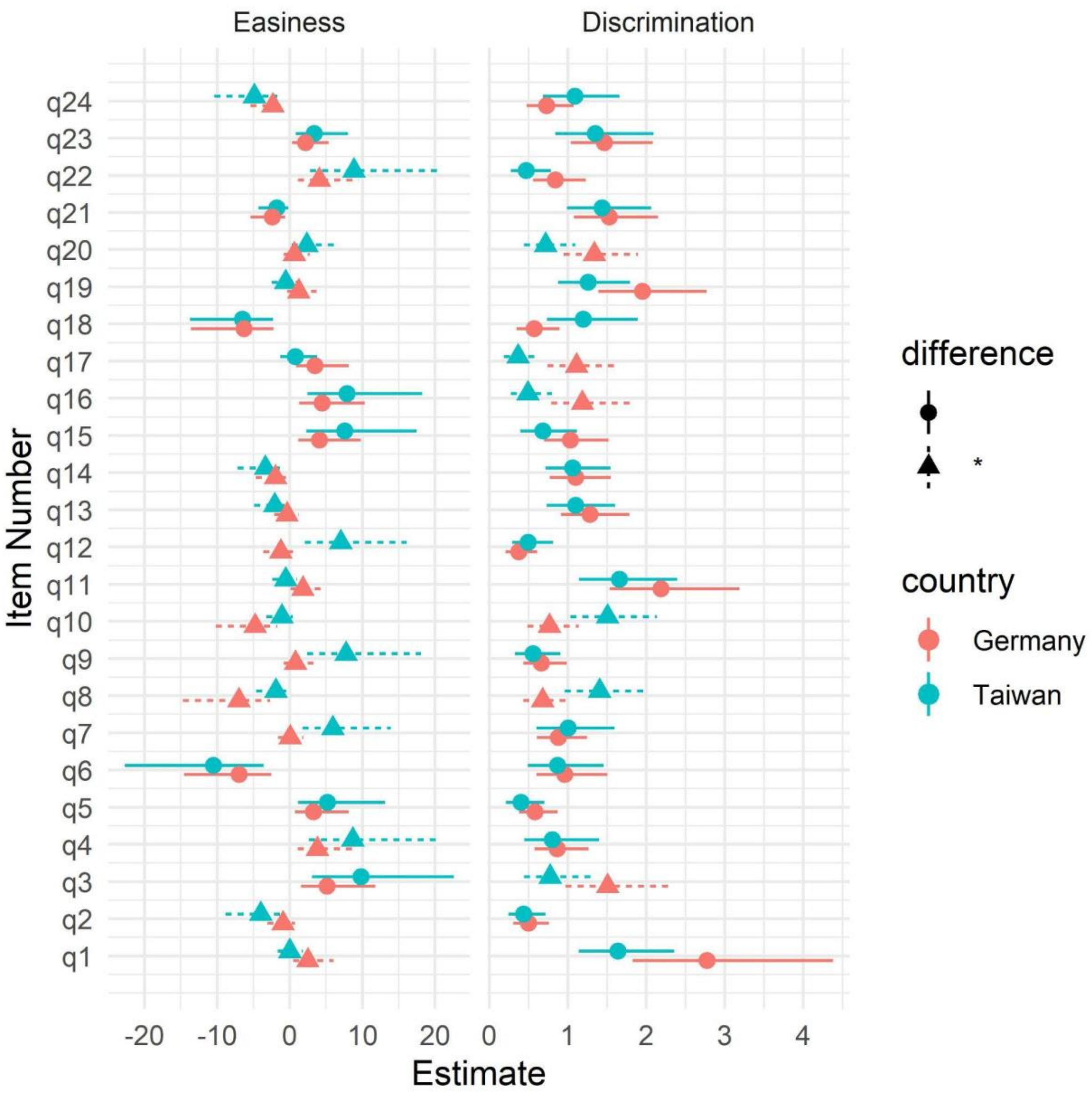

Figure A5. Results of the 2PL IRT model with 24 knowledge questions.

Note: Estimates for Easiness and Discrimination are shown with 95% Credible Intervals. Items with country differences at $\alpha < .001$ are shown with a dashed line.

In a first step, we used a 2-parameter logistic item response theory (2PL IRT) model with all 24 knowledge questions. It contained country (Taiwan or Germany) as a covariate, included varying slopes on the item level, and was fitted with the R package *brms*. First, we tested for *uniform DIF* by examining if country explains overall differences. The 95% CI [-0.38, 3.53] does not indicate uniform DIF. We then tested for *non-uniform DIF* on the item level, which would occur if there are differences for individual knowledge questions as to how easy they are for German vs. Taiwanese respondents (Teresi & Fleishman, 2007). Our model predicted the easiness (eta) as well as the discrimination (logalpha) of the 24 items (see Figure A5). For both these parameters, we specified varying slopes on country level. We also fixed the intercepts and then used Bayesian hypothesis testing with $\alpha < .001$. A substantial effect (a < .001) would suggest a difference in item easiness/discrimination between Germany and Taiwan, i.e., is an indicator for potential non-uniform DIF.

We decided to drop, if possible, items that showed different difficulty levels in each country. We found a few difficulty differences, some of which could be due to the different development of the COVID-19 pandemic in Germany vs. Taiwan. For example, the higher easiness of the question about the false positive rate in Taiwan (q10) could be explained with the overall better performance of Taiwanese students in the PISA ranking in science and math. In contrast, the higher easiness of the vaccine development question in Germany (q11) could be explained with the stronger focus on vaccine development in the public debate in Germany at the time of data collection. Yet removing these questions might lead to a too homogenous set of questions that do not measure all relevant aspects of knowledge (see Bürkner, 2021). Instead, these items do help to identify higher ability levels.

We selected three items for each of the four knowledge dimensions (actual vs. perceived knowledge about COVID-19 vs virology/epidemiology), i.e. 12 items in total, aiming to remove items that showed DIF. For example, the *COVID-19 factual knowledge* question about the HIV drug Kaletra (q2) exhibited different levels of easiness across countries, perhaps because it was too specific, so we excluded it. Meanwhile, all *COVID-19 procedural knowledge* questions showed different levels of easiness for both countries, so we selected items with the smallest cross-country differences and varying overall easiness levels. For the *virology/epidemiology factual knowledge* dimension, we selected two items without DIF and one item that showed DIF but was conceptually important for this dimension. For the *virology/epidemiology procedural knowledge* dimension we could use three items without any substantial difference between countries and varying levels of easiness.

