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Mapping, understanding and reducing belief in misinformation about electric vehicles

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Misinformation about electric vehicles (EVs) poses significant challenges to the global transition to energy efficient transportation. We investigated the prevalence of misinformation about EVs, predictors of misinformation endorsement and two potential interventions for reducing its impact. Surveys across four countries (Studies 1 and 2, N = 6,341) revealed that more respondents agreed with misinformation statements about EVs than disagreed with them. Conspiracy mentality emerged as the strongest predictor of such beliefs, whereas education played no role. In Study 3 (N = 1,500) we tested two interventions—a fact sheet and dialogues with artificial intelligence (ChatGPT)—for reducing belief in misinformation and increasing pro-EV policy support and purchase intentions. Both strategies showed modest effectiveness immediately post-intervention, and positive effects on misinformation beliefs remained significant at a 10-day follow-up. Our results highlight the prevalence of EV misinformation, the role of mistrust in shaping it and the potential for conventional and novel informational strategies to reduce it.

Electric vehicles (EVs) play an important role in tackling climate change. Over their lifetime, EVs have lower total greenhouse gas emissions compared to internal combustion engine vehicles, even when accounting for emissions from electricity generation and battery production. Despite these benefits, EVs have legitimate limitations that blur positive sentiment. Scholars, for example, have stressed that by still relying on individual-based mobility, as supposed to shared mobility, EVs do not help resolve problems with congestion, accidents and quality of public transportation; nor do they promote healthier forms of mobility[1,2]. Many consumers express legitimate anxiety that the battery of an EV will run out of charge before reaching the destination or a charging station[3,4] or that EV fires are difficult to extinguish.

Other concerns about EVs appear to be grounded in myth. For example, despite lithium-ion batteries in EVs being less likely to catch fire than gasoline vehicles on a per-vehicle basis, EVs have been described in the media as highly combustive, 'like a bomb'[5]. Other concerns expressed in consumer reports include discredited notions that EVs are less safe in a collision than traditional vehicles, that EVs emit electromagnetic fields that damage health and that the lifespan carbon emissions of EVs exceed those of traditional cars[6,7]. Statements such as these can be classified as misinformation, defined as information that, relative to scientific evidence, is deceptive or misleading and stands in contrast to discourse from institutions adhering to scientific principles[8]. Misinformation thus encompasses not only demonstrably false claims but also misleading oversimplifications and assertions lacking credible empirical support, particularly when they contradict established scientific consensus.

There is evidence that ideological positions may predispose individuals to believe in misinformation about EVs. For example, conservative think tanks are increasingly moving from outright climate change denial to disseminating potentially false or misleading information about renewable energy and climate policies[9,10]. The spread of misinformation in conservative communication channels raises concerns that attitudes about EVs have been drawn into the culture wars defining and prescribing what it means to be liberal and conservative. When this happens, beliefs about EVs can become influenced by partisanship and biased reasoning, as it has done for issues such as climate change[11–17]. Indeed, conservatives are already less supportive of EVs compared to

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those with more liberal political orientations[18–20], a pattern that extends to a range of other clean energy technologies such as wind farms[21,22], solar energy[23–25] and heat pumps[26].

Another ideological position that has been implicated in willingness to believe misinformation about technologies is the conspiracy mentality. Conspiracy mentality refers to the generalized tendency to believe conspiracies occur[27–29]. This worldview has been strongly associated with opposition to various science-backed technologies including vaccinations[30–32] and wind farms[21,22]. The most common version of this systemic mistrust is that for profit motives or for nefarious political reasons, governments and industry conspire to exaggerate the benefits of a technology and disguise its dangers. Given that EVs are a multi-billion-dollar industry frequently supported by emissions-sensitive governments, it seems plausible they could become targets of suspicion for those who see such relationships through the lens of corruption and secret agendas.

If the community has mainstream concerns about EVs, and if some of those concerns are based in myth, this will be consequential for our collective ability to decarbonize at the speed and scale required to avoid the worst consequences of climate change. The studies reported in this paper map the prevalence and content of misinformation about EVs in four nations, examine the psychological, cognitive and demographic predictors of these beliefs and test two potential interventions against it.

In Studies 1 and 2, we asked participants from four nations to rate their agreement with misinformation statements about EVs and explored individual-level predictors of misinformation agreement. In Study 3, we tested two informational strategies for reducing misinformation about EVs. One was a traditional fact-sheet intervention in which arguments for EVs were laid out and myths challenged. We compared this informational intervention with a more recent innovation: conversations with ChatGPT. Generative artificial intelligence (AI) systems have potential to become the most prominent information source for the public and are already integrated into most internet search engines. However, it remains unclear how this transformation in information technology affects the way people engage with EV information. At the time of writing, there is only one published study that has examined the effect of dialogues with AI on public mistrust, and the outcome was encouraging. Costello and colleagues found that dialogues with ChatGPT resulted in large and durable decreases in individuals' conspiracy theorizing[33]. Although this study was not focused on scientific misinformation, it raises hopes that informational interventions can be effective in correcting misinformation about a range of trust-sensitive issues, including EVs. As elaborated below, our data reveal high population prevalence of myths about EVs among non-EV owners in Germany, Austria, Australia and the United States (Study 1) and even among EV owners in the United States (Study 2). Indeed, for six of nine misinformation statements, more people agreed than disagreed with the statements. In Study 3, however, we found modest success in reducing misinformation through both traditional informational interventions (a fact sheet) and more innovative information-based strategies (conversations with AI).

Agreement with misinformation and its predictors

Study 1 was a pre-registered survey conducted among non-EV owners in Germany, Austria, Australia and the United States (N = 4,205; Supplementary Table 1). We measured agreement with nine contrarian claims about EVs using a Likert scale from (1) = 'Strongly disagree' to (5) = 'Strongly agree' (participants also had a 'don't know' option). In Fig. 1 we aggregated participants' responses on the misinformation items so that those who selected 'Somewhat agree' and 'Strongly agree' were coded as 'Agree' and those who selected 'Somewhat disagree' and 'Strongly disagree' were coded as 'Disagree'. Substantial agreement with misinformation was found across all domains, including concerns about health and safety, concerns about the environment, concerns about secret activities to under-report EV accidents and concerns about unethical profit-driven decisions.

Despite diverse content in the misinformation items, moderate-to-high positive correlations emerged among them (Pearson's rs 0.37 to 0.63). This is consistent with work on wind farms, where logically orthogonally pieces of misinformation correlated so highly that they formed what appeared to be a 'monological' mindset[21]. Indeed, a confirmatory factor analysis (Supplementary Table 2) showed support for a single factor. As such, the items were averaged to form a single measure of misinformation agreement.

Using the total number of responses across all misinformation statements, we then calculated the proportion of each response category across the sample (Fig. 2). Overall, more people agreed with the misinformation statements (36.2%) than disagreed with them (23.1%). Misinformation agreement was highest in Germany and lowest in the United States, but there was only a 4.4 percentage point difference between them.

