Journal of Environmental Psychology 104 (2025) 102620

Contents lists available at ScienceDirect

Journal of Environmental Psychology

journal homepage: www.elsevier.com/locate/jep

Conspiracy belief and opposition to wind farms: A longitudinal study

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ARTICLE INFO

Handling Editor: W. Schultz

Keywords:
Conspiracy mentality
Wind farm opposition
Longitudinal study
Conspiracy theories

ABSTRACT

The extension of wind energy plays a crucial role in achieving global climate goals. However, wind farms often face opposition by local communities. Recent research found cross-sectional evidence that conspiracy belief is an important predictor of wind farm opposition. The current work extends this finding and sheds light on the temporal relationship between these variables. A preregistered, three-wave study among German adults (N = 297) using Random-Intercept Cross-Lagged Panel analyses found support for our hypothesis that an increase in conspiracy mentality (i.e., the general propensity to believe conspiracy theories) predicts more negative attitudes towards wind farms close to one's hometown four months later. We also found evidence for the opposite direction, namely that an increase in negative attitudes predicts higher conspiracy mentality four months later. Thus, conspiracy belief and wind farm opposition seem to mutually reinforce each other. Interventions and preventive measures should aim to break this vicious cycle that otherwise might curb the progress of the energy transition.

1. Introduction

The transition towards wind energy is a cornerstone of climate change mitigation (IPCC, 2011). But even if governments set ambitious goals to promote wind energy, realizing these goals can be thwarted by community resistance (Enevoldsen & Sovacool, 2016; Reusswig et al., 2016). Research suggests that belief in conspiracy theories and misinformation plays an important role in predicting opposition to wind farms (Winter et al., 2022, 2024). Due to the cross-sectional nature of these studies, however, it remains unclear whether changes in conspiracy belief temporally precede wind farm opposition. Examining the temporal order of this relationship is informative regarding the causes and consequences of wind farm opposition and relevant to designing successful interventions.

1.1. *The role of conspiracy belief in predicting opposition to wind farms*

Acceptance of wind farm developments is higher when people trust the relevant actors (Hall et al., 2013; Liu et al., 2020a) and when perceived procedural fairness of a project is high (Enevoldsen & Sovacool, 2016; Hall et al., 2013; Liu et al., 2020b). In addition, anticipated economic effects, general attitudes towards the energy transition, perceived impacts on humans and nature, and social norms are relevant predictors of residents' acceptance of wind farms in their community (Hübner et al., 2023). In addition to these context-specific predictors, people's general worldviews play an important role in predicting wind farm opposition (Winter et al., 2022, 2024). Most relevant to the current paper, the propensity to believe conspiracy theories (i.e., a conspiracist worldview) is strongly associated with wind farm opposition.

Conspiracy theories are "explanations for important events that involve secret plots by powerful and malevolent groups" (Douglas et al., 2017, p.538). The term conspiracy belief denotes either belief in *specific conspiracy theories* (e.g., that negative health effects of wind farms are being covered up) or the propensity to generally see conspiracies determining the course of societal events (i.e., a so-called *conspiracy mentality*; Imhoff & Bruder, 2014). Conspiracy theories about wind farms exist and are spread by influential public figures (Bump, 2019). Surveys in Australia, the United Kingdom and the United States reveal

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https://doi.org/10.1016/j.jenvp.2025.102620
Received 17 January 2025; Received in revised form 31 March 2025; Accepted 8 May 2025
Available online 9 May 2025

over a quarter of respondents agreed with wind-farm related conspiracy theories and misinformation (Winter et al., 2024). Believing conspiracy theories can have detrimental consequences for the support of climate-friendly policy in general (Biddlestone et al., 2022; Spampatti, Hahnel, et al., 2024), and wind-energy policy in particular (Winter et al., 2024).

The link between believing in *specific* conspiracy theories about wind farms and wind farm opposition is quite obvious. If someone believes, for instance, that profit motives lead government and industry to exaggerate benefits and conceal dangers of wind farms, this belief should lower acceptance. For the *general* conspiracy mentality this link is less obvious but still plausible for several reasons. First, conspiracy mentality is assumed to be a relatively stable personal characteristic that predisposes people to believe specific conspiracy theories in a concrete situation (Imhoff et al., 2022). Second, as outlined above, wind farm acceptance is trust sensitive, and conspiracy mentality is associated with lower trust, particularly in political and scientific authorities (Imhoff et al., 2018; Imhoff & Bruder, 2014; Pummerer et al., 2022) – key players in promoting wind energy extension. In line with these arguments, recent studies show that both conspiracy mentality and belief in specific conspiracy theories correlate with wind farm opposition – much more strongly than age, gender, education, or political orientation (Winter et al., 2022). Moreover, conspiracy mentality outperformed other ideological and epistemological variables in predicting agreement with misinformation and conspiracy theories about wind farms (Winter et al., 2024).

