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Public agreement with misinformation about wind farms

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Misinformation campaigns target wind farms, but levels of agreement with this misinformation among the broader public are unclear. Across six nationally quota-based samples in the United States, United Kingdom, and Australia (total $N = 6008$), over a quarter of respondents agree with half or more of contrarian claims about wind farms. Agreement with diverse claims is highly correlated, suggesting an underlying belief system directed at wind farm rejection. Consistent with this, agreement is best predicted (positively) by a conspiracist worldview (i.e., the general tendency to believe in conspiracy theories; explained variance $\Delta R^2 = 0.11–0.20$) and (negatively) by a pro-ecological worldview ($\Delta R^2 = 0.04–0.13$). Exploratory analyses show that agreement with contrarian claims is associated with lower support for pro-wind policies and greater intentions to protest against wind farms. We conclude that wind farm contrarianism is a mainstream phenomenon, rooted in people's worldviews and that poses a challenge for communicators and institutions committed to accelerating the energy transition.

To meet their net-zero targets, most nations need to dramatically ramp up their investment in wind energy[1]. The German cabinet approved plans to require its states to allocate at least 2% of its land to onshore wind farms by 2032[2], and modelling from Princeton University suggests several-fold increases in land dedicated to wind farms are required for the United States to meet its 2050 net-zero targets[3]. This huge increase in investment means that the public will have much greater exposure to wind farm construction in the coming decades than they do currently. Public resistance to wind farms could be a disincentive for governments and industry to implement change. Therefore, maintaining community support is important to ensuring this energy transformation is sustainable.

Previous literature has highlighted several legitimate reasons why people might object to wind farms when the technology is implemented at the local level, for instance, concerns about visual impact[4] or decreasing real estate prices[5]. The focus of this paper is not on these legitimate local concerns, but rather on misinformation that is absorbed by and communicated within the broader public. In line with previous work, we define scientific misinformation as publicly available information that is misleading or deceptive when compared to the best available scientific evidence and that runs contrary to any scientific consensus or the claims of acknowledged experts in the domain[6]. Defining misinformation as contrarian claims allows for the possibility that there may be grains of truth in some of the claims, that in a philosophical sense objective truth is often unknowable, and that some claims are not falsifiable. In the current studies, we include statements that cover topics as diverse as (1) that decision-makers conspire to mask wind farms' dangers and exaggerate their benefits; (2) that wind farms are detrimental to human health; (3) that they are ineffective; and (4) that they are harmful to the natural environment.

Scholars have documented a long history in the United States of vested interests, often with the support of think tanks and political leaders, engaging in campaigns of misinformation designed to scramble the debate on certain scientific topics such as acid rain, the health impacts of tobacco, and climate change[7]. In the United States, Europe, and Australia, there are emerging signs that a similar campaign might be underway with respect to wind farms. For example, computer-assisted classification of contrarian claims about climate

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change suggests that conservative think tanks have shifted their focus away from denying climate change toward spreading misinformation about climate-friendly policies and renewable energy[8,9]. In line with this notion, anti-wind farm lobby groups have gained increasing media traction, many of them leaning on claims that are not sustained by scientific research[10,11]. Some of this misinformation has been amplified by political leaders, including former President of the United States Donald Trump who described wind turbines as “industrial monstrosities”, has frequently claimed they are ineffective, and once declared that wind turbines cause cancer[12]. Textual analysis of Facebook Community Pages in Ohio revealed increasing perceptions that wind farms pose a risk to human health and public safety, based on widespread sharing of misinformation and the broad construal of institutional decision-makers as untrustworthy[13]. In 2022, representative surveys in Germany revealed that the general propensity to believe in conspiracy theories – so-called conspiracy mentality – was the biggest predictor of willingness to vote against wind farms, explaining five times more variance than political conservatism and approximately 20 times more variance than education[14].

Together, these signals bear close parallels to the information environment around vaccination: funded campaigns of misinformation[15], magnified by public thought-leaders[16], distributed through social media[17,18], and correlated strongly with the psychological predisposition to believe conspiracy theories[19,20]. As for wind farms, public sentiment toward vaccination was historically relatively positive, but events during the COVID-19 pandemic highlighted how quickly this can change in the face of misinformation campaigns[21], how dramatically misinformation can cause social schism[22], and how easy it is for the scientific community to be left unprepared in the face of so-called anti-science beliefs. Empirical research on wind farm misinformation can contribute to ensuring that governments, industry and scientists can anticipate and address public resistance going forward, and yet no large-scale, systematic empirical work exists.

In addition to gauging the prevalence of agreement with misinformation about wind farms, the current surveys are designed to provide clues as to how campaigns should be designed to address unfounded anti-wind farm sentiments. The most intuitive – and the most common – method of responding to misinformation is through education and debunking campaigns[23,24]. These strategies presume a deficit model such that misinformation is more likely to be believed among individuals with lower educational attainment or who are less knowledgeable about basic scientific facts. In the case of wind farms, however, subjecting this presumption to empirical scrutiny is an important element of academic due diligence before recommending investment in informational campaigns. Moreover, this work contributes to understanding the motivations and thinking of people who object to wind farms and might help better address their concerns.

Although there is some evidence that information-based campaigns can reduce anti-science beliefs[25,26], it is important to note that this is not always the case. With some controversial scientific issues – for example, related to vaccination and climate change – resistance to scientific messaging is less associated with education than it is with people's values and worldviews[19,27]. Another clue that susceptibility to misinformation is grounded in worldviews more so than information deficits is if there are very high correlations between ostensibly unrelated arguments. For example, believing that wind farms are ineffective in reducing carbon emissions should technically be independent of believing that wind farms are harmful to health, or that wind farms are harmful to the natural environment. High correlations among these beliefs suggest what in the conspiracy theory literature is referred to as a monological pattern[28]: a cognitively closed mindset whereby underlying worldview ties together individual beliefs into a mutually reinforcing belief system, independent of whether those beliefs are grounded in fact or logically connected with each other.

To examine the relative importance of epistemological variables and worldviews in determining who agrees with contrarian claims about wind farms, we include several predictors in our studies. As measures of people's worldviews, we assess environmental self-identity, political orientation (left-wing/liberal to right-wing/conservative), the New Ecological Paradigm (NEP), and conspiracy mentality. Environmental self-identity reflects the degree to which people see themselves as pro-environmental persons, which predicts support for climate change mitigation measures[29]. A more right-wing political orientation is related to climate change scepticism – at least in the United States and Australia[30] – and might thus predict higher agreement with contrarian claims about wind farms. NEP captures the worldview that human activity threatens the natural environment, which questions humans' superiority to nature[31]. This worldview is strongly linked to pro-environmental behaviour[32] and so should predict less agreement with contrarian claims about wind farms. Conspiracy mentality denotes the general tendency to believe societal events are grounded in conspiracies concocted in secret by powerful actors[33], a worldview which might translate into agreement with contrarian claims about wind farms.