Linear regression models simultaneously estimated the effect of various predictor variables on (1) agreement with EV misinformation, (2) support for EV policies and (3) intentions to purchase an EV. Full measures are itemized in Supplementary Table 3; means, correlations and reliabilities are presented in Supplementary Table 4. We plotted regression results for each outcome variable in Fig. 3, and full results are presented in Supplementary Table 5.

The strongest predictor of agreement with misinformation was conspiracy mentality. The overall model accounted for 29% of variance (R^2) and conspiracy mentality explained 79% of that variance. Misinformation agreement was also associated with lower pro-ecological worldview, weaker environmental identity and greater self-identification as conservative, although these explained (in total) less than one-sixth of the variance captured by conspiracy mentality in the model (13%). Women and older respondents showed somewhat higher misinformation agreement, but there was no relationship between misinformation agreement and respondents' region. Misinformation agreement was not reliably associated with education, scientific knowledge or performance on the cognitive reflection test, which is unusual in the context of misinformation discrimination studies[34].

In terms of EV policy support and purchase intentions, more pro-EV responses were displayed by younger respondents and those who identified as pro-environmental. The strongest negative predictors were conspiracy mentality, self-reporting as conservative and being female. Other predictors, including education, scientific knowledge and performance on the cognitive reflection task, were either non-significantly or trivially associated with policy support and purchase intentions.

Finally, misinformation agreement was strongly and negatively correlated with support for EV policies ($r = -0.34$) and intentions to purchase an EV in the future ($r = -0.36$, both Ps < 0.001) even after controlling for the predictors summarized in Fig. 3. Although correlational, this lends support for the notion that misinformation endorsement is associated with self-reported action.

To explore whether patterns of prediction differed across nations, we ran 120 regression models (ten predictors × four nations × three outcome variables). After adjusting for multiple comparisons ($P < 0.001$), only four interactions across all outcome variables were statistically significant, suggesting patterns of prediction were relatively stable across nations. The significant interactions are described in Supplementary Figs. 1–4.

Study 2 extended Study 1 by (1) expanding the sample to incorporate EV owners and (2) adjusting some misinformation items to reduce ambiguity and to more closely correspond with our definition of misinformation (Table 1). A study with 2,136 US participants completed the same variables as in Study 1 (Supplementary Table 6 provides demographics). The sample was almost evenly split between

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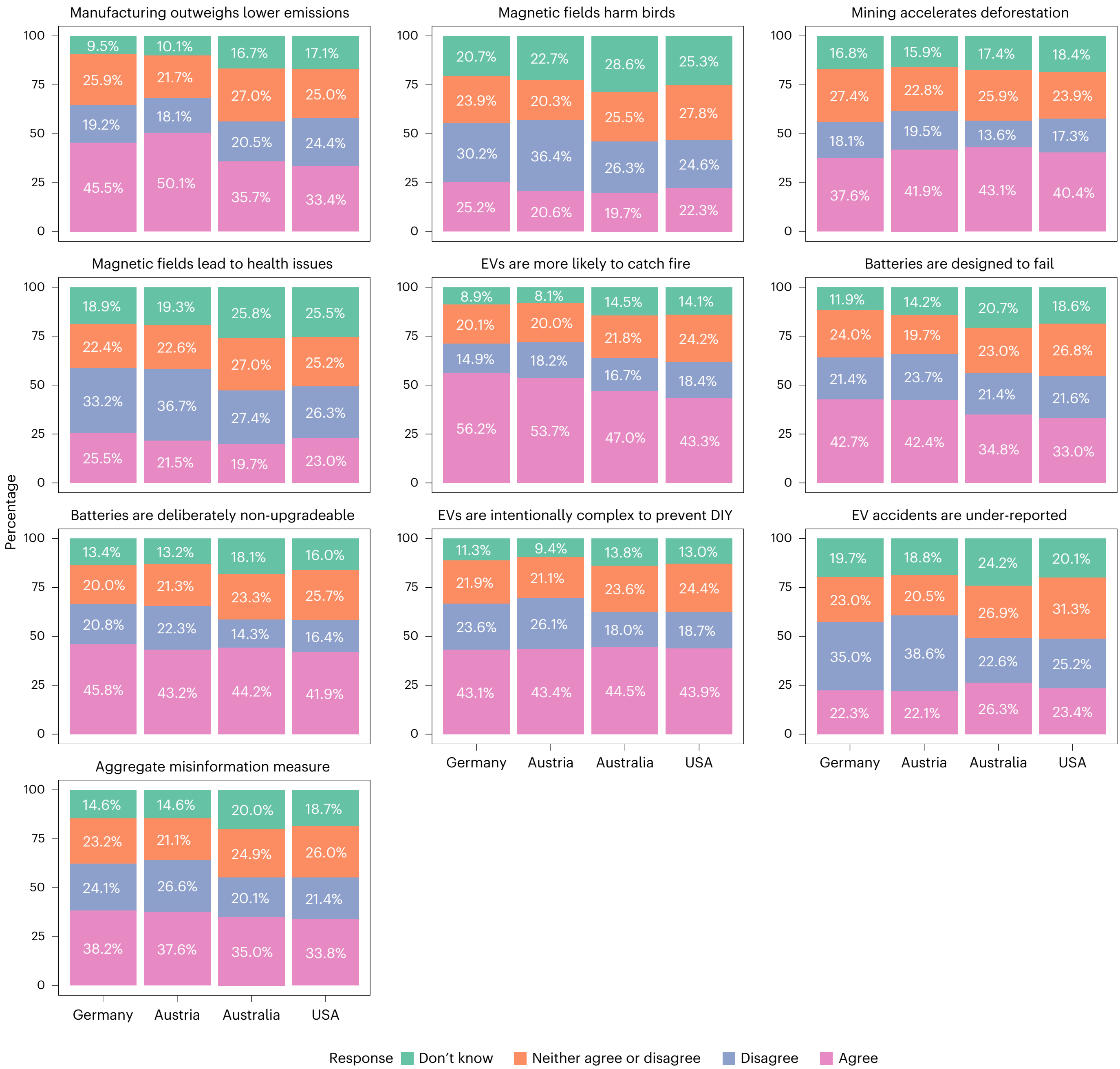

Fig. 1 | Proportion of respondents per EV misinformation item, response category and country. Response categories were 'Agree', 'Disagree', 'Neither agree or disagree' and 'Don't know' (N = 4,184).

those who owned an EV (47.1%) and those who did not (52.9%). Half the participants were shown the original wording of the misinformation and truth scale; half received an amended version (Supplementary Table 3). The amendments were made to make the statements more focused (for example, making it clear that a statement was comparing EVs with petrol cars or by making specific reference to carbon emissions as opposed to more general claims about environmental harm).