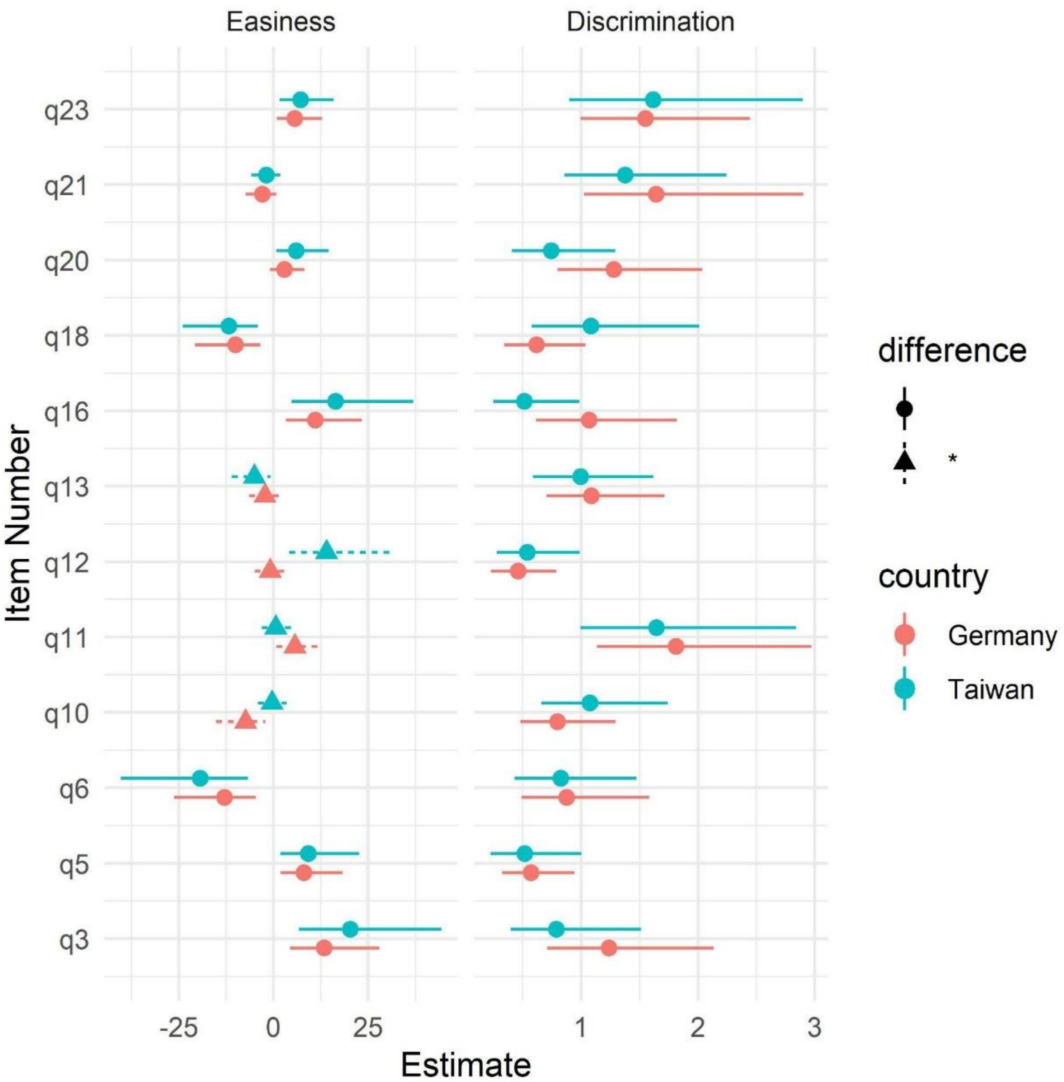

Figure A6. Results of the 2PL IRT model with 24 knowledge questions.

Note: Estimates for Easiness and Discrimination are shown with 95% Credible Intervals. Items with country differences at $\alpha < .001$ are shown with a dashed line.

In a second step, we ran another 2PL IRT model that only contained the 12 previously selected knowledge items. First of all, we tested for uniform DIF by checking if the country variable explained an overall difference. The 95% CI [-2.80, 5.23] did not indicate uniform DIF. We then checked for non-uniform DIF on item level again (see Figure A6).

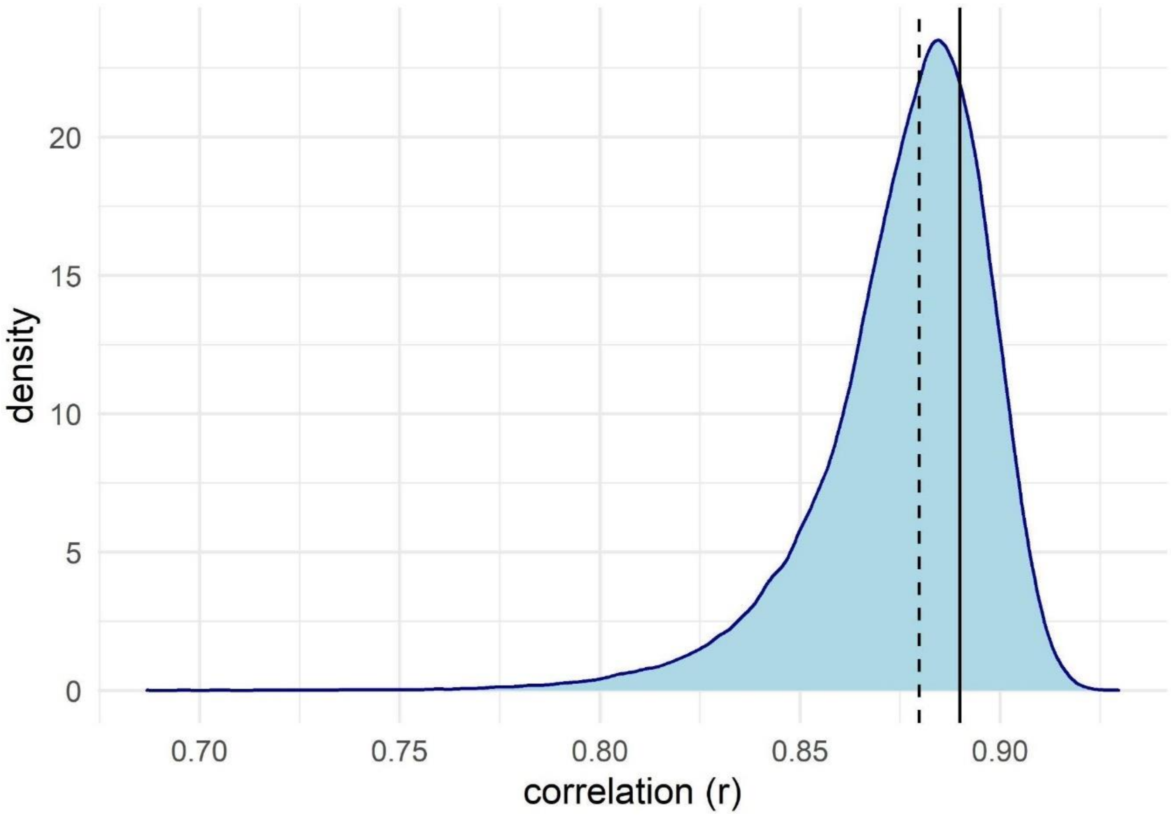

Figure A7. Density plot with all correlations between the 24-item knowledge score and every unique 12-item score

Note: Density plot covers all 160,000 unique 12 question combinations with three items from each dimension. The vertical dashed line indicates the median correlation. The solid line indicates our 12-item solution used in the study.

As an additional test, we ran a simulation in which we compared the correlation of our final 12-item knowledge measure with all other possible 12-item combinations that include 3 items from each dimension. We calculated knowledge scores for 160,000 unique combinations. To do so, we did not use the ability estimates of 2PL IRT models, however, because this would not be computationally feasible (running a single 2PL IRT model takes around 2 hours on a standard computer). Instead, we used a sum index of correct answers. We then calculated the correlation (*r*) between the knowledge scores of the complete 24-item measurement and every possible 12-item combination. Our analysis showed that overall, all combinations strongly correlate with the 24-item measurement. Moreover, the simulation indicated that our final 12-item measurement (see above) performed better ($r = 0.89$) than the majority of other possible combinations (median correlation score $r = 0.88$; see Figure A7).