Based on the above reasoning it appears plausible that conspiracy mentality temporally precedes wind farm opposition. However, it could also be that wind farm opposition predicts conspiracy belief at a later time. People who oppose wind farms might engage in confirmatory information searches, thereby being introduced to conspiracy theories about wind farms and a broader set of concerns about the role of government and industry. Such conspiracy theories could then be used to rationalize negative attitudes towards wind farms and feed broader skepticism against government and industry, resulting in higher conspiracy mentality (see also Nera, 2024). Such reverse effects on conspiracy beliefs (including conspiracy mentality) have been found for health-protective behaviors during the COVID-19 pandemic (van Prooijen & Böhm, 2023; van Prooijen et al., 2023).

To provide insights into the temporal relationship of conspiracy belief and wind farm opposition, we conducted a three-wave longitudinal study. We preregistered the hypothesis that increases in conspiracy mentality predict more opposition to wind farms across time. The study was carried out in accordance with ethical guidelines of the American Psychological Association and the German Research Foundation and received ethics approval by the local ethics committee of the Leibniz-Institut für Wissensmedien (Tübingen, Germany; LEK 2019/001). https://aspredicted.org/qy8z-f9jj.pdf, https://aspredicted.org/83gf-jkv8.pdf). Data and code are available at PsychArchives (data: https://doi.org/10.23668/psycharchives.16349, code: https://doi.org/10.23668/psycharchives.16350).

2. Method

2.1. Design and participants

This study used a longitudinal design with three waves approximately four months apart (T1: November/December 2022; T2: March/April 2023, T3: August 2023). Sample size considerations relied on the original study plan including two waves only. T3 was collected in order to run more appropriate analyses (see preregistrations: https://aspredicted.org/qy8z-f9jj.pdf, https://aspredicted.org/83gf-jkv8.pdf). We aimed for a sample size of $N = 400$ at T2 to be able to identify a small effect ($f^2 = .02$) in a multiple regression analysis testing R^2-change by one of two predictors (power: .80; $\alpha = .05$). Accounting for 40 % attrition, we aimed for $N = 670$ at T1. Participants were German adults recruited via Clickworker who received 5 Euros for participation in all waves. At T1, our survey was completed by 661 participants of which 637 fulfilled preregistered inclusion criteria and were invited for participation at T2 (partly overlapping exclusions: 12 failing both attention check items, 14 for completing T1 twice, 1 who did not speak German fluently). At T2, 424 participants completed our survey of which seven were excluded based on our preregistration (1 failing both attention check items, 6 for completing the T2 survey twice). One additional participant could not be matched to T1 data. At T3, 310 participants completed our survey. We excluded 13 participants based on preregistered criteria (4 for completing the T3 survey twice, 9 statistical outliers). Thus, a final sample of $N = 297$ (age at T3: range 19–75, $M = 41.79$ years, $SD = 12.31$; 114 female, 183 male) was included in longitudinal analyses. We observed 35 % attrition from T1 to T2 and 29 % from T2 to T3. There was no systematic drop-out with regard to the main variables (attrition analyses are presented in the Supplement). Half the sample (i.e., 49 %) had a university degree and 82.6 % were employed at T1.