We also include two epistemological variables based on deficit models of science rejection: (1) highest level of educational attainment and (2) science knowledge measured by asking participants to record true-false answers to a 9-question quiz about scientific issues (e.g., “Lasers work by focusing sound waves”[34]). Both education and science knowledge are assumed to play a role in the rejection of scientific misinformation[35,36] and could thus be related to lower agreement with contrarian claims. It is important to note that none of the predictor measures described above referred to wind farms in any regard. For a complete list of measures and items, see Supplementary Table 1.

In this work, we measure the prevalence of agreement with misinformation about wind farms and examine the psychological factors that predict this agreement. We find substantial agreement with contrarian claims about wind farms in six samples collected in the United States, United Kingdom, and Australia (total $N = 6008$). Moreover, agreement with claims with unrelated content is highly correlated in all countries, suggesting an underlying belief system directed at the rejection of wind farms. Our data provide evidence that this belief system is largely predicted by worldviews (primarily conspiracy mentality) and only to a small extent by epistemological factors (e.g., level of education). In turn, agreement with contrarian claims is strongly related to willingness to engage in collective action (e.g., protest) against wind farms and rejection of wind energy-friendly policy. These findings provide evidence for the high prevalence of false and exaggerated beliefs about wind farms and highlight the challenges associated with relying solely on informational campaigns to debunk such misinformation.

Results

Study 1: Agreement with misinformation about wind farms in three countries

We recruited 1000 participants in each of the United States, United Kingdom, and Australia (total $N = 3000$) via the recruiting company Cint. Age, gender (coding: −1 male, +1 female), and educational attainment were nationally quota-balanced according to the distribution of these variables in the respective country (based on census data; see Supplementary Table 2). Participants rated 16 contrarian claims from 1 (strongly disagree) to 5 (strongly agree). We counted participants as agreeing with a contrarian claim if they responded 4 (rather agree) or 5 (strongly agree). Depending on the statement, agreement with contrarian claims ranged from 22.6% to 47.4% in the United States, 16.6% to 39.0% in the United Kingdom, and 18.3% to 41.1% in Australia (see Fig. 1; see Table 1 for means). Almost 80% of participants agreed with at least one contrarian claim (United States: 79.8%, United Kingdom: 75.9%, Australia: 77.4%), almost 30% agreed with half or more of

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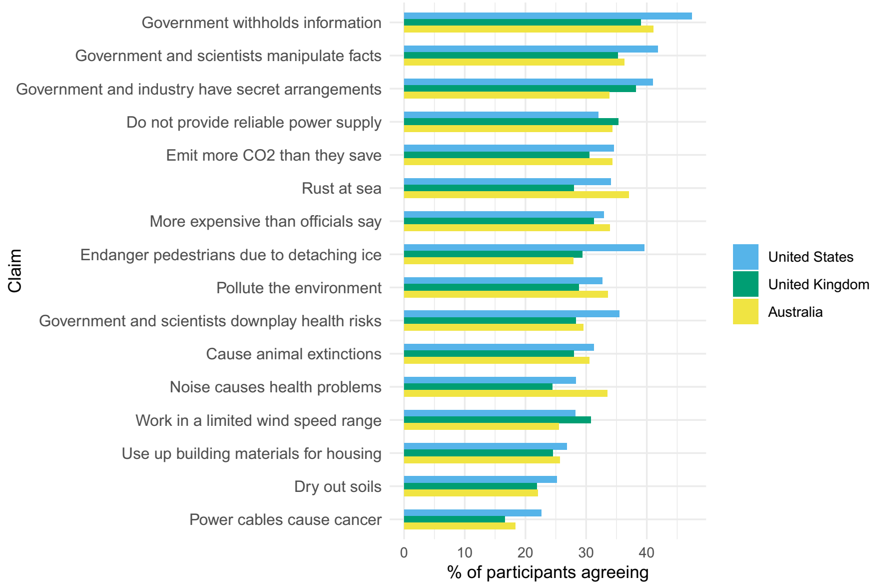

Fig. 1 | Percentage of participants who rated "rather agree" or "strongly agree" with 16 contrarian claims (Study 1). Claims are sorted by decreasing the average level of agreement across countries. Exact wordings can be found in Table 1. United States: $N = 1000$, United Kingdom: $N = 1000$, Australia $N = 1000$. Source data are provided as a Source Data file.

Table 1 | Contrarian claims about wind farms and the average level of agreement (Study 1; $N = 1000$ in all countries)

Claim	*M* (*SD*)		
	United States	**United Kingdom**	**Australia**
The government withholds important information that speaks against the extension of wind energy.	3.34 (1.16)	3.18 (1.06)	3.24 (1.08)
The numbers and facts presented to the public by the government and so-called "climate scientists" are manipulated to portray wind energy in a particularly positive light.	3.16 (1.21)	3.06 (1.12)	3.13 (1.11)
The government has secret arrangements with energy companies that would make both sides profit financially from the extension of wind energy.	3.20 (1.17)	3.14 (1.13)	3.09 (1.10)
Contrary to official claims, wind energy is very expensive compared to other energy sources.	3.02 (1.13)	3.02 (1.04)	3.12 (1.04)
The health risks to the public posed by wind turbines are downplayed by the government and the scientific community.	3.00 (1.20)	2.86 (1.11)	2.95 (1.08)
The noise from wind turbines can cause health problems in humans (e.g., headaches, impotence).	2.81 (1.17)	2.70 (1.12)	3.00 (1.12)
The underground power cables of wind turbines can cause cancer in local residents.	2.79 (1.11)	2.54 (1.09)	2.70 (1.05)
In winter, wind turbines pose a high risk to pedestrians because pieces of ice can detach during operation.	3.13 (1.17)	2.87 (1.10)	2.88 (1.07)
Wind turbines only work in a small wind speed range and do not provide electricity or break down in high winds.	2.92 (1.12)	2.97 (1.07)	2.95 (0.99)
Wind turbines at sea rust in the water and are therefore no longer functional after a short time.	3.09 (1.09)	2.89 (1.10)	3.19 (1.00)
Wind energy does not provide a reliable power supply, as there will not be sufficient storage facilities available in the future.	2.89 (1.22)	2.99 (1.09)	3.02 (1.13)
Due to the massive extension of wind energy, hardly any building material is available for housing and only at very high prices.	2.79 (1.19)	2.69 (1.17)	2.80 (1.09)
Wind turbines cause the extinction of whole bird and wildlife populations.	2.89 (1.21)	2.77 (1.16)	2.90 (1.14)
Wind turbines pollute the environment because after their demolition, the rotor blades are buried as hazardous waste and the bases are left in the ground.	2.97 (1.17)	2.89 (1.12)	3.05 (1.10)
The increasing dryness of our soils can be attributed to wind turbines slowing down wind speed and thus providing lower amounts of rain.	2.74 (1.16)	2.60 (1.13)	2.72 (1.07)
The disposal of wind turbines releases more CO2 than is saved by their operation, since many parts cannot be recycled but must be incinerated.	3.12 (1.08)	3.04 (1.00)	3.15 (1.00)

Scale ranges from 1 = "strongly disagree" to 5 = "strongly agree". Claims were presented in a randomised order.
M mean, *SD* standard deviation.

them (United States: 29.4%, United Kingdom: 24.5%, Australia: 29.3%), and approximately 5% agreed with all claims (United States: 5.2%, United Kingdom: 5.4%, Australia: 4.1%). An exploratory factor analysis revealed that only one factor had an eigenvalue >1 in each country. This factor solution explained more than 50% of the variance (United States: 52.79%, United Kingdom: 54.09%, Australia: 53.17%). Despite the diversity of their content, the 16 contrarian claims formed a single, coherent index (Cronbach's $\alpha = 0.94$ in all countries; $\omega_{hierarchical}$ United States: 0.84, United Kingdom: 0.86, Australia: 0.87).