Appendix 5: Detailed Results of Hypothesis Tests

Table A4

OLS Multiple linear regressions. H1a/H1b/H6 with knowledge overestimation as outcome variable

Predictors	COVID-19 knowledge overestimation (TWN)			COVID-19 knowledge overestimation (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.01	0.03	<0.001	0.02	0.04	<0.001
Science-related populist attitudes	0.22	0.03	<0.001	0.24	0.03	<0.001
SNS exposure to COVID-19 information	0.00	0.03	0.952	-0.04	0.03	0.201
IM exposure to COVID-19 information	0.02	0.03	0.473	0.03	0.03	0.287
Legacy media exposure to COVID-19 information	0.16	0.03	<0.001	-0.02	0.03	0.498
Age	-0.02	0.03	0.506	0.05	0.03	0.077
Gender (1 = male)	0.00	0.03	0.994	-0.03	0.03	0.190
Education (1 = Master or higher)	-0.13	0.03	<0.001	-0.03	0.03	0.321
Income	-0.05	0.03	0.082	-0.06	0.03	0.023
Political orientation (7 = right)	0.02	0.03	0.374	0.01	0.03	0.724
Trust in scientists	0.14	0.03	<0.001	0.12	0.03	<0.001
Affected by COVID-19 (1 = tested/risk group)	0.07	0.09	0.453	-0.03	0.05	0.537
Attitudes toward COVID-19	0.11	0.03	0.001	0.09	0.03	0.004
Attention to COVID-19 information in legacy media	0.05	0.04	0.223	0.14	0.03	<0.001
Attention to COVID-19 information on SNSs/IMs	0.05	0.04	0.258	0.09	0.03	0.003
n			1,207			1,493
R^2 / R^2 adjusted			0.189 / 0.179			0.112 / 0.103

Table A5

OLS multiple linear regressions. H2a/H7a with SNS engagement as outcome variable

Predictors	SNS engagement with COVID-19 content (TWN)			SNS engagement with COVID-19 content (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.03	0.02	<0.001	0.00	0.03	0.517
COVID-19 knowledge overestimation	0.10	0.03	<0.001	0.16	0.02	<0.001
Science-related populist attitudes	0.18	0.03	<0.001	0.19	0.03	<0.001
SNS exposure to COVID-19 information	0.25	0.03	<0.001	0.35	0.03	<0.001
IM exposure to COVID-19 information	0.04	0.03	0.167	0.11	0.03	<0.001
Legacy media exposure to COVID-19 information	0.17	0.03	<0.001	-0.02	0.02	0.327
Age	-0.12	0.03	<0.001	0.01	0.02	0.723
Gender (1 = male)	0.03	0.02	0.242	0.02	0.02	0.399
Education (1 = Master or higher)	-0.03	0.02	0.213	0.00	0.02	0.908
Income	-0.03	0.02	0.192	-0.04	0.02	0.112
Political orientation (7 = right)	0.06	0.02	0.011	0.04	0.02	0.048
Trust in scientists	0.03	0.03	0.271	0.00	0.03	0.854
Affected by COVID-19 (1 = tested/risk group)	0.28	0.08	<0.001	0.00	0.05	0.955
Attitudes toward COVID-19	0.06	0.03	0.050	-0.05	0.03	0.063
Attention to COVID-19 information in legacy media	0.11	0.04	0.005	0.06	0.03	0.030
Attention to COVID-19 information on SNSs/IMs	0.02	0.04	0.678	0.10	0.03	<0.001
n			1,207			1,493
R^2 / R^2 adjusted			0.346 / 0.338			0.294 / 0.287

Table A6

OLS multiple linear regressions. H2b/H7b with IM engagement as outcome variable

Predictors	IM engagement with COVID-19 content (TWN)			IM engagement with COVID-19 content (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.02	0.03	<0.001	-0.02	0.03	0.104
COVID-19 knowledge overestimation	0.04	0.03	0.136	0.13	0.02	<0.001
Science-related populist attitudes	0.22	0.03	<0.001	0.20	0.03	<0.001
SNS exposure to COVID-19 information	0.12	0.03	<0.001	0.09	0.03	0.001
IM exposure to COVID-19 information	0.10	0.03	0.001	0.34	0.03	<0.001
Legacy media exposure to COVID-19 information	0.18	0.03	<0.001	-0.03	0.02	0.303
Age	-0.10	0.03	<0.001	-0.11	0.02	<0.001
Gender (1 = male)	0.04	0.03	0.112	0.00	0.02	0.893
Education (1 = Master or higher)	0.01	0.03	0.706	-0.01	0.02	0.675
Income	-0.03	0.03	0.331	-0.01	0.02	0.809
Political orientation (7 = right)	0.03	0.03	0.238	0.02	0.02	0.338
Trust in scientists	0.07	0.03	0.011	0.01	0.03	0.625
Affected by COVID-19 (1 = tested/risk group)	0.16	0.08	0.060	0.05	0.05	0.305
Attitudes toward COVID-19	0.04	0.03	0.219	-0.01	0.03	0.645
Attention to COVID-19 information in legacy media	0.06	0.04	0.131	0.08	0.03	0.009
Attention to COVID-19 information on SNSs/IMs	0.05	0.04	0.277	0.06	0.03	0.015
n			1,207			1,493
R^2 / R^2 adjusted			0.267 / 0.258			0.289 / 0.282

Table A7

OLS multiple linear regressions with negative commenting as outcome variable

Predictors	Intentions to respond with negative comment/reply (TWN)			Intentions to respond with negative comment/reply (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	0.11	0.05	0.038	0.07	0.05	0.139
Visibility (1 = public)	-0.22	0.07	0.002	-0.12	0.06	0.033
Knowledge overestimation	0.17	0.05	0.001	0.11	0.04	0.008
Visibility × Knowledge overestimation	-0.05	0.07	0.509	-0.01	0.06	0.796
Trust in government	-0.17	0.04	<0.001	-0.31	0.03	<0.001
Affected by COVID-19 (1 = tested/risk group)	0.05	0.12	0.648	-0.02	0.06	0.667
SNS engagement with COVID-19 content	0.27	0.04	<0.001	0.23	0.03	<0.001
n			698			993
R^2 / R^2 adjusted			0.134 / 0.127			0.184 / 0.179

Table A8

OLS multiple linear regressions with positive commenting as outcome variable

Predictors	Intentions to respond with positive comment/reply (TWN)			Intentions to respond with positive comment/reply (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	0.11	0.05	0.030	0.13	0.05	0.010
Visibility (1 = public)	-0.21	0.07	0.002	-0.37	0.06	<0.001
Knowledge overestimation	0.08	0.05	0.091	0.16	0.04	<0.001
Visibility × Knowledge overestimation	0.02	0.07	0.768	-0.05	0.06	0.351
Trust in government	0.21	0.03	<0.001	0.19	0.03	<0.001
Affected by COVID-19 (1 = tested/risk group)	-0.01	0.11	0.928	0.11	0.06	0.055
SNS engagement with COVID-19 content	0.35	0.04	<0.001	0.23	0.03	<0.001
n			698			993
R^2 / R^2 adjusted			0.228 / 0.221			0.160 / 0.155

Appendix 6: A Note on Sample Representativity

We checked whether the samples of the main surveys (total *N* = 2,882) were balanced in terms of key demographic variables, i.e. gender, education, and age. We find that men and women were almost equally represented in both the German and the Taiwanese sample. In addition, both samples showed no bias towards higher or lower formal education. Average age was close to population means in Germany and Taiwan. However, age distributions differed slightly between populations and samples as some strata were underrepresented (minor underrepresentation of younger participants in Germany, see Table A8; overrepresentation of younger participants in Taiwan, see Table A9). However, this does not pose a severe limitation to our study, because we were not interested in specific point estimates but in the correlation between different variables, for which slightly skewed distributions of sample characteristics are usually unproblematic. Hence, our sample is appropriate for the current study.

Overrepresentation of younger participants (in the Taiwanese sample) is also less a problem as this allowed us to provide better estimates of those people that our study focuses on, i.e. young Internet users challenged by the large amount of information on COVID-19 circulating in social media and instant messengers. Accordingly, overrepresentation of younger strata lends our study higher ecological validity.