2.2. Procedure and measures

Participants were recruited to complete an online questionnaire for a study on “energy transition in Germany and political decisions”. At all waves, we included the following measures in the indicated order (mostly adopted from Winter et al., 2022) after giving informed consent. First, we measured *general attitude towards wind farms* with four adjective pairs completing the statement “In general, I find the construction of wind farms …” (e.g., from 1 = *bad* to 7 = *good*; αs = .96-.97; for all items, see Supplement). The same items were then used to capture *attitude towards wind farms close to one’s hometown* completing the statement “In the area where I live, I find the construction of wind farms …” (all αs = .97). Then, we measured *belief in a specific conspiracy theory* about the extension of wind farms in Germany with five items (e.g., “The government withholds important information that speaks against the extension of wind energy”; from 1 = *do not agree at all* to 7 = *fully agree*; αs = .89-.91). Last, we measured *conspiracy mentality* with 12 items (e.g., “There are many very important things happening in the world about which the public is not informed”; from 1 = *do not agree at all* to 7 = *fully agree*; αs = .94-.95; Imhoff & Bruder, 2014). At T2 and T3, we measured participants’ *willingness to vote in favor of constructing a wind farm* close to their hometown in a fictitious referendum with one item (from 0 % = *I would definitely vote with no* to 100 % = *I would definitely vote with yes*) at the outset of the survey. Note that only *conspiracy mentality* and the *attitude towards wind farms close to one’s hometown* were used in the preregistered main analysis, while the other measures were included for exploratory purposes. Descriptive statistics and bivariate correlations are presented in Table 1.

2.3. Analytic strategy

As preregistered, we analyzed the longitudinal relationships between conspiracy mentality and attitude towards wind farms close to one’s hometown using random-intercept cross-lagged panel models (RI-CLPMs; Hamaker et al., 2015; see Fig. 1). In the RI-CLPM, measurements at any time point are predicted by all measurements at the previous time point and by a latent intercept (also called “random intercept”; variables RI-Att and RI_CM in Fig. 1). The latent intercept varies between participants. The variance of the latent intercept (var_RI-Att and var_RI_CM in Fig. 1) represents the between-person difference in the stable part of each measurement. The latent intercept can, for example, model a stable trait. The regression parameters from one time point to the next model the dependency between states, that is, the short-term deviation from the intercept between two time points. Regression parameters from a variable to itself (i.e., the auto-regressive effect; see, for example, *a11* in Fig. 1) at the next time point provide an indication of the stability of a state over time. The regression parameter between different concepts

Table 1
Means, standard deviations and bivariate correlations (only including the final sample; $N = 297$).

	Measure	T1				T2					T3				
		CM	CB	ATC	ATG	CM	CB	ATC	ATG	Vote	CM	CB	ATC	ATG	Vote
	M (*SD*)	3.72 (1.40)	3.22 (1.48)	5.24 (1.72)	5.87 (1.35)	3.58 (1.45)	3.10 (1.53)	5.11 (1.78)	5.74 (1.57)	72.51 (27.51)	3.57 (1.48)	3.20 (1.56)	5.06 (1.78)	5.70 (1.58)	71.20 (29.34)
T1	CM	–	.71	−.39	−.37	.86	.66	−.41	−.39	−.41	.88	.71	−.44	−.38	−.42
	CB		–	−.56	−.52	.68	.76	−.58	−.55	−.58	.69	.78	−.60	−.58	−.58
	ATC			–	.79	−.41	−.56	.81	.72	.73	−.40	−.53	.82	.73	.75
	ATG				–	−.37	−.53	.68	.77	.63	−.37	−.51	.70	.76	.68
T2	CM					–	.78	−.45	−.41	−.45	.89	.75	−.49	−.42	−.44
	CB						–	−.62	−.59	−.62	.70	.80	−.63	−.57	−.60
	ATC							–	.79	.84	−.47	−.61	.86	.74	.77
	ATG								–	.76	−.44	−.58	.77	.82	.77
	Vote									–	−.45	−.59	.78	.73	.82
T3	CM										–	.82	−.49	−.46	−.45
	CB											–	−.61	−.61	−.59
	ATC												–	.83	.85
	ATG													–	.82
	Vote														–

Note. CM = Conspiracy mentality, CB = Belief in a specific conspiracy theory about wind farms, ATC = Attitude towards wind farms close to one's hometown, ATG = Attitude towards wind farms in general, Vote = Willingness to vote in favor of wind farm in a referendum. All correlations are significant at $p < .001$.

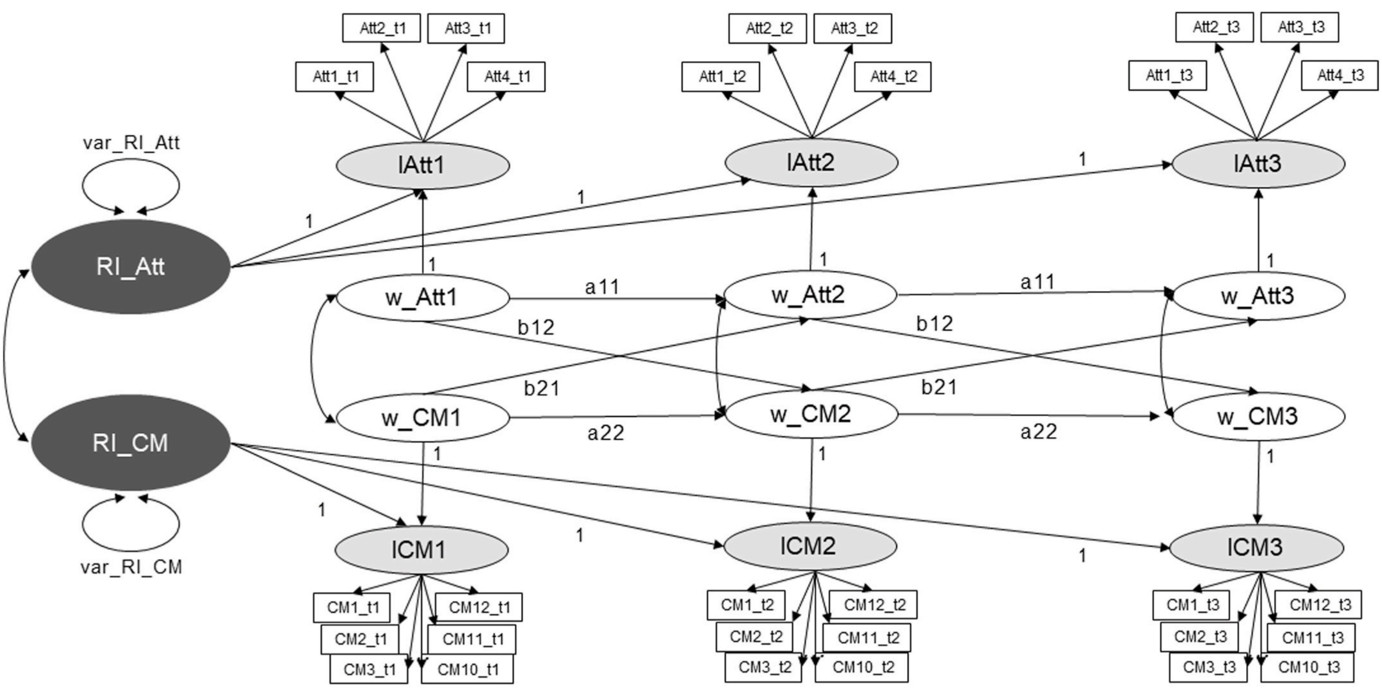

Fig. 1. Random-Intercept Cross-Lagged Panel Model. In the statistical model, factor loadings were additionally constrained to be equal over time and within-item co-variance of residuals over time were modelled, neither of which are depicted here.

across time (i.e., the cross-lagged effect; see, for example, *b12* in Fig. 1) are estimates of the relationship of the variations of one concept (beyond the stable part captured by the intercept) with the variations of another concept at a later point in time – providing an indication of the impact of the former concept on the latter.

3. Results

3.1. Preliminary analyses

Only participants who completed data at all measurement timepoints were included ($N = 297$). All analyses were conducted in R (R Core Team, 2020) using *lavaan* (Rosseel, 2012) with maximum likelihood estimation (see also Liekefett et al., 2023). There was no reason to expect different factor loadings between time points. To investigate whether measurement invariance was contradicted by the data, we first performed a factor analysis, testing a model that included all measured variables and their latent concepts (i.e., lAtt1, lAtt2, lAtt3, lCM1, lCM2, lCM3), where all factor loadings of the measured items were estimated freely, model fit: χ^2 (1065) = 3204.78, $p < .001$, RMSEA = .08, CFI = .88, TLI = .87, SRMR = 06), and compared it to a model with factor loadings constrained to be equal across time, model fit: χ^2 (1093) = 3235.26, $p < .001$, RMSEA = .08, CFI = .87, TLI = .87, SRMR = .07. The chi-square difference test revealed no significant difference between the models, $\Delta\chi^2$ (28) = 30.49, $p = .340$. We further tested whether model fit improves when allowing co-variance of item-specific residuals. This was the case, $\Delta\chi^2$ (20) = 1307.60, $p < .001$, resulting in a model with good fit, χ^2 (1045) = 1897.21, $p < .001$, RMSEA = .05, CFI = .95, TLI = .95, SRMR = .07. Thus, the analyses were performed with factor loadings constrained to be equal over time, allowing the co-variance of item-specific residuals.

In the following, we report the unstandardized estimates (*a11, a22, b12, b12*) of the effects together with the averaged standardized coefficients (α11, α22, β12, β21). We explored the structure of residual variances and covariances of the within constructs (i.e., w_CM1-3, w_Att1-3) in the complete random intercept cross-lagged panel model, noting changes in residual variances and covariances between T2 and T3, which was also confirmed by the model with unconstrained (co) variances receiving a better model fit, $\Delta\chi^2$ (3) = 18.18, $p < .001$. Thus, we did not constrain variances and covariances to be equal between T2 and T3 in any of the models reported below (Orth et al., 2021). However, for full transparency, we report analyses with constrained (co)variances in the Supplement. This did not change the interpretation of the main analysis.

3.2. *Conspiracy mentality and attitudes towards wind farms*

The specified model had good model fit, χ^2 (1050) = 1902.83, $p <$ .001, RMSEA = .05, CFI = .95, TLI = .95, SRMR = .07. Both random intercepts of the measures of attitude towards windfarms in one's community and conspiracy mentality were significantly correlated, $r = -.44$, 95 % CI [-.55; −.34]. There were also cross-lagged effects (i.e., β12 and β21 in Fig. 2) of both concepts on the other variable. An increase in conspiracy mentality (compared to the random intercept) subsequently predicted a more negative attitude towards wind farms, $b21 = -.47$, SE = .13, 95 % CI [−.72, −.22], β21 = −.28, $p < .001$. Likewise, an increase in the attitude towards wind farms (compared to the random intercept) predicted less conspiracy mentality at the later time point, $b12 = -.25$, SE = .06, 95 % CI [−.37, −.12], β12 = −.34, $p < .001$. According to a chi-square difference test, the cross-lagged effects significantly differed, $\Delta\chi^2$ (1) = 4.92, $p = .027$. There was an autoregressive effect (i.e., α11 and α22 in Fig. 2) of conspiracy mentality, $a22 = .25$, $SE = .12$, 95 % CI [.02, .48], α22 = .21, $p = .032$, as well as attitudes, $a11 = .30$, $SE = .11$, 95 % CI [.08, .52], α11 = .29, $p = .007$. We obtained very similar results for the longitudinal relationship between specific conspiracy beliefs and attitudes towards wind farms (see Supplement).

4. Discussion

This study aimed to gain a deeper understanding of the role conspiracy belief plays in shaping opposition to wind farms. Building on prior cross-sectional research, we examined the temporal relationship between conspiracy mentality and wind farm opposition. As hypothesized, increases in conspiracy mentality predicted more opposition to wind farms over time. This adds to research demonstrating longitudinal effects of conspiracy belief on societally relevant outcomes (e.g., Bierwiaczonek et al., 2020; Pummerer et al., 2022; van Prooijen et al., 2023). We also found evidence for the reverse effect (which was actually larger), namely that increases in wind farm opposition predicted higher conspiracy mentality. This bidirectional pattern resembles previous work on the relationship between conspiracy belief and vaccine hesitancy (van Prooijen & Böhm, 2023). These longitudinal analyses provide important insights into the relationship between conspiracy belief and wind farm opposition. In addition, they have broader implications for the theorizing on conspiracy belief.

Although generally conceived as a relatively stable characteristic (Imhoff et al., 2022; but see Nera, 2024), the current data and previous longitudinal work (Liekefett et al., 2023; van Prooijen & Böhm, 2023) suggests that conspiracy mentality can be subject to situational variation. While specific conspiracy theories might be adopted as post-hoc rationalization of negative attitudes (van Prooijen et al., 2023), this reasoning is hard to apply to the general conspiracy mentality. However, (selective) exposure to specific conspiracy theories and misinformation might play a crucial role as a binding element potentially explaining the bidirectional effect between conspiracy mentality and wind farm opposition. Both individuals with a high conspiracy mentality and those who oppose wind farms close to their hometown might be more receptive to conspiracy theories and misinformation about wind farms (see also Winter et al., 2024). Exposure to this information might drive wind farm opposition among those with high conspiracy mentality. Conversely, wind farm opponents might search for information backing up their anti-wind farm sentiments, thereby being exposed to broader suspicions about the role of government and industry, thus contributing to a broader conspiracy mentality. Future research should focus on the conditions and mechanisms that explain the bidirectional effect found here.

Several aspects potentially limit the generalizability and reliability of the findings. This includes study design (i.e., relatively short time intervals, only self-report measures), the sample (i.e., only Germans, relatively small N in the final analysis) and the fact that energy policy was heavily discussed in Germany at the time the study was conducted due to the Russian invasion in Ukraine and its consequences on energy supply. Thus, the results should be replicated in other contexts with potentially larger and more diverse samples. In addition, it seems worthwhile to examine whether dispositional distrust is a common cause underlying wind farm opposition and conspiracy mentality (see also Thielmann & Hilbig, 2023).

A pessimistic interpretation of the current findings would be that it

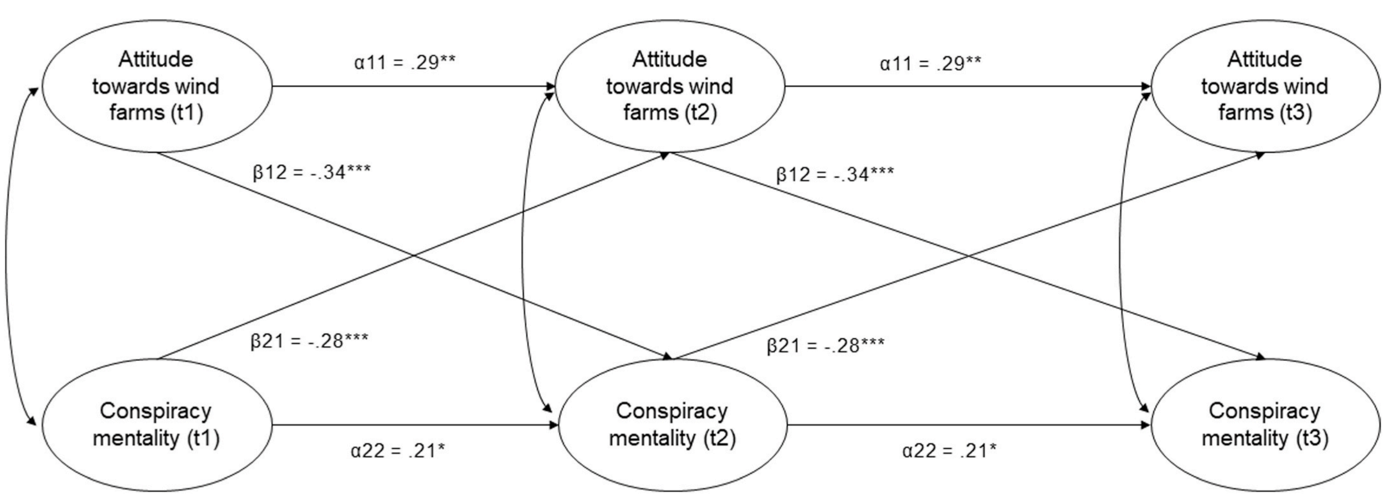

Fig. 2. Averaged standardized coefficients for auto-regressive (α11, α22) and cross-lagged effects (β12, β21) from a Random-Intercept Cross-Lagged Panel Model (N = 297). *$p < .05$, **$p < .01$, ***$p < .001$.

implies a vicious cycle in which conspiracy belief and wind farm opposition mutually reinforce each other. More optimistically, however, they might inform ways to break this cycle. Tailoring information provision and increasing resilience against conspiracy theories about wind farms might be useful approaches among both individuals high in conspiracy mentality and those with negative attitudes towards a local wind farm. Previous work showed that informing people about the benefits of wind farms increases the likelihood of accepting them, even among those high in conspiracy mentality (Winter et al., 2022). Besides providing information, building up trust in the responsible parties and public participation in the planning process could play an important role (Liu et al., 2020a, Liu et al., 2020a; Spampatti, Brosch, et al., 2024). If people have no reason to assume that there are secret arrangements between politics and industry, there might be less breeding ground for conspiracy theories.

CRediT authorship contribution statement

Kevin Winter: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lotte Pummerer:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Timo von Oertzen:** Writing – review & editing, Validation, Formal analysis. **Matthew J. Hornsey:** Writing – review & editing, Funding acquisition, Conceptualization. **Kai Sassenberg:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Funding

This research was funded by a grant of the Deutsche Forschungsgemeinschaft (DFG, #SA800/17–1) awarded to Kai Sassenberg and Matthew J. Hornsey.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvp.2025.102620.

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