We tested several predictor variables including worldviews (conspiracy mentality, political orientation, NEP, environmental self-identity) and epistemological variables (education, science knowledge). We preregistered (https://aspredicted.org/cs97x.pdf) the hypothesis that conspiracy mentality would be a significant predictor of agreement

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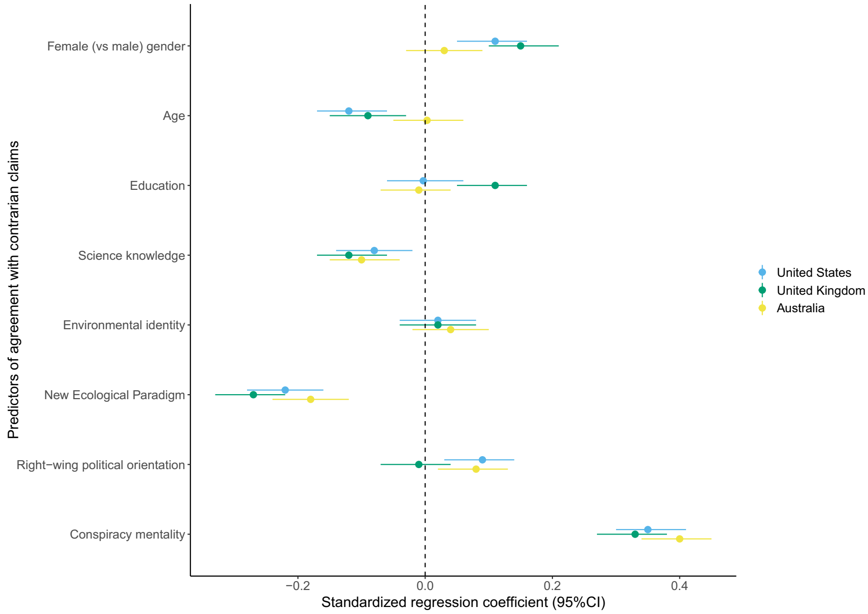

Fig. 2 | Multiple regression analyses with gender, age, education, science knowledge, environmental identity, New Ecological Paradigm, political orientation and conspiracy mentality predicting agreement with contrarian claims (Study 1). Data are presented as standardised regression coefficients β with their 95% confidence intervals. Tests were two-sided and no adjustments for multiple comparisons were made (α = 0.05). Gender was coded −1 male and +1 female, so positive coefficients represent higher scores for females (vs. males). Participants not identifying as male or female were not included in these analyses. United States: N = 989, United Kingdom: N = 996, Australia N = 998. Source data are provided as a Source Data file.

with contrarian claims beyond the other predictor variables (included simultaneously in a multiple regression analysis). Multiple regression analyses across countries revealed that participants agreed more with contrarian claims the higher their conspiracy mentality, the lower their scores on the NEP, and the lower their science knowledge. Conspiracy mentality was the strongest predictor in all countries (standardized regression coefficient β = 0.33–0.40) followed by NEP (β = −0.18 to −0.27) and science knowledge (β = −0.08 to −0.12). Other predictors were smaller and less consistent: younger participants (β = −0.09 to −0.12) and women (β = 0.11–0.15) reported stronger agreement in the United States and the United Kingdom, higher educational attainment predicted stronger agreement in the United Kingdom (β = 0.11), and a more right-wing political orientation related to stronger agreement in the United States (β = 0.09) and Australia (β = 0.08). Standardised regression coefficients are displayed in Fig. 2, and detailed results of the regression analyses are in Table 2. For zero-order correlations, internal consistencies, means (*M*) and standard deviations (*SD*), see Supplementary Table 3. Given that our preregistration did not explicitly specify that we would analyse the three countries separately, we report the results of a multiple regression analysis merging across all countries in Supplementary Table 4.

To gain insight into how much variance was explained by each predictor, we conducted separate regression analyses for each predictor, in which we first entered age and gender as a baseline model and then entered the respective predictor variable in a second step. The baseline model explained 3.1% of the variance of agreement with contrarian claims in the United States, 9.9% in the United Kingdom, and 0.001% in Australia. When adding single psychological concepts to the regression analyses, conspiracy mentality was the predictor that explained most additional variance with 13.2% in the United States, 11.3% in the United Kingdom, and 17.8% in Australia followed by NEP with 4–8% (for detailed results on explained variance, see Supplementary Table 5).

Study 2: Extended replication

Study 2 served to replicate the patterns found in Study 1 but with several important modifications: (1) we adapted the set of contrarian claims to make sure they could all be clearly identified as false or implausible and so fulfilled a stricter definition of the term misinformation (for fact-checking information, see Supplementary Table 6); (2) we included some true (positive) claims in order to control for response biases (for a complete list of statements, see Table 3); (3) we made sure that the claims did not contain double-barrelled formulations; (4) we included two measures of potential downstream consequences of agreement with contrarian claims: intention to engage in collective action against wind farms and policy support in favour of wind farms. The predictor variables were unchanged except we did not measure environmental self-identity due to weak predictive value in Study 1.

We recruited 3008 participants (United States: N = 1000, United Kingdom: N = 1004; Australia: N = 1004) via Cint, applying the same distributions of age, gender (coding: −1 male, +1 female), and educational attainment as in Study 1 to achieve nationally quota-balanced samples. Participants were presented with 13 contrarian claims and four true (positive) claims about wind farms in a randomised order. Agreement with contrarian claims ranged from 22.7% to 43.6% in the United States, 14.7% to 36.5% in the United Kingdom, and 26.2% to 45.7% in Australia (see Fig. 3). Again, up to 78% of participants agreed with at least one contrarian claim (United States: 77.9%, United Kingdom: 71.5%, Australia: 78.4%), up to 31% agreed with more than half of them (United States: 26.0%, United Kingdom: 17.6%, Australia: 31.4%), and up to 10% agreed with all claims (United States: 5.2%, United Kingdom: 2.8%, Australia: 10.5%). Agreement with the true claims ranged from 31.9% to 64.9% in the United States, 29.6% to 68.4% in the United Kingdom, and 37.0% to 64.8% in Australia.