As can be seen in Fig. 4 (and Supplementary Table 7), EV-owning individuals agreed more with true items compared to non-owners. EV owners, however, did not significantly differ in their agreement with misinformation compared to non-owners. The fact that even owners had high levels of misinformation agreement underscores the extent to which misinformation has permeated the population. Superficially, however, the null result seems inconsistent with the strong negative correlation between misinformation agreement and purchase intentions observed in Study 1. One possibility is that consumers are drawn to EVs by perceived benefits (for example, environmental impact, cost savings), but owners become more sensitive to negative claims about health and environmental impacts. This heightened vigilance may not deter initial adoption but could undermine long-term satisfaction or re-purchase intentions. Future research should examine whether misinformation exerts greater influence at later stages of ownership, potentially affecting continued market uptake.

Importantly, the phrasing of the items did not influence agreement levels, confirming that the high levels of misinformation agreement in Study 1 were not an artefact of potentially ambiguous or misleading wording of the items. Furthermore, linear regression results showed substantial overlap with Study 1 (Supplementary Table 8), with conspiracy mentality being the biggest predictor of agreement with misinformation.

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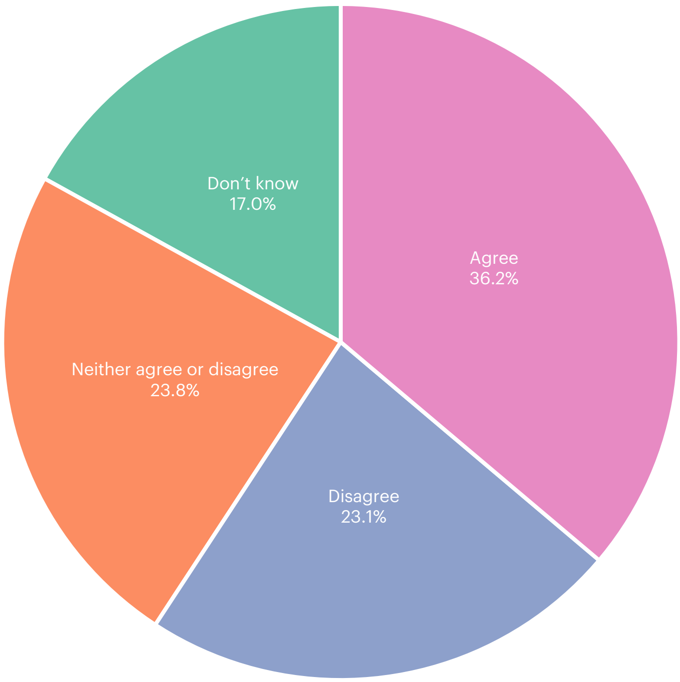

Fig. 2 | Total proportion of responses per response category across all misinformation items and countries. We created four response categories: 'Agree', 'Disagree', 'Neither agree or disagree' and 'Don't know' (N = 4,184).

Interventions to reduce agreement with misinformation

Study 3 was a pre-registered experiment testing two informational interventions designed to reduce EV misinformation. Participants either engaged with GPT 4o-Turbo in a three-round conversation about EVs ('AI: EV' condition) or they were presented with a fact sheet about EVs created by the US Department of Energy ('fact sheet' condition). As a control condition, participants had a three-round conversation with ChatGPT on an unrelated topic ('AI: sport' condition). After the intervention, and during a 10-day follow-up, participants rated their agreement with EV misinformation, support for EV expansion policies and their intentions to purchase EVs (0 = strongly disagree, 100 = strongly agree).

Multi-level analyses, controlling for age, gender and education, showed significant condition × time interactions across all dependent variables (Supplementary Table 9 provides full analyses). Interactions are displayed in Fig. 5; marginal means and simple effects are summarized in Supplementary Tables 10–12.

When measured immediately after the interventions, we observed modest increases in pro-EV sentiment compared to the control condition. Compared to the control (sport) condition, agreement with misinformation was 7.55 percentage points (pp) lower in the fact sheet condition and 5.30 pp lower in the AI: EV condition (Ps < 0.002; when expressed as a function of the mean in the control condition, the reduction in misinformation agreement was 16% and 11%, respectively). Participants also supported EV policies more strongly after both informational intervention conditions compared to the control condition (Ps < 0.044). Finally, purchase intentions were higher in the AI: EV condition compared to the control condition (P = 0.013), whereas the fact sheet condition did not reliably differ from either of those conditions. At the 10-day follow-up, the positive effects of both informational interventions (fact sheet and AI: EV), compared to the control condition, remained for misinformation agreement (both Ps < 0.025) but not for EV policy support and purchase intentions (all Ps > 0.24).

At the 10-day follow-up—after re-measuring the dependent variables—we measured several exploratory variables: conspiracy mentality, pro-ecological worldview, environmental identity, science knowledge, EV salience, cognitive reflection test, political ideology, reactance and trust in AI. None were significantly influenced by the manipulation (all Ps > 0.05). Consistent with the pre-registration, this enabled us to test whether these variables moderated the effect of condition over time. We also tested the potential for moderation as a function of education, gender and age, resulting in 36 exploratory analyses. After controlling for multiple comparisons (P < 0.001), we did not find any additional moderations with our condition × time interaction.

Finally, in line with DeVerna and colleagues[35], we fact checked ChatGPT's responses in the EV condition using Anthropic's Claude 3.5 Sonnet. Of 1,206 individual ChatGPT responses, we found no evidence that ChatGPT spread misinformation in its responses (Methods).

Discussion

Given the need to transition towards more sustainable transport options, the prevalence of misinformation surrounding EVs is concerning. Overall, our samples were more likely to agree than to disagree with misinformation, and this was even true among those who owned an EV. Mainstream acceptance of misinformation was found across multiple domains, including concerns about secret activities to exaggerate the benefits of EVs, concerns about unethical profit-driven decisions and unfounded or exaggerated concerns about the damage of EVs towards health and the environment. Across a range of items, our data highlight the broader challenge of clear science communication in an informational landscape shaped by myths, selective

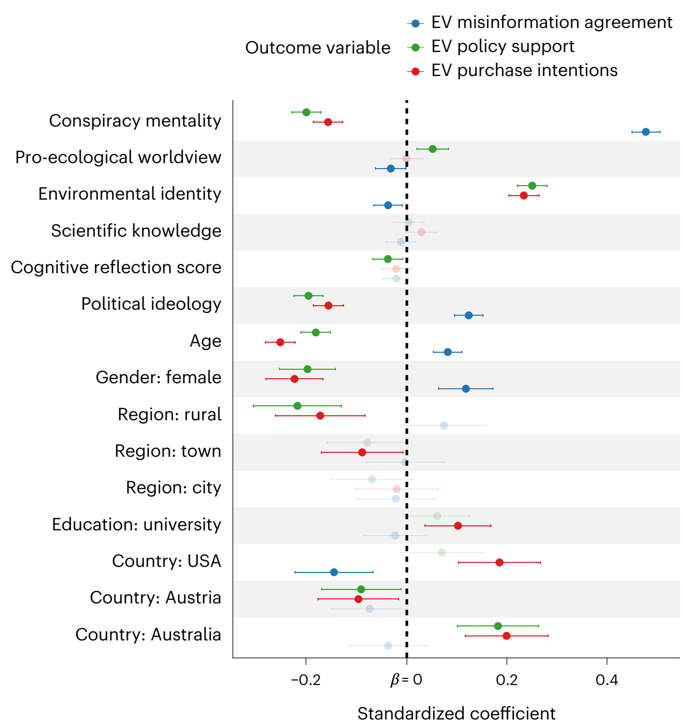

Fig. 3 | Standardized linear regression coefficients and 95% confidence intervals per outcome variable. The graph shows standardized regression coefficients (as mean values) extracted from linear regression models for the relationship between each predictor and three outcome variables: misinformation agreement (n = 3,875, blue), pro-EV policy support (n = 3,984, green) and EV purchase intentions (n = 3,983, red). Error bars represent 95% confidence intervals. Coefficients with P > 0.050 are greyed out. Statistical tests were two sided. The reference groups for gender, region, education, and country are, respectively, 'Male', 'Large city', 'No university degree' and 'Germany'. Positive βs indicate that scores were higher in the predictor category than the reference category.