Table A8

Gender and age distribution in the survey and in the population: Germany

Age group	male		female	
	population	survey	population	survey
18-29	8.6%	3.7%	7.9%	5.2%
30-39	8.3%	7.9%	7.9%	6.4%
40-49	7.6%	9.6%	7.5%	5.6%
50-59	10.0%	14.7%	9.9%	13.3%
60 or older	15.0%	18.2%	17.3%	15.3%

Note: Population data was downloaded from the Federal Statistical Office of Germany: https://www-genesis.destatis.de/genesis/online?sequenz=statistikTabellen&selectionname=12411#abreadcrumb. Percentages were calculated for the people between the age of 18 and 85 in the year 2020.

Table A9

Gender and age distribution in the survey and in the population: Taiwan

Age group	male		female	
	population	survey	population	survey
18-29	9.5%	11.9%	8.8%	12.8%
30-39	8.9%	12.0%	8.8%	12.5%
40-49	9.5%	11.0%	9.8%	14.4%
50-59	9.1%	13.3%	9.4%	10.9%
60 or older	12.2%	0.7%	13.9%	0.4%

Note: Population data was downloaded from the National Development Council: https://pop-proj.ndc.gov.tw/main_en/dataSearch4.aspx?uid=78&pid=78 Percentage was calculated for the people between the age of 18 and 85 in the year 2020.

Appendix 7: Specification Curve Analysis

We also ran specification curve analyses for all correlational analyses as a robustness check. This approach, which was introduced by Simonsohn et al. (2020), tests all theoretically justified models that the researcher could also specify but chose not to – because of unconscious preferences, arbitrary reasons, or theoretical assumptions and previous research. We ran this analysis for each correlational hypothesis: For example, H6 regressions included knowledge overestimation as the outcome variable and the SciPop Score (i.e., science-related populist attitudes) as the independent variable. Moreover, these regression models contained the 12 preregistered covariates (see Table A4). To probe the robustness of the regression estimates, we ran a specification analysis that tested 8,192 alternative regression models, which included knowledge overestimation and the SciPop Score – as well as all possible combinations of covariates. Results of this analysis showed that science-related populist attitudes had a positive coefficient in all of these 8,192 models, and that all of these coefficients were significant at the $p < 0.05$ level (see Table A10 and Figure A8).

Table A10

Results of specification curve analysis

	Hypothesis	Germany	Taiwan
H1a	Positive effect SNS exposure → knowledge overestimation	0%	19.9%
H1b	Positive effect IM exposure → knowledge overestimation	17.1%	37.8%
H2a	Positive effect knowledge overestimation → SNS engagement	100%	100%
H2b	Positive effect knowledge overestimation → IM engagement	100%	88.6%
H6	Positive correlation SciPop ↔ knowledge overestimation	100%	100%
H7a	Positive effect SciPop → SNS engagement	100%	100%
H7b	Positive effect SciPop → IM engagement	100%	100%

Note. For every hypothesis, this table shows the percentage of models that have a significant positive coefficient ($p < .05$), and would thus confirm the original hypotheses. SNS = social networking sites; IM = instant messengers.

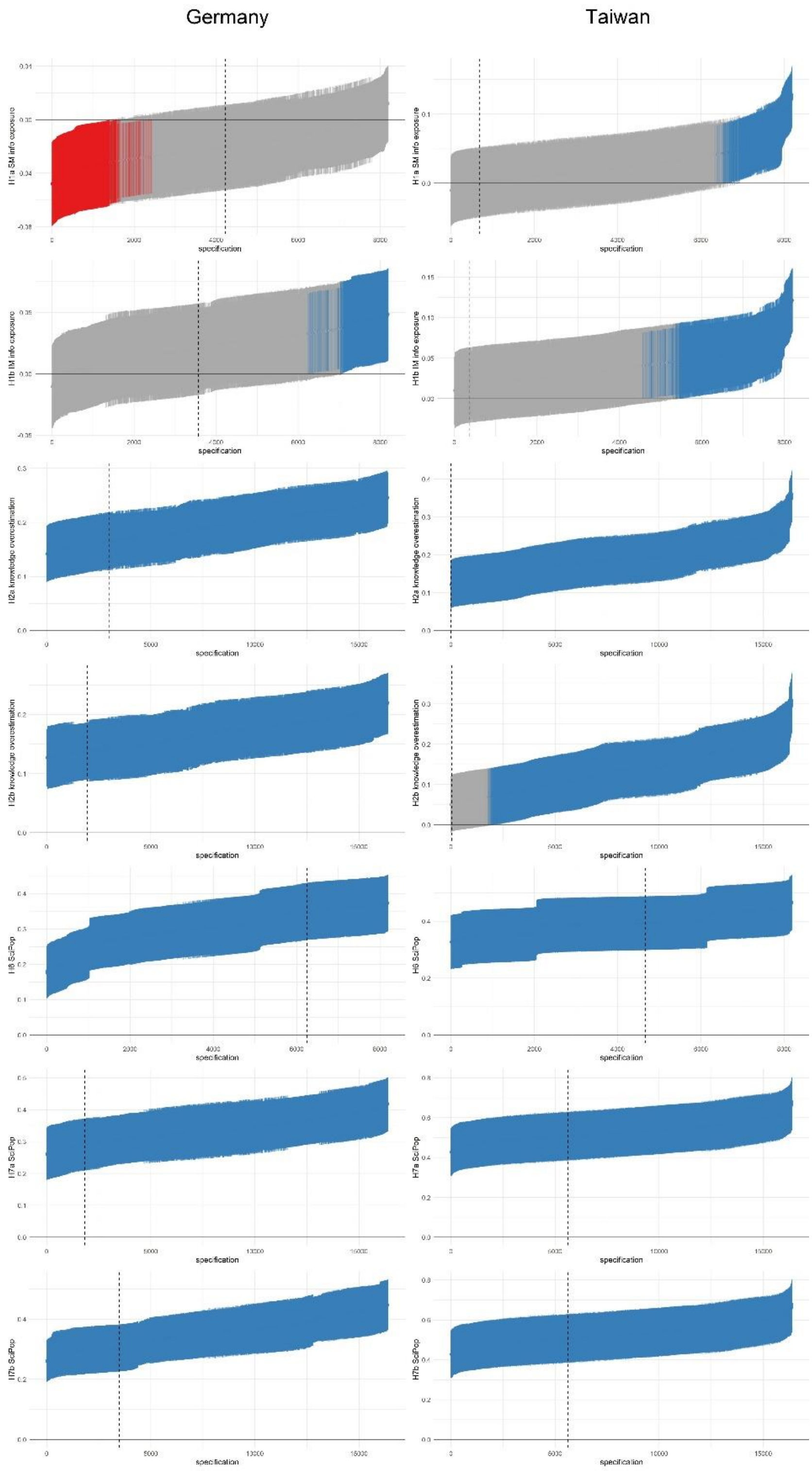

Figure A8. Specification curve analysis for all hypotheses in both countries (left: Germany; right: Taiwan).

Note: Vertical dashed line indicates the estimate of our preregistered model, whose results are reported in the article. Models are ordered by the magnitude of the coefficient of the independent variable. Non-standardized estimates are shown. Blue color indicates a significant positive coefficient, red a significant negative coefficient, grey a non-significant coefficient (at the $p < 0.05$ level).

Almost all specification curve analyses for the other hypotheses confirmed our findings. However, H2b should probably not be discarded for Taiwan but considered for future studies, because 88.6% of alternative model specifications showed a significant positive correlation of knowledge overestimation and IM engagement (with $p < 0.05$; see Table A10).