We conducted a confirmatory factor analysis with varimax rotation to test whether participants differentiated between contrarian and true claims about wind farms. Indeed, analyses in all three countries confirmed the existence of two factors mapping onto the intended distinction between contrarian (Factor 1: eigenvalues ranging from 6.63 to 7.71; explained variance from 38.98% to 45.35%) and true claims (Factor 2: eigenvalues ranging from 1.91 to 2.24; explained variance from 11.23% to 13.18%). Factor loadings are presented in Supplementary Table 7. As in Study 1, the contrarian claims

Table 2 | Multiple regression analyses with gender, age, education, science knowledge, environmental identity, New Ecological Paradigm, political orientation and conspiracy mentality predicting agreement with contrarian claims (Study 1)

	β	*B* (*SE*)	95% CI	*t*	*p*
United States (*N* = 989)					
Gender (−1 male, +1 female)	0.11	0.09 (0.03)	0.04, 0.14	3.60	3.30e-4
Age	−0.12	−0.06 (0.02)	−0.09, −0.03	−3.92	9.55e-5
Education	0.00	0.00 (0.04)	−0.08, 0.07	−0.10	0.925
Science knowledge	−0.08	−0.04 (0.02)	−0.07, −0.01	−2.65	0.008
Environmental identity	0.02	0.02 (0.03)	−0.03, 0.07	0.76	0.445
New Ecological Paradigm	−0.22	−0.35 (0.05)	−0.44, −0.25	−7.34	4.42e-13
Political orientation	0.09	0.08 (0.03)	0.03, 0.14	2.83	0.005
Conspiracy mentality	0.35	0.41 (0.03)	0.35, 0.48	12.10	1.70e-31
United Kingdom (*N* = 996)					
Gender (−1 male, +1 female)	0.15	0.12 (0.02)	0.08, 0.17	5.46	6.17e-8
Age	−0.09	−0.05 (0.02)	−0.08, −0.02	−3.15	0.002
Education	0.11	0.11 (0.03)	0.05, 0.17	3.57	3.72e-4
Science knowledge	−0.12	−0.06 (0.01)	−0.09, −0.03	−4.14	3.79e-5
Environmental identity	0.02	0.02 (0.03)	−0.04, 0.07	0.63	0.529
New Ecological Paradigm	−0.27	−0.39 (0.04)	−0.48, −0.31	−9.01	6.41e-19
Political orientation	−0.01	−0.01 (0.03)	−0.08, 0.05	−0.40	0.692
Conspiracy mentality	0.33	0.35 (0.03)	0.29, 0.41	11.92	1.08e-30
Australia (*N* = 998)					
Gender (−1 male, +1 female)	0.03	0.02 (0.02)	−0.02, 0.07	1.06	0.291
Age	0.00	0.00 (0.02)	−0.03, 0.03	0.12	0.902
Education	−0.01	−0.01 (0.03)	−0.07, 0.05	−0.44	0.662
Science knowledge	−0.10	−0.05 (0.01)	−0.07, −0.02	−3.19	0.001
Environmental identity	0.04	0.04 (0.03)	−0.02, 0.09	1.23	0.219
New Ecological Paradigm	−0.18	−0.25 (0.04)	−0.33, −0.16	−5.67	1.93e-8
Political orientation	0.08	0.09 (0.04)	0.02, 0.16	2.54	0.011
Conspiracy mentality	0.40	0.45 (0.03)	0.39, 0.52	13.73	2.13e-39

Test were two-sided and no adjustments for multiple comparisons were made (α = 0.05).
β standardised regression coefficient, *B* unstandardised regression coefficient, *SE* standard error, *CI* confidence interval, *t* test statistic from the multiple regression analysis.

formed a highly reliable index in each country (αs = 0.92–0.94; $\omega s_{\text{hierarchical}}$ = 0.84–0.91). Agreement with true claims formed an indicator with considerably lower internal consistency (αs = 0.59–0.69; $\omega s_{\text{hierarchical}}$ = 0.62–67). Thus, people differentiated between contrarian and true claims, but at the same time, correlations between claims diverse in content were much higher for contrarian than for true claims. It should be noted that all anti-wind farm statements we included were false and all pro-wind farm statements were true. Although this leaves some ambiguity with regard to the interpretation of the two factors found, the results still indicate that the high correlations between contrarian claims are not simply a reflection of response bias.

The pattern of predictors in Study 2 resembled that found in Study 1: worldviews predicted agreement with contrarian claims to a much stronger degree than did epistemological variables. In line with our preregistered hypothesis (https://aspredicted.org/iy37h.pdf), a higher conspiracy mentality predicted stronger agreement with contrarian claims beyond the other predictor variables simultaneously included in a multiple regression analysis. Furthermore, as in Study 1, the lower the participants scored on the NEP, and the lower their science knowledge, the more they agreed with contrarian claims. Again, conspiracy mentality was the strongest predictor in all countries (βs = 0.36–0.41) followed by NEP (βs = −0.20 to −0.31) and science knowledge (βs = −0.09 to −0.15). In addition, age and gender were significant predictors in all countries: younger participants (βs = −0.06 to −0.13) and women (βs = 0.08–0.17) reported stronger agreement with contrarian claims. Less consistent effects were found for political orientation and education. Standardised regression coefficients are displayed in Fig. 4, and detailed results of the regression analyses are in Table 4. The explained variance of each predictor compared to a baseline model including age and gender can be found in Supplementary Table 5. Notably, the results of the regression analyses hold when including agreement with true claims as a covariate (see Supplementary Table 8), further supporting that the correlations are not simply resulting from response bias. Results of a regression analysis merging across countries can be found in Supplementary Table 9.

Going beyond Study 1, we ran similar exploratory multiple regressions with all predictor variables included simultaneously predicting agreement with true claims. Only science knowledge and education were significant predictors in all three countries: lower science knowledge (βs = −0.10 to −0.15) and higher educational attainment (βs = 0.07 to 0.16) predicted stronger agreement with true claims about wind farms. Less consistent effects were found for other variables (for standardised regression coefficients, see Supplementary Fig. 1, and for results of the regression analyses, see Table 5). Thus, in contrast to the pattern of predictors for contrarian claims, agreement with true claims about wind farms was more strongly predicted by epistemological variables than by worldviews. Taken together, these results clearly underscore that agreement with contrarian claims on the one hand, and true claims on the other hand, are not two sides of the same coin but separable constructs.