Table 1 | Revised misinformation and truth items

Construct	Item
Agreement with misinformation about electric vehicles	Due to the resource intensity of the production process, electric vehicles produce more carbon emissions across their lifespan than petrol cars do.
	The electromagnetic fields emitted by electric vehicles majorly disrupt the migratory patterns of birds and other wildlife.
	Electric vehicles do not reduce climate change because their production requires mining rare minerals, which causes deforestation, thus increasing CO_2 in the atmosphere.
	Electric vehicles emit electromagnetic fields that can lead to serious health issues, including cancer.
	Electric vehicles are more likely to catch fire than petrol cars.
	Electric vehicle batteries are designed to fail after a set number of charge cycles to boost manufacturer profits through replacements.
	Electric vehicle batteries are deliberately made non-upgradeable to force consumers into purchasing replacements.
	Compared to petrol car technology, electric vehicle technology is designed to be unnecessarily complex to prevent DIY repairs and force people into expensive service centres.
	Electric vehicle accidents are deliberately under-reported by authorities.
Agreement with true claims about electric vehicles	Electric vehicles produce zero tailpipe emissions, thereby producing fewer greenhouse gases than petrol cars.
	Compared to petrol cars, electric vehicles produce fewer pollutants like nitrogen oxides and particulate matter, improving air quality and public health.
	Compared to petrol cars, electric vehicles reduce reliance on imported oil and fossil fuels, contributing to national energy security and reducing the impact of oil price fluctuations.
	Electric vehicles are generally cheaper to run than vehicles using petrol or diesel.

DIY refers to 'Do it yourself' and means that activities are completed by oneself rather than by employing another party.

framing and speculative reasoning that distort public understanding of EV impacts.

When exploring variation in our three outcome measures (misinformation agreement, policy support, purchase intentions), there was stronger evidence for the predictive role of political ideology, environmental beliefs and conspiracy mentality than for education and indices of cognitive sophistication. Results show the embeddedness of false information in society and the strong association of this misinformation belief with ideology, identity and worldviews. Of particular concern is the fact that the strongest predictor of misinformation endorsement was conspiracy mentality, a systemic mistrust of 'elites' that has historically been difficult to address[36,37].

Reducing the influence of misinformation is a key challenge to overcome when transitioning to more sustainable futures. On this note, we found some cause for optimism. Both the traditional informational intervention (a fact sheet) and an AI-based strategy produced 11–16% drops in misinformation endorsement compared to a control condition, effects that remained significant after 10 days. The success of the interventions was remarkably resilient across demographic sub-samples and emerged regardless of participants' levels of dispositional reactance, their capacity for analytical thinking and their trust in AI.

Positive effects of the AI intervention were somewhat lower than achieved by Costello and colleagues in their conspiracy theory intervention[33]. Furthermore, unlike Costello and colleagues, we observed decay in treatment effects over time, particularly for policy support and purchase intentions, suggesting that our interventions would not be successful without additional booster shots[38]. One reason may be cultural in that gasoline-powered cars have been deeply embedded into our understanding of mobility that individuals will naturally gravitate towards the status quo and away from technologies that question it[39]. Another reason might be because Costello and colleagues provided the AI with a back-end prompt to try to convince the participants to change their views, whereas we did not. Regardless, Study 3 provides the first evidence that non-curated, in-the-wild conversations with Generative AI can have positive effects on misinformation. Reassuringly, our analyses found no clear cases of the AI generating misinformation or reinforcing conspiracy theories. Furthermore, generative AI tools have advantages that are difficult or impossible for traditional informational tools to match: they are highly accessible, tailored to each individual's specific concerns and operate fluidly in multiple languages. These qualities raise hopes that generative AI will one day be used as a tool for large-scale, solution-focused interventions, an aspirational goal for most climate-focused behavioural scientists[40].

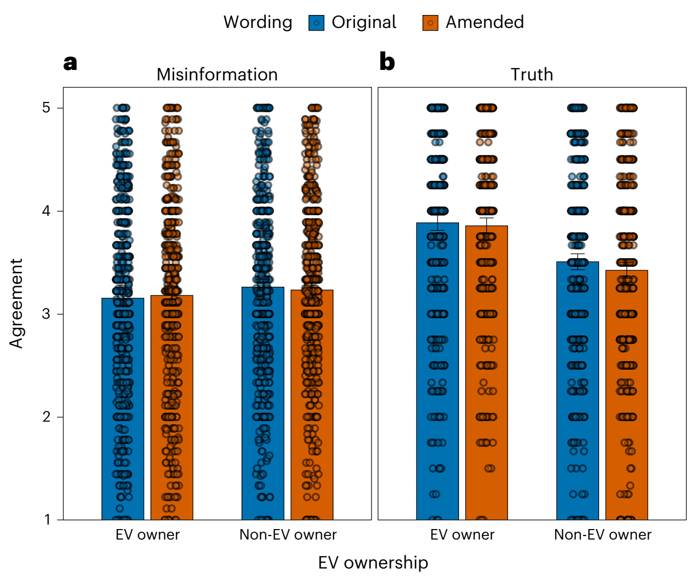

Fig. 4 | Overall agreement with misinformation and truth items. a,b, Overall agreement with misinformation (**a**) and truth items (**b**) per wording condition and EV ownership. Bars represent mean values and error bars represent 95% confidence intervals ($n_{\text{EV owner-original wording}} = 525$, $n_{\text{EV owner-amended wording}} = 481$, $n_{\text{non-EV owner-original wording}} = 526$, $n_{\text{non-EV owner-amended wording}} = 537$). Multivariate tests used were two sided and showed a main effect of EV ownership, $F(2,2064) = 55.48$, $P < 0.001$, $\eta_p^2 = 0.05$, but no effect of item wording, $F(2,2064) = 1.12$, $P = 0.328$, $\eta_p^2 = 0.00$ and no interaction, $F(2,2064) = 0.56$, $P = 0.571$, $\eta_p^2 = 0.00$. The underlying data and more details on statistical tests can be found in Supplementary Table 7.