Appendix 8: Preregistered Hypotheses Not Discussed in the Main Paper

We preregistered two hypotheses not discussed in the main paper, because testing them did not provide relevant insights for our general research objective. Rather, these hypotheses address questions that go beyond the scope of the main paper. However, we report and discuss the results here.

Table A11. *Overview of preregistered hypotheses not discussed in the main paper*

H/RQ	Relationship	Wording
H1c	Positive effect legacy media exposure → knowledge overestimation	There will be a positive correlation between contact with COVID-19 information in social media and COVID-19 knowledge overestimation.
H8	Positive effect of preference for SNS over IM → knowledge overestimation	There will be a positive correlation between COVID-19 knowledge overestimation and participants' tendency to prefer social networking sites (over instant messengers) when engaging with COVID-19 content (or messaging about COVID-19).

Note. SNS = social networking sites; IM = instant messengers.

The results for H1c are reported in Table A4 in Appendix 5. While we do not find significant results for Germany, the results for Taiwan indicate that higher exposure to information about COVID-19 in legacy media is associated with higher the COVID-19 knowledge overestimation. This can be explained by the overall quality of news in Taiwan: While there are prominent legacy media outlets with a good reputation, the quality of journalism in most daily newspapers is problematic, and trust in journalism is low in Taiwan (Newman et al., 2021). Thus, consuming legacy media, in general, does not equate automatically with receiving high-quality information.

For H8, we do not find significant results in both countries (see Table A12). This hypothesis was rather explorative.

Table A12

OLS multiple linear regressions with preference for SNS vs. IM as outcome variable (H8).

Predictors	Preference for SM over IM (TWN)			Preference for SNS over IM (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.02	0.03	0.286	0.02	0.04	0.937
COVID-19 knowledge overestimation	0.06	0.03	0.051	0.02	0.03	0.431
Age	-0.06	0.03	0.032	0.09	0.03	0.001
Gender (1 = male)	-0.03	0.03	0.352	0.00	0.03	0.958
Education (1 = Master or higher)	-0.06	0.03	0.049	0.00	0.03	0.968
Income	-0.01	0.03	0.740	-0.05	0.03	0.047
Political orientation (7 = right)	0.02	0.03	0.484	0.02	0.03	0.519
Trust in scientists	-0.05	0.03	0.093	-0.02	0.03	0.461
Affected by COVID-19 (1 = tested/risk group)	0.20	0.09	0.026	-0.03	0.05	0.564
Attitudes toward COVID-19	0.03	0.03	0.323	-0.04	0.03	0.178
Attention to COVID-19 information in legacy media	0.06	0.05	0.178	-0.01	0.03	0.710
Attention to COVID-19 information on SNSs/IMs	-0.02	0.05	0.651	0.06	0.03	0.032
n			1,295			1,587
R^2 / R^2 adjusted			0.023 / 0.014			0.016 / 0.009

Appendix 9: Alternative Model Specifications

The difference score approach to operationalizing knowledge overestimation, as employed in our study, has faced criticism in the literature, notably by Baek et al. (2019). Thus, following suggestions in the literature on third-person and presumed media effects, which mainly also used difference scores, we estimated additional regression models. These models treat actual knowledge and perceived knowledge as separate variables (see Table A13 and A14), and include an interaction term involving both variables (see Table A15 and A16). This approach has been suggested by a number of studies (e.g., Baek et al., 2019; Wintterlin et al., 2021). We thus present a model with actual knowledge and perceived knowledge as separate predictors — an approach used by Lee et al. (2023) — and a model where we additionally include an interaction term (Baek et al., 2019; Wintterlin et al., 2021).

In our models, the interaction terms are not significant (see Table A15 and A16). Furthermore, in the model without an interaction term, both perceived knowledge and actual knowledge are significant predictors (see Tables A13 and A14). However, the results from these models do not show significance for Taiwan and IM engagement, as demonstrated in the main paper. Interestingly, perceived knowledge shows a larger effect size. This finding indicates that overestimation plays indeed a role.

Table A13

OLS multiple linear regression with SM engagement as outcome variable

Predictors	SM engagement with COVID-19 content (TWN)			SM engagement with COVID-19 content (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.03	0.02	<0.001	0.00	0.03	0.176
COVID-19 knowledge	-0.06	0.03	0.017	-0.09	0.02	<0.001
Perceived knowledge	0.09	0.03	0.002	0.16	0.02	<0.001
Science-related populist attitudes	0.18	0.03	<0.001	0.19	0.03	<0.001
Age	-0.12	0.03	<0.001	0.02	0.02	0.520
Gender (1 = male)	0.03	0.02	0.281	0.01	0.02	0.521
Education (1 = Master or higher)	-0.03	0.02	0.182	-0.01	0.02	0.625
Income	-0.03	0.02	0.181	-0.04	0.02	0.060
Political orientation (7 = right)	0.06	0.02	0.010	0.05	0.02	0.038
Trust in scientists	0.02	0.03	0.373	-0.02	0.03	0.513
Affected by COVID-19 (1 = tested/risk group)	0.28	0.08	<0.001	0.00	0.05	0.979
Attitudes toward COVID-19	0.05	0.03	0.056	-0.05	0.03	0.090
Attention to COVID-19 info in legacy media	0.11	0.04	0.008	0.06	0.03	0.061
Attention to COVID-19 info on SNSs/IMs	0.02	0.04	0.701	0.09	0.03	<0.001
Legacy media exposure to COVID-19 information	0.17	0.03	<0.001	-0.03	0.02	0.291
SNS exposure to COVID-19 information	0.25	0.03	<0.001	0.35	0.03	<0.001
IM exposure to COVID-19 information	0.04	0.03	0.174	0.10	0.03	<0.001
n			1,207			1,493
R^2 / R^2 adjusted			0.347 / 0.338			0.297 / 0.289

Table A14

OLS multiple linear regression with IM engagement as outcome variable

Predictors	IM engagement with COVID-19 content (TWN)			IM engagement with COVID-19 content (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.02	0.03	<0.001	-0.02	0.03	0.967
COVID-19 knowledge	-0.01	0.03	0.773	-0.07	0.02	0.004
Perceived knowledge	0.06	0.03	0.055	0.14	0.02	<0.001
Science-related populist attitudes	0.22	0.03	<0.001	0.20	0.03	<0.001
Age	-0.10	0.03	<0.001	-0.10	0.02	<0.001
Gender (1 = male)	0.04	0.03	0.151	0.00	0.02	0.959
Education (1 = Master or higher)	0.01	0.03	0.842	-0.02	0.02	0.447
Income	-0.03	0.03	0.303	-0.01	0.02	0.604
Political orientation (7 = right)	0.03	0.03	0.224	0.02	0.02	0.295
Trust in scientists	0.06	0.03	0.030	0.00	0.03	0.97
Affected by COVID-19 (1 = tested/risk group)	0.15	0.08	0.073	0.05	0.05	0.318
Attitudes toward COVID-19	0.03	0.03	0.251	-0.01	0.03	0.756
Attention to COVID-19 info in legacy media	0.06	0.04	0.183	0.07	0.03	0.020
Attention to COVID-19 info on SNSs/IMs	0.04	0.04	0.301	0.06	0.03	0.023
Legacy media exposure to COVID-19 information	0.18	0.03	<0.001	-0.03	0.02	0.271
SNS exposure to COVID-19 information	0.12	0.03	<0.001	0.09	0.03	0.001
IM exposure to COVID-19 information	0.10	0.03	0.001	0.34	0.03	<0.001
n			1,207			1,493
R^2 / R^2 adjusted			0.268 / 0.258			0.291 / 0.284