In two exploratory multiple regression analyses, we tested whether agreement with contrarian and true claims differentially predict outcomes with real-world implications. We found that the intention to

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Table 3 | Claims about wind farms and the average level of agreement (Study 2)

Claim	*M* (*SD*)		
	United States	United Kingdom	Australia
Contrarian claims			
The government withholds important information that speaks against the extension of wind energy.*	3.25 (1.17)	3.05 (1.12)	3.30 (1.12)
Climate scientists manipulate facts in order to portray wind energy in a particularly positive light.	3.09 (1.23)	2.87 (1.19)	3.14 (1.22)
The government has secret arrangements with energy companies that would make both sides profit financially from the extension of wind energy.*	3.12 (1.17)	3.05 (1.11)	3.25 (1.13)
The health risks to the public posed by wind turbines are downplayed by the scientific community.	3.00 (1.18)	2.72 (1.11)	3.04 (1.16)
The noise from wind turbines can cause health problems in humans.	2.71 (1.18)	2.56 (1.13)	3.03 (1.18)
The underground power cables of wind turbines can cause cancer in local residents.*	2.76 (1.16)	2.39 (1.10)	2.79 (1.18)
In winter, wind turbines pose a high risk to pedestrians because pieces of ice can detach during operation.*	3.10 (1.13)	2.80 (1.11)	2.99 (1.16)
Wind turbines are responsible for the mass extinction of birds.	2.88 (1.23)	2.61 (1.14)	2.92 (1.24)
The increasing dryness of our soils can be attributed to wind turbines slowing down wind speed and thus providing lower amounts of rain.*	2.77 (1.16)	2.52 (1.12)	2.85 (1.21)
The construction of wind turbines releases more CO2 than is saved by their operation.	3.05 (1.08)	2.87 (1.04)	3.15 (1.09)
The massive extension of wind energy is responsible for the shortage of building materials that are available for housing.	2.67 (1.18)	2.51 (1.12)	2.82 (1.19)
Wind turbine generators have to be replaced after only three to four years of operation.	3.16 (0.99)	2.92 (0.96)	3.18 (0.99)
Wind turbines have to run continuously for 50 years to recoup the financial costs of manufacturing and installation.	3.06 (1.12)	2.93 (1.01)	3.20 (1.06)
True claims			
If forest land is cleared for the construction of wind turbines, the wind turbines save significantly more CO2 than could be saved by keeping the trees.	3.00 (1.14)	2.96 (1.06)	3.08 (1.17)
About 90% of the materials used to build wind turbines are recyclable.	3.45 (1.03)	3.45 (0.93)	3.44 (1.00)
The extension of wind energy creates well-paid jobs.	3.73 (0.96)	3.77 (0.89)	3.73 (0.88)
Wind turbines recoup the energy required to build them within a year of normal operation.	3.38 (1.01)	3.34 (0.91)	3.40 (0.94)

Scale ranges from 1 = "strongly disagree" to 5 = "strongly agree". Claims were presented in a randomised order. United States: $N = 1000$, United Kingdom: $N = 1004$, Australia $N = 1004$.
M mean, *SD* standard deviation.
*denotes claims that were adopted verbatim from Study 1.

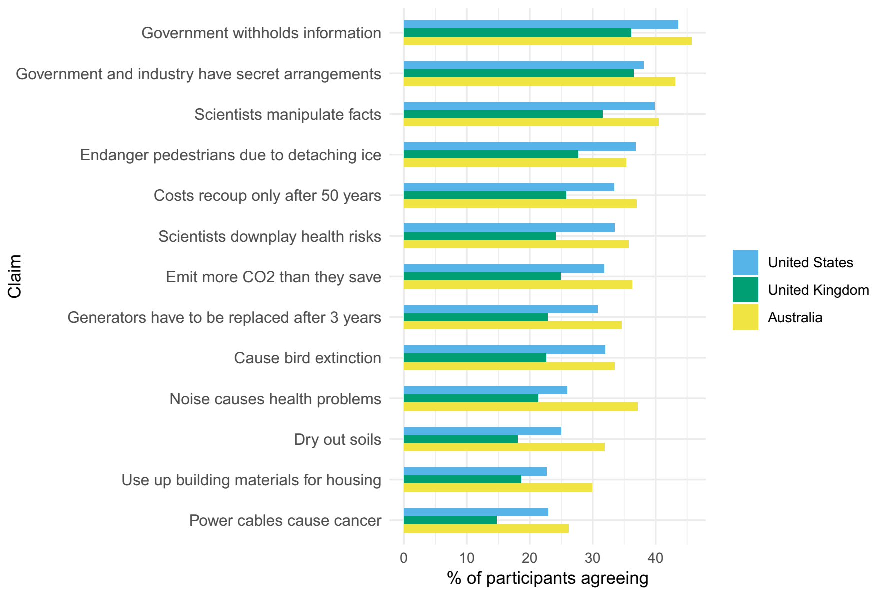

Fig. 3 | Percentage of participants who rated "rather agree" or "strongly agree" with 13 contrarian claims (Study 2). Claims are sorted by decreasing the average level of agreement across countries. Exact wordings can be found in Table 3. United States: $N = 1000$, United Kingdom: $N = 1004$, Australia $N = 1004$. Source data are provided as a Source Data file.

engage in collective action against wind farms was much more strongly predicted by (higher) agreement with contrarian claims (βs = 0.69–0.75) than by (lower) agreement with true claims (βs = −0.08 to −0.17). The opposite pattern was found when using support for wind energy policy as an outcome variable: (higher) agreement with true claims (βs = 0.50 to 0.67) was a somewhat stronger predictor of policy support than (lower) agreement with contrarian claims (βs = −0.32 to −0.42). Note that agreement with both types of claims were significant predictor of both outcome variables (see Supplementary Fig. 2 and Supplementary Table 10). For zero-order

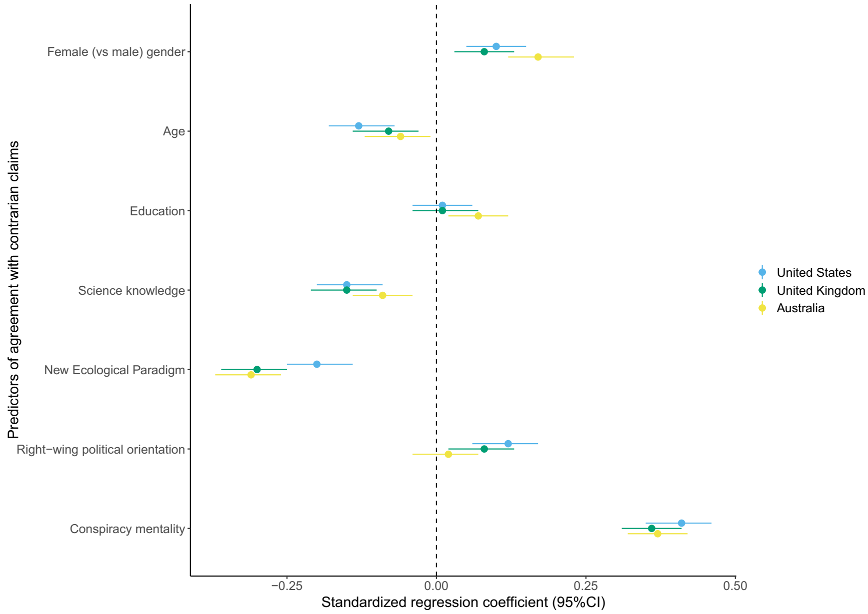

Fig. 4 | Multiple regression analyses with gender, age, education, science knowledge, New Ecological Paradigm, political orientation and conspiracy mentality predicting agreement with contrarian claims (Study 2). Data are presented as standardised regression coefficients β with their 95% confidence intervals. Tests were two-sided and no adjustments for multiple comparisons were made (α = 0.05). Gender was coded −1 male and +1 female, so positive coefficients represent higher scores for females (vs. males). Participants not identifying as male or female were not included in these analyses. United States: N = 995, United Kingdom: N = 1003, Australia N = 1001. Source data are provided as a Source Data file.