However, it is important to temper this optimism with caution. It should be emphasized that we did not find robust evidence that the AI intervention outperformed the fact sheet intervention: if documents such as these had broad population penetration, there is not yet reason

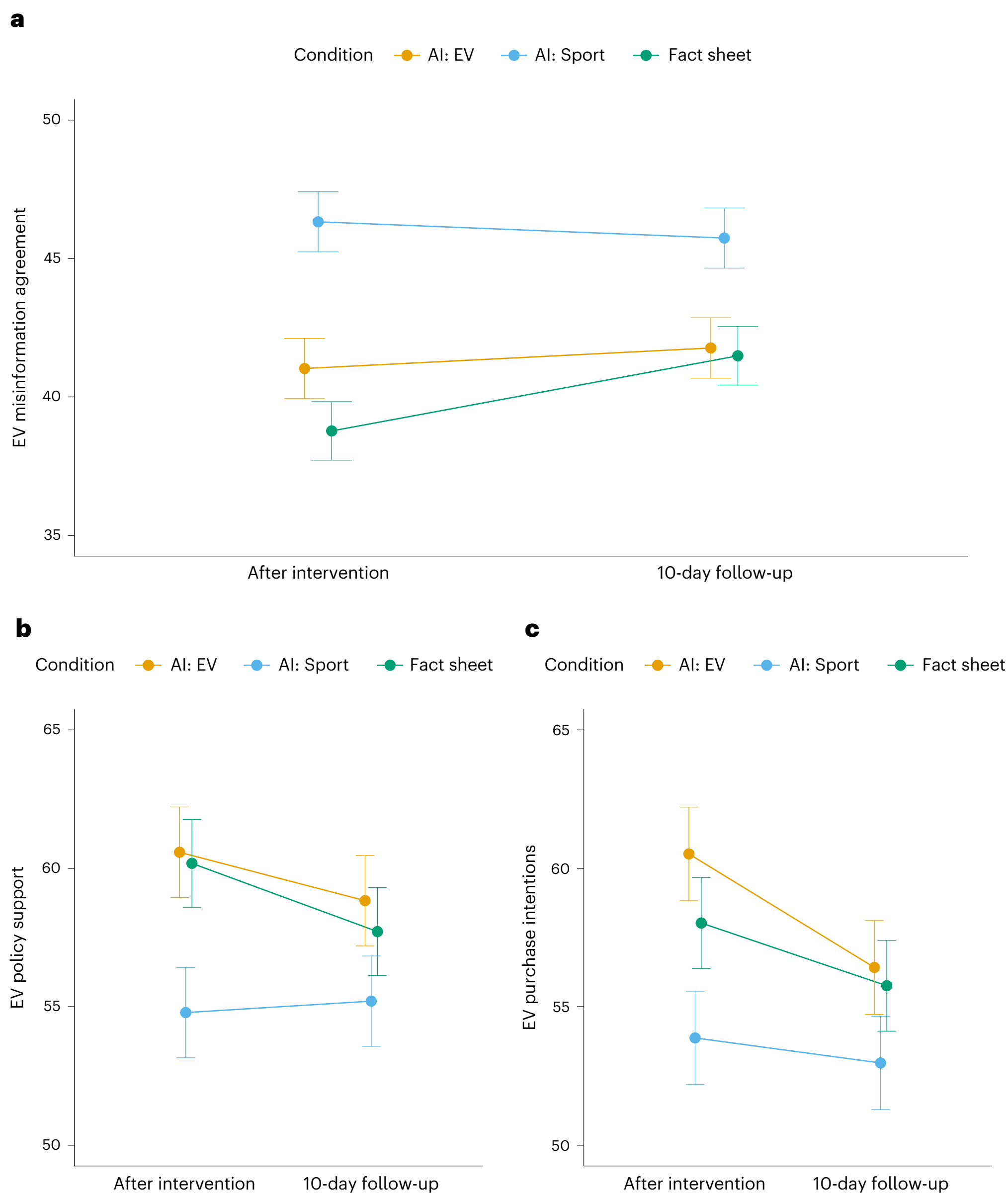

Fig. 5 | Agreement with EV misinformation, policy support and purchase intentions. a–**c**, Agreement with EV misinformation (**a**), EV policy support (**b**) and EV purchase intentions (**c**) for each experimental condition across two time points. In the AI conditions, participants had three-round conversations with AI, either about EVs or their favourite sport ($n_{\mathrm{AI:EV}} = 396$, $n_{\mathrm{AI:Sport}} = 398$, $n_{\mathrm{Fact\,sheet}} = 421$). Data are presented as mean values and error bars represent standard errors. Statistical tests were two sided. Each variable was measured on a scale from (0) = 'Strongly disagree' to (100) = 'Strongly agree'.

to think they would be less influential than AI interventions. There are also ongoing concerns about the integrity of AI tools, including the non-transparency of many AI algorithms[41], the lack of governance mechanisms applied to large technology companies in their development of AI[42] and the potential for manipulation and interference by bad-faith actors. It is also important to state that ChatGPT and AI in general require substantial amounts of energy and water[43]. Therefore, to adequately evaluate the potential of interventions leveraging AI to combating climate change, we need to assess the extent to which the benefits of using AI outweigh AI's environmental impact. In sum, AI interventions currently show promise, but these interventions need to be monitored closely to guard against declines in information integrity over time.

Methods

Four-nation survey (Study 1)

Participants and study design. We pre-registered our survey (https://osf.io/gsdnq) and collected data via the market research firm Cint. Aligned with our pre-registration, we screened out participants who either owned an EV, ordered an EV or failed an attention check embedded within the misinformation scale. We received 4,205 valid responses (Germany: 1,046; Austria: 1,062; Australia: 1,033; United States: 1,064). Data were representative in terms of age, gender and education for each of the four countries (Supplementary Table 1). We selected Germany and the United States because of their strong automotive industries that rely heavily on the sale of petrol and diesel cars. For each of these nations we chose a culturally similar counterpoint nation that does not have a domestic automobile industry: Australia and Austria. All four nations have a high level of private car ownership and all four have been identified as nations for which the energy transition has become a point of political contest. The survey was developed in English and then translated into German by three bilingual members of the research team.

Measures. *Misinformation statements* were developed, guided by the definition of misinformation provided by Southwell and colleagues[8].

We first reviewed media articles, social media postings and academic literature to develop an archive of criticisms of EVs. From this archive, we removed beliefs that were grounded in documentable problems (for example, concerns about expense, EV fires being difficult to extinguish, EVs being 'too quiet', range anxiety) and collapsed those which could be seen as redundant or overlapping. When developing the final set of items, we sought to canvass statements that captured four dimensions of concern: environmental harm, threats to health and safety, profit motive and corporate secrecy.