Table A15

OLS multiple linear regression with SM engagement as outcome variable

Predictors	SM engagement with COVID-19 content (TWN)			SM engagement with COVID-19 content (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.03	0.02	0.272	0.00	0.03	0.932
COVID-19 knowledge	-0.06	0.03	0.017	-0.09	0.02	<0.001
Perceived knowledge	0.09	0.03	0.001	0.16	0.02	<0.001
Science-related populist attitudes	0.18	0.03	<0.001	0.19	0.03	<0.001
Age	-0.12	0.03	<0.001	0.02	0.02	0.528
Gender (1 = male)	0.03	0.02	0.277	0.01	0.02	0.546
Education (1 = Master or higher)	-0.03	0.02	0.184	-0.01	0.02	0.651
Income	-0.03	0.02	0.173	-0.05	0.02	0.057
Political orientation (7 = right)	0.06	0.02	0.011	0.05	0.02	0.038
Trust in scientists	0.03	0.03	0.340	-0.02	0.03	0.472
Affected by COVID-19 (1 = tested/risk group)	0.28	0.08	<0.001	0.00	0.05	0.991
Attitudes toward COVID-19	0.05	0.03	0.064	-0.05	0.03	0.090
Attention to COVID-19 info in legacy media	0.11	0.04	0.008	0.06	0.03	0.058
Attention to COVID-19 info on SNSs/IMs	0.02	0.04	0.693	0.09	0.03	<0.001
Legacy media exposure to COVID-19 information	0.17	0.03	<0.001	-0.03	0.02	0.278
SNS exposure to COVID-19 information	0.25	0.03	<0.001	0.35	0.03	<0.001
IM exposure to COVID-19 information	0.04	0.03	0.174	0.10	0.03	<0.001
COVID-19 knowledge × Perceived knowledge	-0.02	0.02	0.332	-0.02	0.02	0.449
n			1,207			1,493
R^2 / R^2 adjusted			0.347 / 0.338			0.297 / 0.289

Table A16

OLS multiple linear regression with IM engagement as outcome variable

Predictors	IM engagement with COVID-19 content (TWN)			IM engagement with COVID-19 content (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	-0.01	0.03	0.587	-0.02	0.03	0.579
COVID-19 knowledge	-0.01	0.03	0.770	-0.07	0.02	0.004
Perceived knowledge	0.06	0.03	0.049	0.14	0.02	<0.001
Science-related populist attitudes	0.22	0.03	<0.001	0.20	0.03	<0.001
Age	-0.09	0.03	<0.001	-0.10	0.02	<0.001
Gender (1 = male)	0.04	0.03	0.149	0.00	0.02	0.918
Education (1 = Master or higher)	0.01	0.03	0.837	-0.02	0.02	0.477
Income	-0.03	0.03	0.292	-0.01	0.02	0.577
Political orientation (7 = right)	0.03	0.03	0.232	0.02	0.02	0.295
Trust in scientists	0.06	0.03	0.026	0.00	0.03	0.956
Affected by COVID-19 (1 = tested/risk group)	0.15	0.08	0.068	0.04	0.05	0.328
Attitudes toward COVID-19	0.03	0.03	0.273	-0.01	0.03	0.758
Attention to COVID-19 info in legacy media	0.06	0.04	0.190	0.07	0.03	0.019
Attention to COVID-19 info on SNSs/IMs	0.04	0.04	0.297	0.06	0.03	0.023
Legacy media exposure to COVID-19 information	0.18	0.03	<0.001	-0.03	0.02	0.255
SNS exposure to COVID-19 information	0.12	0.03	<0.001	0.09	0.03	0.001
IM exposure to COVID-19 information	0.10	0.03	0.001	0.34	0.03	<0.001
COVID-19 knowledge × Perceived knowledge	-0.02	0.02	0.362	-0.02	0.02	0.299
n			1,207			1,493
R^2 / R^2 adjusted			0.269 / 0.258			0.292 / 0.284

Appendix 10: Regression Models with Pooled Data and Country as Dummy Variable

This appendix reports results of regression analyses that test our main hypotheses using data from both countries with single models (not separate models, see Appendix 5) and a dummy variable for country (1 = Taiwan). The results are more or less the same as in the separate models. However, due to the increased sample size, some of the variables that were significant predictors in only one country are significant in the models with the pooled data (e.g., the effect of Affected by COVID-19 on SNS engagement). Moreover, gender, which was not a significant predictor of IM engagement in either country, became significant (see Table A19). These models help evaluate for which outcome variables we find country differences – that is, SNS and IM engagement but not knowledge overestimation – and show the overall effects on knowledge overestimation (Table A17), SNS engagement (Table A18), and IM engagement (Table A19). However, separate models per country still allow a more nuanced assessment of country-specific relationships between our predictor and outcome variables.

Table A17

OLS multiple linear regressions. H1a/H1b/H6 with knowledge overestimation as outcome variable for both countries

Predictors	Knowledge overestimation		
	β	*SE*	*p*
Intercept	0.00	0.02	<0.001
Science-related populist attitudes	0.25	0.02	<0.001
SNS exposure to COVID-19 information	-0.02	0.02	0.441
IM exposure to COVID-19 information	0.04	0.02	0.135
Legacy media exposure to COVID-19 information	0.06	0.02	0.006
Age	0.01	0.02	0.511
Gender (1 = male)	-0.01	0.02	0.697
Education (1 = Master or higher)	-0.08	0.02	<0.001
Income	-0.06	0.02	0.006
Political orientation (7 = right)	0.01	0.02	0.453
Trust in scientists	0.13	0.02	<0.001
Affected by COVID-19 (1 = tested/risk group)	-0.01	0.04	0.745
Attitudes toward COVID-19	0.10	0.02	<0.001
Attention to COVID-19 information in legacy media	0.11	0.02	<0.001
Attention to COVID-19 information on SNSs/IMs	0.08	0.02	0.001
Country (1 = Taiwan)	-0.04	0.03	0.116
n			2,700
R^2 / R^2 adjusted			0.134 / 0.129

Table A18

OLS multiple linear regressions. H2a/H7a with SNS engagement as outcome variable for both countries

Predictors	SNS engagement		
	β	*SE*	*p*
Intercept	-0.02	0.02	0.007
COVID-19 knowledge overestimation	0.14	0.02	<0.001
Science-related populist attitudes	0.20	0.02	<0.001
SNS exposure to COVID-19 information	0.32	0.02	<0.001
IM exposure to COVID-19 information	0.09	0.02	<0.001
Legacy media exposure to COVID-19 information	0.06	0.02	0.001
Age	-0.06	0.02	0.001
Gender (1 = male)	0.04	0.02	0.017
Education (1 = Master or higher)	-0.02	0.02	0.317
Income	-0.03	0.02	0.056
Political orientation (7 = right)	0.05	0.02	0.003
Trust in scientists	0.01	0.02	0.516
Affected by COVID-19 (1 = tested/risk group)	0.08	0.04	0.048
Attitudes toward COVID-19	0.00	0.02	0.902
Attention to COVID-19 information in legacy media	0.07	0.02	0.001
Attention to COVID-19 information on SNSs/IMs	0.07	0.02	<0.001
Country (Taiwan = 1)	0.06	0.02	0.009
n			2,700
R^2 / R^2 adjusted			0.341 / 0.337

Table A19

OLS multiple linear regressions. H2b/H7b with IM engagement as outcome variable for both countries