Table 4 | Multiple regression analyses with gender, age, education, science knowledge, New Ecological Paradigm, political orientation and conspiracy mentality predicting agreement with contrarian claims (Study 2)

	β	*B* (*SE*)	95% CI	*t*	*p*
United States (*N* = 995)					
Gender (–1 male, +1 female)	0.10	0.08 (0.02)	0.04, 0.13	3.79	1.61e-4
Age	−0.13	−0.07 (0.02)	−0.10, −0.04	−4.73	2.62e-6
Education	0.01	0.01 (0.04)	−0.06, 0.08	0.33	0.739
Science knowledge	−0.15	−0.07 (0.01)	−0.10, −0.05	−5.36	1.02e-7
NEP	−0.20	−0.30 (0.04)	−0.38, −0.21	−7.05	3.46e-12
Political orientation	0.12	0.11 (0.03)	0.06, 0.15	4.18	3.16e-5
Conspiracy mentality	0.41	0.45 (0.03)	0.39, 0.51	15.32	1.10e-47
United Kingdom (*N* = 1003)					
Gender (–1 male, +1 female)	0.08	0.06 (0.02)	0.02, 0.10	3.12	0.002
Age	−0.08	−0.04 (0.01)	−0.07, −0.02	−3.01	0.003
Education	0.01	0.01 (0.03)	−0.04, 0.07	0.53	0.596
Science knowledge	−0.15	−0.07 (0.01)	−0.10, −0.05	−5.48	5.31e-8
NEP	−0.30	−0.40 (0.04)	−0.48, −0.33	−10.89	3.70e-26
Political orientation	0.08	0.08 (0.03)	0.02, 0.13	2.85	0.004
Conspiracy mentality	0.36	0.37 (0.03)	0.32, 0.42	13.87	4.17e-40
Australia (*N* = 1001)					
Gender (–1 male, +1 female)	0.17	0.15 (0.03)	0.11, 0.20	6.19	9.06e-10
Age	−0.06	−0.04 (0.02)	−0.07, −0.01	−2.31	0.021
Education	0.07	0.08 (0.03)	0.02, 0.15	2.49	0.013
Science knowledge	−0.09	−0.05 (0.02)	−0.08, −0.02	−3.29	0.001
NEP	−0.31	−0.50 (0.04)	−0.58, −0.41	−11.41	2.07e-28
Political orientation	0.02	0.02 (0.04)	−0.05, 0.09	0.53	0.597
Conspiracy mentality	0.37	0.46 (0.03)	0.40, 0.53	13.73	2.20e-39

Tests were two-sided and no adjustments for multiple comparisons were made (α = 0.05).
β standardised regression coefficient, *B* unstandardised regression coefficient, *SE* standard error, *CI* confidence interval, *t*-test statistic from the multiple regression analysis.

Table 5 | Multiple regression analyses with gender, age, education, science knowledge, New Ecological Paradigm, political orientation and conspiracy mentality predicting agreement with true claims (Study 2)

	β	*B* (*SE*)	95% CI	*t*	*p*
United States (*N* = 995)					
Gender (−1 male, +1 female)	0.02	0.01 (0.02)	−0.03, 0.06	0.58	0.559
Age	−0.07	−0.03 (0.02)	−0.06, −0.00	−2.05	0.040
Education	0.07	0.08 (0.04)	0.01, 0.15	2.09	0.037
Science knowledge	−0.15	−0.06 (0.01)	−0.09, −0.04	−4.70	2.97e-6
NEP	0.03	0.03 (0.04)	−0.05 0.12	0.77	0.444
Political orientation	−0.19	−0.15 (0.03)	−0.20, −0.10	−5.66	1.94e-8
Conspiracy mentality	0.07	0.07 (0.03)	0.01, 0.13	2.30	0.022
United Kingdom (*N* = 1003)					
Gender (−1 male, +1 female)	−0.02	−0.01 (0.02)	−0.05, 0.03	−0.62	0.537
Age	−0.06	−0.02 (0.01)	−0.05, 0.01	−1.61	0.107
Education	0.13	0.10 (0.03)	0.05, 0.16	4.00	6.92e-5
Science knowledge	−0.11	−0.04 (0.01)	−0.07, −0.02	−3.18	0.002
NEP	−0.06	−0.07 (0.04)	−0.14, 0.00	−1.90	0.058
Political orientation	−0.05	−0.04 (0.03)	−0.09, 0.01	−1.52	0.129
Conspiracy mentality	0.04	0.03 (0.03)	−0.02, 0.08	1.14	0.254
Australia (*N* = 1001)					
Gender (−1 male, +1 female)	0.10	0.07 (0.02)	0.03, 0.12	3.10	0.002
Age	−0.09	−0.04 (0.02)	−0.07, −0.01	−2.89	0.004
Education	0.16	0.15 (0.03)	0.09, 0.21	4.94	9.10e-7
Science knowledge	−0.10	−0.05 (0.01)	−0.07, −0.02	−3.27	0.001
NEP	−0.11	−0.14 (0.04)	−0.22, −0.06	−3.39	7.25e-4
Political orientation	−0.09	−0.10 (0.03)	−0.16, −0.03	−2.88	0.004
Conspiracy mentality	0.02	0.02 (0.03)	−0.04, 0.08	0.57	0.571

Tests were two-sided and no adjustments for multiple comparisons were made (α = 0.05).

β standardised regression coefficient, *B* unstandardised regression coefficient, *SE* standard error, *CI* confidence interval, *t* test statistic from the multiple regression analysis.

correlations, internal consistencies, *M*s and *SD*s of all measures, see Supplementary Table 11.

Discussion

The purpose of this research was to shed light on a phenomenon that has largely evaded the attention of academic research: the prevalence of, and psychological underpinnings of, agreement with misinformation about wind farms. In two studies comprising more than 6000 participants in the United States, United Kingdom, and Australia, we observed consistent patterns of results: (1) agreement with contrarian claims was high, (2) agreement with a highly diverse set of contrarian claims formed a coherent index and (3) conspiracy mentality was the best predictor of agreement with contrarian claims. Moreover, in Study 2 we found that agreement with contrarian claims was related to greater willingness to engage in collective action against wind farms and lower support for pro-wind energy policies, underlining the potential for misinformation to have relevant real-world consequences. This is consistent with recent research suggesting that climate disinformation can affect pro-environmental behaviour[37].

Agreement with contrarian claims ranged from 15% for blatantly false statements (i.e., that power cables of wind farms cause cancer) to more than 40% for statements assuming secret arrangements between politicians and other agents when it comes to wind farms. Averaging across samples, 27.7% of respondents in the United States, 21.1% of respondents in the United Kingdom, and 30.4% of respondents in Australia agreed with half or more of the contrarian claims we provided. For those invested in wind energy as a key ingredient for rapid decarbonisation, the apparent mainstreaming of contrarian claims about wind farms is concerning. As just one example, it is sobering that approximately a third of participants in the United States and Australia believe that the disposal of wind farms causes more CO2 than is saved by their operation.

It should be noted that some theorists are sceptical of the role of public opinion in obstructing the implementation of wind energy, arguing instead for the primary role of institutional capital[38]. In democratic nations, however, where political and financial capital is staked on popular support for initiatives, it seems reasonable to argue that mainstream misinformation about wind energy threatens future wind energy projects, and both qualitative and quantitative research has identified local opinion as having the biggest influence on decisions made by local authorities[39]. Indeed, it might not require a majority of the population to oppose wind energy; a substantially-sized and vocal minority could be enough to cast doubt. Together with the current findings, this suggests that the levels of agreement with misinformation found in our studies might be sufficient to hamper the large-scale expansion of wind energy.

Levels of agreement with the contrarian claims in our studies were highly correlated with each other, despite the diversity of their content. In other words, when people believed in one contrarian claim (e.g., that wind farms extinguish whole bird populations), they were more likely to believe in any other contrarian claim (e.g., that wind farms cause health problems). As such, agreement with contrarian claims about wind farms appears to form a monological belief system: scepticism or resistance towards wind farms emerges in response to any specific claim that is directed against wind farms, regardless of the content of that claim and regardless of logical inconsistencies among them. This is partly in line with the idea of an affect heuristic describing the phenomenon that people use their intuitive affective reaction to make judgements about the risks and benefits of a stimulus and accordingly engage in biased appraisals of any information about it[40].

However, the affect heuristic also predicts that perceived risks and benefits of a stimulus are negatively related (i.e., higher perceived risks correlate with lower perceived benefits)[41]. This is not reflected in our data, where agreement with contrarian and true claims was not (or if anything slightly positively) related. This suggests that an affect heuristic cannot fully explain our results. The question then arises: what is this intuitive judgement grounded in?

One might argue that the social dynamics and pressures in local and regional communities are a primary mechanism for motivating people into opposition[42]. However, it is unlikely that the majority of our participants had direct exposure to wind farms given the proportion of people who indicated to live in rural vs. urban areas (see Supplementary Table 2). Accordingly, this explanation struggles to account for the apparent mainstreaming of agreement with misinformation detectable in the current samples.

Another possibility is that the anti-wind energy heuristic stems from a general failure to understand science and technology. For example, it could be that people with limited education and/or scientific knowledge are relatively cautious about new technologies, more mistrustful of the agents of change, and more cognitively prone to believing scientifically implausible claims. Lower science knowledge did indeed have some predictive value in our studies but only explained <1% of the unique variance overall. Future studies might also include more sophisticated and comprehensive measures of science literacy – for example assessing an understanding of scientific methods and problem-solving abilities – given that science knowledge is only considered one facet of science literacy[43]. However, educational attainment also did not play a predictive role in four of our six samples and was related to greater agreement with contrarian claims in the remaining two. In sum, there was little evidence that wind farm contrarianism in our studies was a straightforward reflection of epistemological deficits.

As has been shown for other instances of scientific rejection, one might assume worldviews as the driving force behind wind farm contrarianism. In an attempt to understand climate scepticism[44,45] and vaccine hesitancy[46], researchers have developed the so-called attitude roots model of science rejection. This model is a trans-theoretical integration of various theories that make the case for why people might be motivated to hold anti-science beliefs, over and above a failure to cognitively understand the evidence. One of these attitude roots is vested interests: people might reject science because it implies a change that is materially painful for themselves or their communities. For instance, people who work in the fossil industry or recently bought a gas-fuelled car might be motivated to reject facts that are in favour of wind farms. This hypothesis is not easy to test given the number of different vested interests that might be at play, although it is difficult to imagine that such an explanation could account for the broad-based agreement with misinformation detected in the current samples.

Another attitude root that has been discussed at length in the climate change literature is ideology. It has been argued, for example, that political conservatives see climate science as paving the way for Big Government regulation that violates their philosophies of how society should be structured[45]. Rather than coming on board with a solution to which they are averse, conservatives might heuristically challenge the underlying climate science[47], and resist any technological solutions implied by that science[48]. There was some evidence for this conservative effect in the current studies, although political orientation was only a modest predictor over and above other variables, and only significant in four of the six samples.

Of course, some ideologies can predispose people to be favourable to a technology. In our studies we measured one such ideology, the NEP, assessing the extent to which participants held a worldview recognizing the need for an ecologically sustainable relationship between humans and the natural environment. To the extent that our participants held this worldview, they were less likely to agree with misinformation about wind farms, a relationship that emerged as significant in all our samples and was the second strongest predictor overall.

The final attitude root relevant to the current studies is the conspiracist worldview. Overall, people with the general worldview that conspiracies are concocted in secret by powerful actors were more likely to agree with contrarian claims about wind farms. Conspiracy mentality was the strongest predictor of agreement with misinformation in all of our samples, in each case explaining more than ten times the variance of education.

Although our samples were designed to be representative of key dimensions (e.g., age, gender, education), we acknowledge that they may have under-represented minority religious and ethnic groups. Moreover, we did not quota-base our samples on other potentially relevant categories such as household income, region or employment status. Another limitation comes with the recruitment via online panels, which generally excludes people who are not registered on such platforms or are less prone to using digital devices. We also emphasise that we sampled exclusively from Western, industrialised nations, so it would be ill-advised to extrapolate from these conclusions to other nations and cultures. Further research is required to provide a global insight into what is potentially a global problem. Future research may also seek to investigate the prevalence (and predictors) of agreement with misinformation about other green innovations such as electric cars, heat pumps, bicycle lanes, and low-speed traffic zones.

Another obvious direction for future research is to design and test strategies to overcome agreement with misinformation about wind farms. One tempting (and intuitively appealing) response to misinformation is to neutralise it with corrective information, for example through debunking or myth-busting campaigns[24]. Such communication strategies might be particularly effective among the large share of people who are undecided with regard to the claims. Targeting the so-called fence-sitters rather than people who are set in their contrarian views has previously been suggested with respect to vaccination[49]. However, the fact that agreement with diverse contrarian claims is highly correlated and cognitively intertwined suggests that to reach those who agree with these claims, information campaigns would have to be broad-based and address the underlying attitude roots (described above) rather than debunking single claims. A more promising approach to science education seems to be enhancing skills that are necessary to evaluate scientific evidence rather than simply communicating facts[23,50].

Importantly, any informational or educational interventions would have to compete with two ideological headwinds. First, agreement with misinformation about wind farms is powerfully associated with a conspiracy mentality, which presents a significant communication challenge. There are not yet robust, documented ways to change the belief structures of those who operate from the worldview that decision-makers cannot be trusted. Second, agreement with misinformation about wind farms is strongly correlated with a rejection of a pro-ecological worldview. As such, it is possible that people's agreement with misinformation is not a result of faulty analysis of evidence, but rather constitutes post-hoc rationalisations of an intuitive aversion grounded in ideology and/or identity (i.e., an example of motivated cognition[51]).

Informational campaigns may also be more effective if they are complemented by interventions that reduce (or at least acknowledge) the underlying worldviews that draw people to misinformation about wind farms[51]. There are several examples of climate change communication that successfully implement this approach, for instance, by aligning climate action with conservative values[52] or highlighting outcomes of climate action that are attractive to those supporting a free-market ideology[48]. Another strategy that has been suggested to reduce polarised attitudes is the inclusion of rhetorical elements that elicit

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conflicting thoughts in message recipients (e.g., asking for alternative courses of events) and that reduce the rigidity with which people hold their beliefs[53]. Refining and applying these communication strategies will be critical as the world engages in the complex process of transitioning to a carbon-constrained world.

Methods

All studies received ethical approval from the Institutional Review Board of the Leibniz-Institut für Wissensmedien (Tübingen, Germany; LEK 2019/001) and were conducted in line with the ethical guidelines of the American Psychological Association. Participants received financial compensation, the amount of which was determined by the panel provider.

Pilot studies

In advance of designing the survey, we identified a set of contrarian claims about wind farms by examining media and internet sources, browsing the scientific literature on wind farm rejection, engaging in personal communication with renewable energy scientists and wind farm opponents, and conducting a survey with an open-ended question on concerns about wind farms in Germany ($N = 109$). In this survey, we told participants that we were interested in the concerns the population sees in the construction of wind farms. Then, we asked them "In your opinion, what arguments speak against the expansion of wind energy?" and provided a text field for participants to respond. Afterwards, we screened participants' answers for potential topics and claims that we could use to design the contrarian claims in our studies. Following this procedure, and in line with recommendations from the misinformation literature[54], we made sure that the statements we chose matched those participants would be actually confronted with in the real (online or offline) world. Moreover, we selected statements that covered a diverse range of topics of misinformation about wind farms. This search resulted in an initial set of 16 contrarian claims (see Supplementary Table 12). We pretested these statements with a quota-based German sample ($N = 501$). This pilot study (reported in detail in Supplementary Note 1) revealed high levels of agreement with the contrarian claims and high intercorrelations among them. This led us to carry out larger surveys in the United States, United Kingdom, and Australia as described below.

Study 1

In September 2023, we conducted a study simultaneously in the United States, the United Kingdom, and Australia. We chose these nations because they are (1) heavily reliant on fossil fuels and responsible for a good share of global carbon emissions, (2) at the same time produce a considerable share of energy by wind farms, and (3) are democracies in which popular opinion affects political decisions. In each country, we collected complete data of $N = 1000$ participants resulting in a total sample of $N = 3000$. Due to the lack of reliable effect size estimates from the literature, we did not run a-priori power analyses. Rather, we based our sample size calculations on the assumption that 1000 participants per country would offer a roughly representative sample of the respective population. A sensitivity analysis revealed that with a sample of this size, we could detect a small effect ($f^2 = 0.01$) of a single regression coefficient in a multiple regression analysis with eight predictors with a power of 90% and an alpha error probability of 5%. In line with our preregistration (https://aspredicted.org/cs97x.pdf), we excluded additional participants (via screen-out during the survey) if they (1) failed both of two attention checks (United States: $n = 145$, United Kingdom: $n = 106$, Australia: $n = 141$) or (2) indicated to have taken the survey multiple times (United States: $n = 87$, United Kingdom: $n = 55$, Australia: $n = 89$).

Each sample was nationally quota-based for age, gender, and highest educational attainment (university degree vs. no university degree) according to official census data. Participants were recruited by the panel provider Cint. The distributions of demographic variables are displayed in Supplementary Table 2. As preregistered, participants' educational attainment was categorised as lower education (none completed, Primary School, Secondary School), medium education (High School/Tertiary/Tech. College), or higher education (University/Higher Education, Postgraduate Education). Gender was coded as −1 male and +1 female. Due to this coding and the low number of cases, participants who did not identify as female or male were not included in the multiple regression analyses.

Participants first responded to the demographic questions that were relevant to ensure the quota-based distribution of age, gender, and educational attainment, after which they gave informed consent for their participation. A short introductory text then revealed the purpose of the study. This text stated that many governments were promoting the expansion of wind energy to meet the goals of the Paris Agreement, that wind energy is generally seen as a means to meet those goals, and that wind turbines are "not without controversy". Participants were asked to rate their agreement with 16 statements about wind energy before responding to several questions said to be about their "general opinion on ecological topics and societal events". Measures were delivered in the following sequence: agreement with contrarian claims about wind farms (statements randomised), New Ecological Paradigm, environmental self-identity, science knowledge, conspiracy mentality, and political orientation. Participants were then asked whether they participated in the survey multiple times and given the possibility to comment on the study. Finally, participants were offered the chance to withdraw their data. All measures including exact wordings are displayed in Supplementary Table 1.

Study 2

Study 2 was conducted in March 2024. Again, we recruited participants in the United States, United Kingdom, and Australia via Cint. We applied the same exclusion criteria as in Study 1: participants were excluded for failing attention checks (United States: $n = 152$, United Kingdom: $n = 67$, Australia: $n = 125$) and/or because they completed the survey multiple times (United States: $n = 106$, United Kingdom: $n = 87$, Australia: $n = 84$). The final sample consisted of $N = 3008$ participants (United States: $n = 1000$, United Kingdom: $n = 1004$, Australia: $n = 1004$) and was again nationally quota-based for age, gender, and education. For education, the achieved distribution deviated by up to 5% from the desired quota. In line with our preregistration (https://aspredicted.org/iy37h.pdf), we coded participants' educational attainment and gender using the same categories as in Study 1.

Before proceeding to the survey, participants completed demographic questions that were relevant to ensure the quota-based distribution (i.e., age, gender, education). Moreover, we collected data on ethnicity and area of residence (for an overview of demographic data, see Supplementary Table 2). The categories used for ethnicity were adapted from official census surveys in the respective countries. Eligible participants were then informed about the purpose of the study and gave consent for their participation.

The introduction to the survey was copied from Study 1 and stated that we were "interested in people's opinions on the construction of wind turbines". First, we presented 17 statements about wind energy (13 being contrarian claims and four being true claims) in a randomised order. Afterwards, measures were presented in the following order: policy support in favour of wind farms, intention to engage in collective action against wind farms, New Ecological Paradigm, science knowledge, conspiracy mentality, and political orientation (for number of items and exact wordings, see Supplementary Table 1). At the end of the survey, we asked participants whether they completed the survey multiple times and whether they had additional comments. Finally, they had the chance to withdraw their data from analyses.

All analyses reported were conducted using IBM SPSS v29. The research data are publicly available via PsychArchives[55].

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Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The data generated in this study have been deposited in the PsychArchives database under accession code https://doi.org/10.23668/psycharchives.15444. Source data for the Figures are provided with this paper.

Code availability

The code used to analyse the data has been deposited in the PsychArchives database under accession code https://doi.org/10.23668/psycharchives.15445.

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Author contributions

K.S. and M.J.H. acquired funding for the studies. K.W., M.J.H. and K.S. conceptualized the study with feedback from L.P. K.W. collected and analysed the data with help from L.P. K.W., M.J.H., K.S. and L.P. interpreted the data. K.W. drafted the article. K.W., M.J.H., L.P. and K.S. provided critical revision and approved the final version of the article.

Competing interests

The authors declare no competing interests.

Additional information

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