Participants responded to each statement on a Likert scale from (1) = 'Strongly disagree' to (5) = 'Strongly agree'. We also gave participants a '*Don't know*' option to allow for the possibility that they had never heard of the statement before. We included a final item stating 'Do you hold any other beliefs about electric vehicles? If so, please write them below' with a free text box to identify any common misinformation beliefs not captured by the scale. When reviewing the free text responses, no additional misinformation themes were identified. As elaborated in the main manuscript, the nine items were combined into a single measure ($\alpha = 0.88$). Deviating from the pre-registration, we excluded three items from analysis— 'Electric vehicles are susceptible to hacking, posing safety and security risks', 'Data gathered by electric vehicles is sold to other corporations' and 'Governments exaggerate electric vehicles' environmental benefits to advance their green agendas'- due to ambiguity about whether they qualify as misinformation. It should be noted, however, the results remain unchanged regardless of whether we included or excluded these items. In Supplementary Table 13, we contextualize each of our statements in terms of how they reconcile with our definition of misinformation.

To check for pattern responding, we embedded four true (and positive) statements about EVs within the misinformation items. The proportion of agreement with each of the items can be found in Supplementary Fig. 5. Pattern responding might be indicated by perverse positive correlations between measures that should be negatively correlated (for example, as participants respond exclusively down the right-hand or left-hand sides of the scale). However, inspection of the correlations in Supplementary Table 4 offers no evidence that this was prevalent in our sample.

Policy support was measured with two items: 'I generally support political measures to expand electric vehicle usage in my country' and 'The government should increase their efforts to expand electric vehicle usage in my country' ($r = 0.79$).

Intention to purchase an EV in the future was measured with two items: 'I would like to own an electric vehicle' and 'I would consider buying an electric vehicle' ($r = 0.87$).

Conspiracy mentality was measured using the Conspiracy Mentality Questionnaire[44]. This is a five-item scale designed to capture respondents' propensity to believe conspiracies (for example, 'Events which superficially seem to lack a connection are often the result of secret activities'). Participants responded on a Likert scale from 1 = 'Strongly disagree' to 5 = 'Strongly agree' ($\alpha = 0.85$).

Pro-ecological worldview was measured using the New Ecological Paradigm, a 15-item scale measured on a five-point Likert scale from 1 = 'Strongly disagree' to 5 = 'Strongly agree' (for example, 'Plants and animals have as much right as humans to exist', $\alpha = 0.84$)[45].

Environmental identity was measured on a three-item scale developed by van der Werff and colleagues[46] (for example, 'I see myself as an environmentally friendly person'; 1 = 'Strongly disagree' to 5 = 'Strongly agree', $\alpha = 0.89$).

Science knowledge was measured using nine items from a test developed by the National Science Foundation Science and Engineering Indicators. Participants indicated for each item (for example, 'The centre of the Earth is very hot') whether they thought it was true or false. The correctly answered items were then summed to create science knowledge score (0–9).

Participants also conducted a revised version of the *cognitive reflection test* (CRT-2)[47]. This test comprises four single-sentence tasks that participants were asked to solve (for example, 'If you are running a race and you pass the person in second place, what place are you in?' correct answer: second, intuitive answer: first). The cognitive reflection score is the sum of the number of items correctly answered (0–4).

Political ideology was measured using two items. In the first item, participants were asked to indicate their political ideology from 1 = 'Very liberal' to 5 = 'Very conservative'. For the second item participants indicated their political orientation on a scale from 1 = 'Very left-wing' to 5 = 'Very right-wing' ($r = 0.56$).

We first measured participants' demographics (age, gender and education) followed by the EV misinformation and true statements. In a random order, we then presented participants with our measures for EV policy support, purchase intentions, pro-ecological worldviews, environmental identity and conspiracist mentality. Then, we randomly presented participants with the science knowledge and CRT measures. Political ideology was measured at the end. Items within all scales were randomized.

As pre-registered, we also measured *self-reported intelligence quotient (IQ)* as an exploratory predictor using a single item graphical measure answered from 1 = 'Mild mental disability' to 7 = 'Gifted'[48]. However, we did not report it in the regression model (or in Study 3) because we did not want to overload the regression with too many conceptually overlapping variables measuring cognitive abilities. For the record, analyses that included self-reported IQ found no significant relationship between this variable and misinformation agreement or policy support. Self-reported IQ positively predicted purchase intentions but the effect was small, $\beta = 0.03$, 95%CI [0.00, 0.06], $P = 0.023$.

Analysis. We conducted linear regressions using agreement with the misinformation scale, EV policy support and EV purchase intentions as outcome variables ('*Don't know*' responses were removed from analysis). Predictors comprised participants' conspiracist mentality, pro-ecological worldview, environmental identity, science knowledge, political ideology and participants' performance in the cognitive reflection test. Age, gender, education, region and country were also included as control variables. In all studies, education was dichotomized to compare those with university education against those without. Data analysis was carried out in RStudio v.4.2.2 and SPSS v.29.

Experiment on item wording and electric vehicle ownership (Study 2)

Participants, procedure and measures. Study 2 sought to demonstrate that the findings from Study 1 also hold for EV owners and with items worded more in line with our definition of misinformation. We sampled US participants via the market research firm Cint. Data were quota-based for age, gender and education. We aimed to obtain half of our sample from EV owners and half from non-EV owners. As in Study 1, we removed participants that failed an attention check. We received 2,136 valid responses (Supplementary Table 6 provides demographics) with 47.1% owning an EV and 52.9% not owning an EV. Participants were randomly allocated to one of two conditions, evenly balanced across EV owners and non-EV owners. In the 'original wording' condition, they were shown the misinformation and truth items from Study 1. In the 'amended wording' condition, participants were shown reworded misinformation and truth items that removed ambiguity potentially present in the original items. The exact wording of the items is shown in Supplementary Table 3. Of the final sample, 525 EV owners and 559 non-EV owners were allocated to the 'original wording' condition, whereas 481 EV owners and 571 non-EV owners were allocated to the 'new wording' condition.

Agreement with misinformation and truth was measured on the same scale used in Study 1, ranging from (1) = 'Strongly disagree' to (5) = 'Strongly agree'. As in Study 1, we also gave participants a '*Don't know*' option. Given that our sample included EV owners, we did not measure EV purchase intentions and EV policy support. After indicating their agreement with misinformation and truth items, participants completed the same predictor variables as in Study 1 (with the exception of self-reported IQ) using the same response scales. The originally worded agreement with misinformation ($\alpha = 0.88$) and truth scales ($\alpha = 0.74$), the amended agreement with misinformation ($\alpha = 0.88$) and truth scales ($\alpha = 0.72$) and measures of conspiracist mentality ($\alpha = 0.79$), pro-ecological worldview ($\alpha = 0.78$), environmental identity ($\alpha = 0.88$) and political ideology ($r = 0.67$) were all reliable.

Analysis. As in Study 1, we calculated a composite measure for misinformation and truth agreement, removing '*Don't know*' responses. We then conducted a MANOVA using agreement with the misinformation and truth measure as dependent variables and EV ownership and our experimental conditions as independent variables. Results are summarized in Supplementary Table 7. To replicate results from Study 1, we also conducted a linear regression using misinformation agreement as the outcome variable. In addition to EV ownership and our experimental condition, predictor variables were the same as in Study 1 (except for country). Results of the regression are presented in Supplementary Table 8. We also explored whether the effect of our ten predictor variables on misinformation agreement was moderated by either our experimental manipulation or by EV ownership, resulting in 20 moderation analyses. After adjusting for multiple comparisons ($P < 0.002$), we did not find any significant moderation effects (all Ps > 0.004).