Predictors	IM engagement		
	β	*SE*	*p*
Intercept	-0.02	0.02	0.013
COVID-19 knowledge overestimation	0.10	0.02	<0.001
Science-related populist attitudes	0.23	0.02	<0.001
SNS exposure to COVID-19 information	0.12	0.02	<0.001
IM exposure to COVID-19 information	0.24	0.02	<0.001
Legacy media exposure to COVID-19 information	0.07	0.02	<0.001
Age	-0.12	0.02	<0.001
Gender (1 = male)	0.04	0.02	0.031
Education (1 = Master or higher)	<0.01	0.02	0.790
Income	-0.02	0.02	0.404
Political orientation (7 = right)	0.02	0.02	0.179
Trust in scientists	0.04	0.02	0.026
Affected by COVID-19 (1 = tested/risk group)	0.07	0.04	0.074
Attitudes toward COVID-19	0.01	0.02	0.591
Attention to COVID-19 information in legacy media	0.07	0.02	0.002
Attention to COVID-19 information on SNSs/IMs	0.06	0.02	0.005
Country (Taiwan = 1)	<0.01	0.02	0.911
n			2,700
R^2 / R^2 adjusted			0.292 / 0.288

Appendix 11: Regression Models Testing Further Effects on Overestimation

This appendix reports results of regression analyses to contextualize our main results. First, we ran additional analyses with two potential moderators of the effect of SNS use on knowledge overestimation, i.e. political orientation and attention to COVID-19 information on SNSs/IMs. Specifically, we tested interaction effects of attention to COVID-19 information on SNSs/IMs × SNS exposure on knowledge overestimation and interaction effects of political orientation × SNS exposure on overestimation. However, our exploratory analysis yielded a significant interaction for attention to COVID-19 information on SNSs/IMs × SNS exposure only in Germany (see Table A20 and Figure A9).

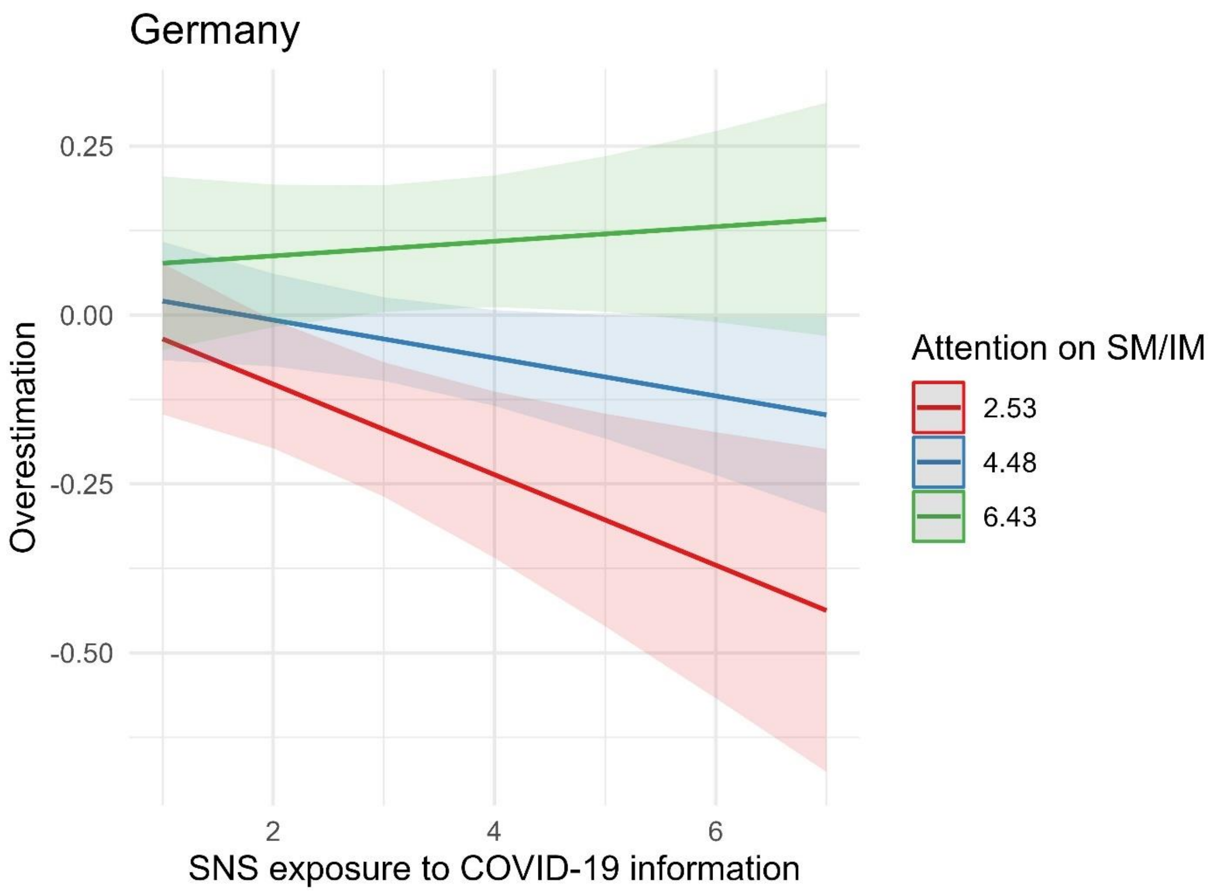

Figure A9. Interaction between SNS exposure to COVID-19 information and attention to COVID-19 information on SNSs/IMs.

Note: The mean value of attention to COVID-19 information on SNSs/IMs as well as one standard deviation below and above mean are used for the plot (see Table A20).

Table A20

OLS Multiple linear regressions. Knowledge overestimation as outcome variable and interaction of SNS exposure to COVID-19 information with political orientation as well as attention to COVID-19 information on SNSs/IMs

Predictors	COVID-19 knowledge overestimation (TWN)			COVID-19 knowledge overestimation (GER)		
	β	*SE*	*p*	β	*SE*	*p*
Intercept	0.00	0.03	0.998	-0.02	0.03	0.493
Science-related populist attitudes	0.22	0.03	<0.001	0.24	0.03	<0.001
SNS exposure to COVID-19 information	0.00	0.03	0.947	-0.05	0.03	0.090
IM exposure to COVID-19 information	0.02	0.03	0.490	0.03	0.03	0.316
Legacy media exposure to COVID-19 information	0.16	0.03	<0.001	-0.02	0.03	0.532
Age	-0.02	0.03	0.528	0.05	0.03	0.088
Gender (1 = male)	0.00	0.03	0.997	-0.04	0.03	0.152
Education (1 = Master or higher)	-0.13	0.03	<0.001	-0.03	0.03	0.298
Income	-0.05	0.03	0.076	-0.06	0.03	0.023
Political orientation (7 = right)	0.02	0.03	0.438	0.01	0.03	0.807
Trust in scientists	0.14	0.03	<0.001	0.13	0.03	<0.001
Affected by COVID-19 (1 = tested/risk group)	0.02	0.03	0.480	-0.01	0.03	0.611
Attitudes toward COVID-19	0.11	0.03	0.001	0.09	0.03	0.004
Attention to COVID-19 information in legacy media	0.05	0.04	0.225	0.13	0.03	<0.001
Attention to COVID-19 information on SNSs/IMs	0.05	0.05	0.249	0.11	0.03	<0.001
Political orientation × SNS exposure to COVID-19 information	0.02	0.03	0.533	0.03	0.02	0.285
Attention to COVID-19 info on SNSs/IMs × SNS exposure to COVID-19 information	0.01	0.02	0.818	0.07	0.03	0.007
n			1,207			1,493
R^2 / R^2 adjusted			0.189 / 0.178			0.116 / 0.107

Second, we explored whether the effect of science-related populist attitudes on knowledge overestimation is moderated by attention to information on COVID-19 in legacy media and SNSs/IMs. This analysis reveals that the effect of science-related populism on knowledge overestimation diminishes as attention to legacy media increases. For individuals scoring low on the science-related populism measure, we observe a reverse effect (see Figure A10). As attention to legacy media decreases, they are less likely to overestimate their knowledge. This interaction was significant only for Germany and not for Taiwan. Furthermore, the analysis did not reveal any significant interaction between attention to COVID-19 information on SNSs/IMs and science-related populist attitudes (see Table A21).

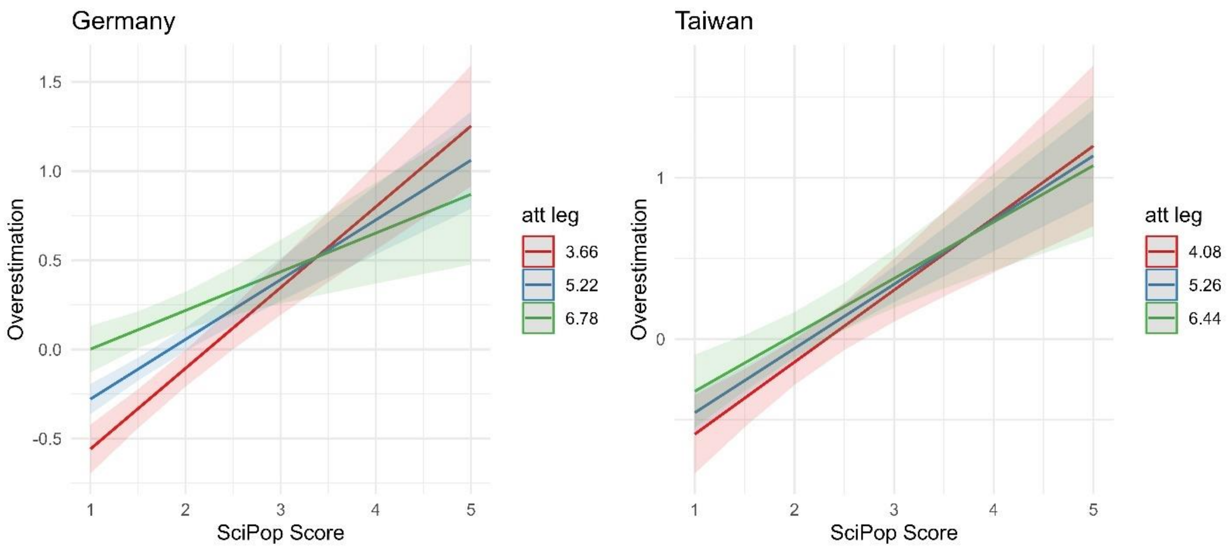

Figure A10. Interaction between science-related populism and attention to COVID-19 information in legacy media (left: Germany; right: Taiwan).

Note: The plot shows effects for the mean values of attention to COVID-19 information in legacy media (GER: 5.22; TWN: 5.26) and for values one standard deviation below and above the means. Only the interaction for Germany is significant (see also Table A21).

Table A21

OLS Multiple linear regressions. Knowledge overestimation as outcome variable and interaction of science-related populism with attention to COVID-19 information in legacy media and on SNSs/IMs

Predictors	COVID-19 knowledge overestimation (TWN)			COVID-19 knowledge overestimation (GER)		
	B	*SE*	*p*	β	*SE*	*p*
Intercept	0.00	0.03	0.989	-0.01	0.02	0.584
Science-related populist attitudes	0.23	0.03	<0.001	0.23	0.03	<0.001
SNS exposure to COVID-19 information	0.16	0.03	<0.001	-0.02	0.03	0.509
IM exposure to COVID-19 information	0.00	0.03	0.953	-0.04	0.03	0.192
Legacy media exposure to COVID-19 information	0.02	0.03	0.471	0.03	0.03	0.322
Age	-0.02	0.03	0.497	0.04	0.03	0.166
Gender (1 = male)	0.00	0.03	0.967	-0.03	0.03	0.220
Education (1 = Master or higher)	-0.13	0.03	<0.001	-0.02	0.03	0.355
Income	-0.05	0.03	0.086	-0.06	0.03	0.016
Political orientation (7 = right)	0.02	0.03	0.376	0.01	0.03	0.653
Trust in scientists	0.14	0.03	<0.001	0.12	0.03	<0.001
Affected by COVID-19 (1 = tested/risk group)	0.02	0.03	0.450	-0.02	0.03	0.499
Attitudes toward COVID-19	0.11	0.03	0.001	0.09	0.03	0.004
Attention to COVID-19 information in legacy media	0.06	0.04	0.192	0.16	0.03	<0.001
Attention to COVID-19 information on SNSs/IMs	0.04	0.05	0.323	0.09	0.03	0.002
Attention to COVID-19 info in legacy media × Science-related populist attitudes	-0.03	0.04	0.459	-0.08	0.03	0.002
Attention to COVID-19 info on SNSs/IMs × Science-related populist attitudes	0.02	0.04	0.614	0.05	0.03	0.092
n			1,207			1,493
R^2 / R^2 adjusted			0.189 / 0.178			0.117 / 0.108

References

Baek, Y. M., Kang, H., & Kim, S. (2019). Fake news should be regulated because it influences both “others” and “me”: How and why the influence of presumed influence model should be extended. *Mass Communication and Society*, *22*(3), 301–323. https://doi.org/10.1080/15205436.2018.1562076

Balkhy, H. H., Abolfotouh, M. A., Al-Hathlool, R. H., & Al-Jumah, M. A. (2010). Awareness, attitudes, and practices related to the swine influenza pandemic among the Saudi public. *BMC Infectious Diseases*, *10*(42). https://doi.org/10.1186/1471-2334-10-42

Betsch, C., Wieler, L., Bosnjak, M., Ramharter, M., Stollorz, V., Omer, S., Korn, L., Sprengholz, P., Felgendreff, L., Eitze, S., & Schmid, P. *Germany COVID-19 Snapshot MOnitoring (COSMO Germany): Monitoring knowledge, risk perceptions, preventive behaviours, and public trust in the current coronavirus outbreak in Germany*. https://doi.org/10.23668/psycharchives.2776

Bürkner, P.-C. (2021). Bayesian Item Response Modeling in R with brms and Stan. *Journal of Statistical Software*, *100*(5). https://doi.org/10.18637/jss.v100.i05

Lau, J. T. F., Griffiths, S., Au, D. W. H., & Choi, K. C. (2011). Changes in knowledge, perceptions, preventive behaviours and psychological responses in the pre-community outbreak phase of the H1N1 epidemic. *Epidemiology and Infection*, *139*(1), 80–90. https://doi.org/10.1017/S0950268810001925

Lee, S., Tandoc Jr, E. C., & Diehl, T. (2023). Uninformed and misinformed: Advancing a theoretical model for social media news use and political knowledge. *Digital Journalism.* Advance online publication. https://doi.org/10.1080/21670811.2023.2180404

Newman, N., Fletcher, R., Schulz, A., Andı, S., Robertson, C. T., & Nielsen, R. K. (2021). *Reuters Institute Digital News Report 2021*. Reuters Institute for the Study of Journalism. https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2021-06/Digital_News_Report_2021_FINAL.pdf

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve analysis. *Nature Human Behaviour*, *4*(11), 1208–1214. https://doi.org/10.1038/s41562-020-0912-z

Teresi, J. A., & Fleishman, J. A. (2007). Differential item functioning and health assessment. *Quality of Life Research*, *16 Suppl 1*, 33–42. https://doi.org/10.1007/s11136-007-9184-6

Wintterlin, F., Frischlich, L., Boberg, S., Schatto-Eckrodt, T., Reer, F., & Quandt, T. (2021). Corrective actions in the information disorder: The role of presumed media influence and hostile media perceptions for the countering of distorted user-generated content. *Political Communication*, *38*(6), 773–791. https://doi.org/10.1080/10584609.2021.1888829