Misinformation reduction interventions (Study 3)

Participants. The experiment in Study 3 was conducted across two pre-registered waves. In the first wave, we collected data from 1,500 US participants via Prolific (pre-registration: https://osf.io/kdazm). Because purchase intention was a key dependent variable in this study, we pre-screened participants so that only those who had a driving license, owned a petrol or diesel car but did not own an EV were eligible to participate. Aligned with our pre-registration, those who passed an attention check in the first wave ($n = 1,454$) were invited to participate in a 10-day follow-up, which again contained an attention check (pre-registration: https://osf.io/xmznf). Overall, we received 1,224 valid responses across the two waves (gender: male = 44.9%, female = 54.3%, other = 0.8%, age: mean = 44.11 years, SD = 13.56 years). The first wave contained experimental manipulations and our main dependent variables. The 10-day follow-up contained the same dependent variables and some exploratory moderators that were measured at the end of the survey: conspiracy mentality, pro-ecological worldview, environmental identity, political ideology, trust in AI, scientific knowledge, EV salience, reactance and the cognitive reflection test. Participants were compensated for their time in line with Prolific's recommendation.

Procedure. We adapted the procedure developed by Costello et al.[33]. with several notable differences. Participants first completed measures of demographics and political ideology. In random order, participants were then asked to enter their favourite sport and their opinion on EVs. When asked about their opinion on EVs, participants were the given a definition ('Unlike conventional vehicles that use a gasoline or diesel engine, an electric vehicle is a car powered entirely by electricity') and asked to: [...] *share your overall perspective on electric vehicles in a few sentences. Consider the following points in your response: Do you generally view electric vehicles as a positive or negative technology? What do you see as the main benefits or drawbacks of electric vehicles? There are no right or wrong answers—we're interested in your honest thoughts and opinions*.

Participants were then presented with their response and asked to [...] *share more about what led you to this opinion? For instance, are there specific pieces of evidence, events, sources of information, or personal experiences that have particularly influenced your perspective? Please describe these in as much detail as you feel comfortable*.

We piped both responses related to EVs (the initial opinion, and the elaboration) into the AI ChatGPT4-o Turbo, which was prompted to summarize participants' views on EVs in a single sentence (Supplementary Fig. 6). We presented this summary to participants and asked them to indicate their level of confidence on a (0–100% scale) that this statement was true. Our paradigm was facilitated by the online AI aggregator 'OpenRouter', which was integrated into Qualtrics to pipe participants' responses back and forth from Qualtrics into GPT 4o-Turbo. We disabled the copy-and-paste function to prevent participants themselves using large language models to create responses.

After ascertaining participants' initial views on EVs, participants were randomly assigned to one of three conditions. Participants in the AI-treatment condition engaged in a three-round conversation with GPT 4o-Turbo about EVs. Although it was fed participants' two initial text entries on EVs, it was not instructed to persuade participants about EVs beyond its default directives, and so the three-round interactions were effectively no different to a participant accessing GPT 4o-Turbo themselves on their own computer and typing their open-ended views about EVs into the chatbox. In the AI-control condition, participants engaged in a three-round conversation with GPT 4o-Turbo about their favourite sport. In the third condition, participants read a three-page fact sheet about EVs (Supplementary Figs. 7–9) created by the US Department of Energy[49]. The fact sheet was 803 words long, which was approximately equal to the average number of words written in the AI: EV condition across the three rounds of conversation (778 words).

After the interventions, participants were presented with their original AI-summarized view on EVs and asked again to indicate their confidence. Participants were also asked to complete the same EV misinformation, policy support and purchase intentions measures used in the initial survey.

Participants who passed an attention check were contacted again 10 days after the experiment for a follow-up survey to test the durability of any attitude change. Participants were presented again with the AI-summarized version of their initial opinion on EVs and asked to indicate their level of confidence. Then, participants were presented again with the EV misinformation, policy support and purchase intentions measures, followed by the exploratory moderators. Of the 1,224 valid responses we received across the two time points, 402 were allocated to the AI: EV, 399 to the AI: sport and 423 to the fact sheet conditions.

Attrition analyses indicated that completers were older ($P < 0.001$) and at baseline had lower EV policy support ($p = 0.007$) and EV purchase intentions ($P = 0.002$) than did non-completers. There was no difference between completers and non-completers in terms of experimental condition, education, gender or baseline agreement with misinformation items (all Ps > 0.17).

Fact checking responses by AI. We followed the procedure by DeVerna and colleagues[35] to fact check ChatGPT's responses in the EV condition using Anthropic's Claude 3.5 Sonnet and the prompt *Please analyse if this response is likely to be true based on known facts and logical consistency. Respond with only 'Likely true' or 'Likely false'*. Of the 1,206 individual ChatGPT responses across the three rounds of conversation in the AI: EV condition, 1,180 (97.8%) were rated as 'Likely true'. Of 26 'Likely false' responses, 19 were due to minor technical errors such as with the API or 'OpenRouter'. Finally, members of the author team examined the remaining seven responses identified as 'Likely false' and concluded that these were likely rated as false because they acknowledged (but did not reinforce) participants' concerns with EVs. We therefore did not find evidence for ChatGPT spreading misinformation.

Measures. Our key dependent variables, agreement with EV misinformation ($\alpha_1 = 0.91$, $\alpha_2 = 0.92$), EV policy support ($r_1 = 0.94$, $r_2 = 0.94$) and EV purchase intentions ($r_1 = 0.93$, $r_2 = 0.94$), were measured directly after the interventions and again in the follow-up with the same items as in the cross-country survey (Supplementary Table 3) but this time on a slider-scale from (0) = 'Strongly disagree' to (100) = 'Strongly agree'. We again embedded our four true items within the misinformation items and found no evidence of pattern responding, as demonstrated by strong negative correlations between the truth and misinformation items at both time points ($r_1 = -0.52$, $r_2 = -0.56$, Ps < 0.001). There was no effect of the interventions on ratings of true statements, which alleviates concerns that the debunking might increase scepticism to all information (as opposed to just the misinformation)[50]. Similarly, participants' confidence in their initial views on EVs was measured at all three time points using a single item on a 0–100% scale. However, this measure is not interpretable without knowing the valence of participants' sentiment towards EVs, which we report further below ('Open-Ended Response Coding and Analyses').

Political ideology was measured in the initial survey alongside demographics (age, gender, education). All other individual difference measures were measured in the follow-up survey. The measures for age, gender, education, political ideology ($r = 0.93$), pro-ecological worldview ($\alpha = 0.89$), environmental identity ($\alpha = 0.92$), science knowledge, conspiracy mentality ($\alpha = 0.88$) and the cognitive reflection test were the same as those used in Study 1 (Supplementary Table 3).

In the follow-up survey, we also administered five items from the psychological reactance scale (for example, 'I resist the attempts of others to influence me') measured on a five-point scale from 1 = 'Strongly disagree' to 5 = 'Strongly agree' ($\alpha = 0.71$)[51]. We also measured with the salience of EVs in the previous 10 days using three items. On a scale from (1) = 'Never' to (5) = 'Often', we measured how often participants were 'thinking', 'talking to others' and "reading information' about EVs in the period since the experiment ($\alpha = 0.89$). Finally, we measured trust in AI using two items ($r = 0.87$): 'How willing are you to trust AI in daily life?' answered on a scale from (0) = 'Very unwilling to trust' to (100) = 'Very willing to trust' and 'To what extent do you accept the use of AI in daily life?' answered on a scale from (0) = 'Not at all' to (100) = 'A great deal'. As per pre-registration, we embedded an attention check among the misinformation statements to filter out inattentive participants in both the experiment and the follow-up.

Open-ended response coding and analyses. Given that individuals with positive views on EVs may respond differently to our interventions, compared to individuals with negative views, we coded the valence of participants' initial beliefs about EVs (that is, their open-text responses to the questions that asked for their views on EVs) and used it as a moderator in our multi-level regression model. Using the valid responses from the first wave, a researcher and Anthropic's Claude 3.5 Sonnet coded each set of open-ended responses as either 'anti' (exclusively negative comments), 'pro' (exclusively positive comments), 'mixed' (a blend of positive and negative comments) or 'uncertain' (responses characterized by self-professed ignorance about EVs). There was substantial agreement between the human and AI coder (80.8%). In cases where there was disagreement between the two raters, a third human rater not part of the research team resolved the discrepancies. We did not observe any three-way interaction across time, condition and participants' views on EVs for our confidence measure (all Ps > 0.32). Similarly, we did not find that participants' views on EVs further moderated the interactions between our interventions and time for our any of our dependent variables (all Ps > 0.08). In other words, there was no evidence that the interventions were more or less effective depending on the valence of participants' initial views on EVs.

Ethics
We adhered to ethical guidelines and obtained ethical approval for all studies reported in this paper (Studies 1 and 2: 2024/HE001718; Study 3: 2024/HE001753). All participants provided informed consent.

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

Data availability
Data for all studies are available via OSF at https://osf.io/xrg42/.

Code availability
We have not developed custom code for data collection.

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Author contributions

C.B., S.P., M.J.H., S.M., K.S., B.W. and K.W. designed the studies. C.B., S.P., M.J.H. and S.M. conducted the analyses, and K.S. and K.W. provided support. C.B. and M.J.H. wrote the paper, and S.P., S.M., K.S., B.W. and K.W. provided support in revising the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	We did not develop custom code and did not use any software for data collection.
Data analysis	Data analysis for all studies was conducted in RStudio 4.2.2 and SPSS 29. Fact checking AI responses and open-response coding in Study 3 was conducted with Anthropic's Claude 3.5 Sonnet. Analysis codes are available on request.

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Data for Study 1 and Study 2 were collected via the market research firm Cint. Data for Study 3 were collected via Prolific. In Study 3, we asked participants to interact with ChatGPT4-o Turbo. The data for all studies are available open-access via OSF (https://osf.io/xrg42/).

Human research participants

Policy information about studies involving human research participants and Sex and Gender in Research.

Reporting on sex and gender	We only collected data on self-reported gender (not on sex) in all Studies. For the linear regression models in Study 1 and Study 2, and for the multi-level model in Study 3, we added gender as covariate. In Study 1, we also tested whether effect of gender on each outcome variable was moderated by country. In Study 2, we tested whether our experimental manipulation or EV ownership moderates the effect of gender on misinformation agreement. In Study 3, we tested gender as an additional moderator for the two-way interaction for each dependent variable.
Population characteristics	See 'Research Sample' below.
Recruitment	Participants in Study 1 and Study 2 were recruited via the market research firm Cint. Participants in Study 3 were recruited via Prolific. The self-selection bias that exists is therefore no different than in any other study that uses either market research panels or online survey panels.
Ethics oversight	We adhered to ethical guidelines and obtained ethical approval for all studies reported in this paper (Study 1 and Study 2: 2024/HE001718; Study 3: 2024/HE001753). All participants provided informed consent. Ethical approval was obtained by the ethical review committee of the institution in which the corresponding author is based (blinded for peer-review).

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Study 1 was a quantitative cross-sectional survey conducted across four countries. Study 2 was an experiment collecting quantitative data conducted on-line where U.S. participants were randomly allocated to one of two conditions. Study 3 was a two-wave online survey experiment collecting quantitative and qualitative data. Wave 1 included the random allocation of U.S. participants into three conditions and post-intervention measurement of key dependent variables. The same variables were then measured again in a 10-day follow-up with exploratory moderators.
Research sample	In Study 1, we instructed Cint to obtain 1,000 participants for each of the four countries (Germany, Austria, Australia, USA) representative in terms of age, gender, and education. The quotas for representativeness and the achieved sample composition can be found in Supplemental Table 1. In Study 2, we again instructed Cint to collect 2,000 U.S. participants representative of age, gender, and education using the U.S. quota from Study 1 (see Table S6 for sample demographics). We also aimed to collect half of the data from EV owners and half from non-EV owners. In Study 3, we sampled 1,500 U.S. participants (gender: male = 44.9%, female= 54.3%, other= 0.8%, age: M = 44.11 years, SD = 13.56 years). In Study 1 and Study 3, we only sampled individuals who did not own (and had not ordered) and electric vehicle at the time the studies were conducted. In Study 3, we additionally selected Prolific's screening to invite only participants that had a drivers license valid in the U.S. and that owned a petrol or diesel car.
Sampling strategy	Other than the pre-screeners described above and the quotas for representativeness, we sampled randomly from Cint's research panel (Study 1 and Study 2) and Prolific's panel (Study 3). Although we did not perform a sample size calculation, we chose our sample sizes of 1,000 participants per country in Study 1 to facilitate representativeness and to adhere to existing precedent in published research. We chose our sample size in Study 2 and Study 3 to obtain roughly 500 participants per cell.
Data collection	All studies were designed via Qualtrics and the data collection was conducted on-line. Participants were instructed to participate via their personal computer. As data collection was conducted on-line participants were not in physical proximity with the researcher.
Timing	Study 1: 28th September - 8th October 2024 Study 2: 27th February - 3rd March 2025 Study 3: 31st October - 1st November 2024 (Experiment), 10th - 13th November 2024 (Follow-up)
Data exclusions	No additional participants were excluded in Study 1 and Study 2. In Study 3, we excluded participants who failed an attention check either in the initial experiment (exclusions = 56) or in the follow-up (exclusions = 17). Due to the longitudinal design, we also had to exclude participants who were invited, but did not participate in the follow-up (exclusions = 203).
Non-participation	As stated above, 203 participants dropped out in Study 3 after the initial experiment.

Randomization	Due to a survey design in Study 1, a randomisation was not required. In Study 2 and Study 3, participants were randomly allocated to one of the experimental groups.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☒	☐	Clinical data
☒	☐	Dual use research of concern

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging