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Divergent effects of economic and behavioural policy coupling on electric vehicle adoption at individual and system levels

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Abstract

Policy mixes are key to accelerate low-carbon transitions, yet, how combined policies impact electric vehicle (EV) adoption decisions and scale to system-level change remains unclear. We bridge these perspectives by integrating choice experiments, attention process tracing, and agent-based modelling of technology diffusion to examine how coupling a carbon tax with an information intervention affects attention, EV adoption, their diffusion, and public support for EV policies. Across four countries (Mexico, South Africa, USA, UK; N=1,589), the policies competed for attention but had additive effects on stated adoption choices. When embedded in diffusion simulations, the behavioural responses translated into super-additive outcomes, increasing EV adoption by up to nine percentage points compared with single policies. Synergies peaked when technology was improving but not yet self-sustaining. Policy coupling also increased public support for policies alongside growing diffusion. Our findings show how integrating actual decision preferences into diffusion models can reveal nonlinear pathways through which policies shape low-carbon transitions.

Keywords: Electric vehicles, Behaviour change interventions, Agent-based modelling, Policy mix, Policy support.

The electrification of transport has evolved from a technological challenge into a behavioural one, requiring policies that motivate consumers to adopt electric vehicles (EVs)¹. Governments are turning to policy mixes^{2,3} that combine, for example, economic instruments like carbon taxes with information-based measures like climate impact labels. Combined policies are widely assumed to be more effective than single measures because they target different decision determinants^{1,4-6}. However, empirical evidence remains mixed. Studies focusing on individual behaviour often find (sub-)additive effects^{7,8}, where combined impact equals to or falls below the sum of the parts. By contrast, system-level analyses find both synergistic³ and antagonistic policy interactions⁹. These diverging effects of policy mixes across levels point to a missing link between individual decisions and aggregate system outcomes. The case of EV adoption illustrates the importance of this link clearly: countless individual purchase decisions accumulate and interact to determine the speed and scale of transport electrification.

Bridging this gap requires starting from a clearer understanding of how policy mixes are cognitively processed and translated into individual decisions. Car purchases involve weighing financial, practical, and environmental considerations. Because people cannot process all available information^{10,11}, they focus on some aspects more than others. This selectivity of attention shapes which factors guide decisions^{10,12,13}. Policy instruments influence behaviour partly by directing attention toward particular attributes. Economic interventions such as carbon taxes provide direct financial incentives by changing the relative operating costs of EVs compared to conventional vehicles, activating financial motives when salient. Information interventions, like climate labels, make environmental consequences tangible by translating complex data (e.g., CO₂ emissions) into intuitive formats (e.g., impact ratings), activating environmental motives^{14,15}. Each type of intervention therefore guides attention and choice through different motivational pathways. When both are implemented together, more information does not automatically lead to better decisions. Because attention is limited, interventions might compete to capture it, and one can overshadow the other^{10,11}. The behavioural outcome of a policy mix thus depends on the incentives it provides as well as on how people allocate attention between policy signals¹⁶.

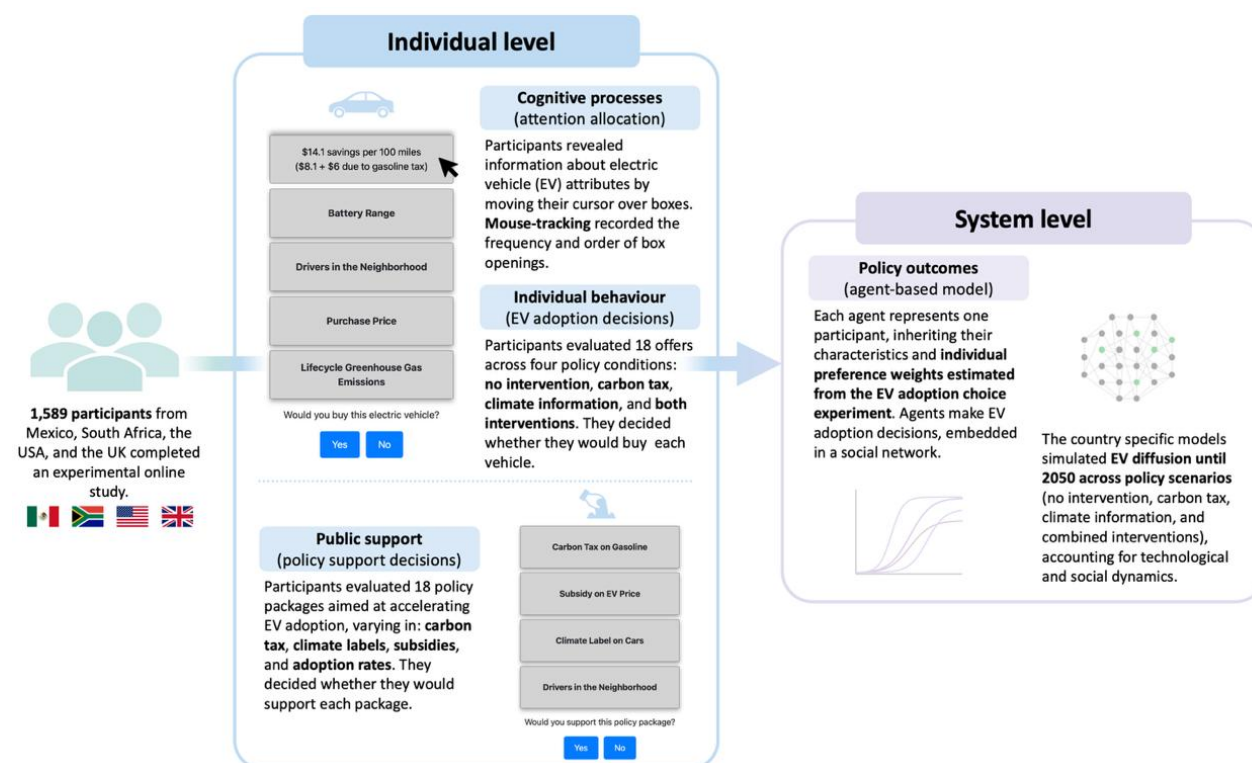
The immediate effectiveness of policy interventions manifests in individual behaviour change, yet their cumulative impact unfolds over time as technology evolves and people influence one another. Experimental studies can identify individual behavioural responses but are limited in capturing long-term effects¹⁷⁻¹⁹. In reality, EV adoption decisions occur within changing social and technological environments^{19,20}, where policy effects might be amplified or dampened by social dynamics and technological change^{21,22}. For example, combined policies' impact on EV uptake can be reinforced by peer effects²³, or stalled if social norms are not yet changing or supportive infrastructure is lacking²⁴. Conversely, system models that capture such dynamics often oversimplify human behaviour, assuming rationality and uniformity, overlooking how behavioural heterogeneity shapes technology diffusion^{25,26}. Integrating empirical data from behavioural experiments into agent-based models (ABM) can overcome both limitations and enables the simulation of long-term EV diffusion grounded in actual human decision-making and accounting for dynamic structural conditions^{18,27}.

When people experience the long-term impacts of implemented policies, they may be more likely to endorse those policies^{28,29}. Policy effectiveness and public support are closely connected: perceived effectiveness can foster support²⁸, and at the same time, support is often needed for measures to be implemented in the first place. France's "yellow vest" protests³⁰ or Australia's reversal of carbon pricing³¹ show how public resistance can derail policy efforts. When combined with more acceptable information interventions, feasibility and legitimacy of unpopular carbon taxes could be strengthened^{32,33}. However, policy coupling does not always increase public support. Interventions like nudges have been found to reduce support for carbon taxes when they are seen as cost-effective alternatives, rather than as complementing measures³⁴. The mutual dependency of policy effectiveness and public support demands an analysis of support alongside effectiveness.

Here, we investigate the effects of a carbon tax and a climate information intervention by combining an online experiment ($N=1,589$) with an ABM of EV adoption (Fig. 1). We focus on tax and information because they are among the most discussed demand-side climate policies^{35,36} and reflect distinct mechanisms of behavioural influence: economic incentives and informational cues. To capture the complexity of real-world policy effects, we examine 1) cognitive mechanisms (attention allocation to EV attributes), 2) individual behaviour (EV adoption), 3) societal outcomes (system-level EV diffusion), and 4) public policy support, across four diverse countries (Mexico, South Africa, USA, and UK), that differ in their economic and policy contexts.

We address four research objectives. First, we examine how carbon tax and climate information influence attention allocation during the decision process, including whether they guide attention toward financial and environmental impact information (H1-H4). Second, we test their effects on hypothetical EV adoption decisions (H5-H8). Third, we integrate the decision data into an ABM to simulate long-term policy effects, accounting for contextual dynamics. Fourth, we assess public policy support (H9-13) and simulate support alongside EV diffusion. Recognizing that intervention effects vary between individuals^{37,38}, we account for the influence of political orientation, an important predictor of responses to climate policy^{28,39}. Hypotheses and analyses were preregistered unless noted otherwise (<https://osf.io/hrzyf>) and are detailed in Methods.

Figure 1: Overview of the study design integrating individual decisions and system-level electric vehicle diffusion simulations



Note. The figure illustrates the study's integrative design, linking individual-level experimental data with agent-based modelling to simulate long-term electric vehicle diffusion across policy scenarios.

Assessing the effects of policy coupling in four countries

We assessed hypothetical EV adoption decisions using an online choice experiment. Participants were sequentially presented 18 EV offers varying in price, battery range, operating cost savings, lifetime greenhouse gas (GHG) emissions, and neighbourhood adoption rates. For each offer, participants decided whether or not they would purchase the EV. The offers were repeated within-participants across four conditions (tax only, information intervention only, coupled interventions, no intervention) allowing for a test of individual and joint policy effects. To manipulate tax, operating cost savings of an EV (vs. conventional car) were increased by a low (\$60 / metric ton of CO₂ [tCO₂], resulting in additional \$3 savings / 100 miles) or high (\$240/tCO₂, additional \$6 savings) tax on gasoline. For the information intervention, we translated lifetime GHG emissions of an EV from metric tons to percentage savings relative to a conventional car, similar to information provided in climate impact labels. To measure attention allocation, we used a MouselabWEB design⁴⁰. During the choice task, attribute information was hidden behind boxes and revealed via mouse hover. Because opening a box requires an intentional action, this measure provides process-level insights into which information participants attended to, serving as a proxy for information processing. Specifically, we used the likelihood of opening savings or emissions first, and the proportion of box openings for each

attribute within a trial as indicators of visual attention. To analyse system-level policy effects, we integrated participants' EV choice preferences derived from the choice experiment into an ABM, in which each participant was represented as an agent. This allowed us to simulate EV diffusion in the four countries from 2024 to 2050 under different policy scenarios, taking into account technological progress (increasing battery ranges, decreasing prices and GHG emissions), social interactions (observing others' adoption of EVs and opinion sharing), and individual decision heterogeneity. To assess policy support, participants evaluated 18 policy packages that varied in carbon taxes (no/low/high tax), manufacturer climate labels (providing climate impact information; no/voluntary/mandatory label), subsidies, and social dynamics (presenting the share of newly registered EVs). We integrated the participant-specific policy evaluations into the ABM to simulate how policy support evolves over time.

Antagonistic policy effects on attention allocation

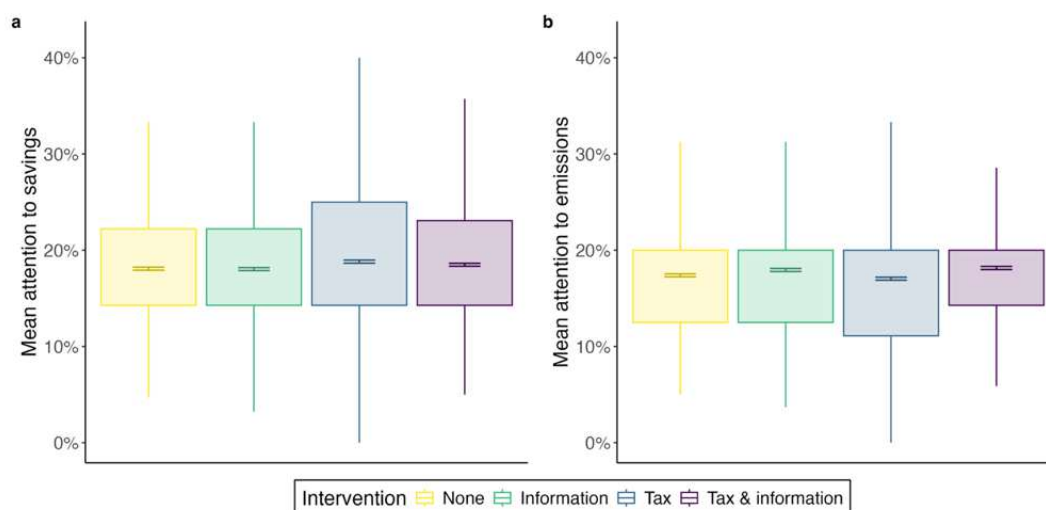
Attention toward financial savings and GHG emissions was significantly related to EV choice (Supplementary Table S1), showing that tax and information influenced decisions partly by directing attention to specific EV information. In particular, the presence of a carbon tax increased attention to financial savings compared to conditions without tax (frequency: $b=0.61$, 95% CI [0.47, 0.74], $p<0.001$; Fig. 2a; view first likelihood: $OR=1.05$, 95% CI [1.02, 1.08], $p=0.003$; evidence for H1). The information intervention increased attention to GHG emissions compared to control (frequency: $b=0.84$, 95% CI [0.70, 0.98], $p<0.001$; Fig. 2b; view first likelihood: $OR=1.06$, 95% CI [1.03, 1.09], $p<0.001$; evidence for H2).

When interventions were combined, tax effects on attention toward financial savings were reduced, indicating an attentional trade-off whereby climate information redirects attention away from tax-related information (frequency: $b=-0.30$, 95% CI [-0.57, -0.03], $p=0.030$; evidence for H3). There was no interaction between tax and climate information on the likelihood of viewing savings first ($OR=0.95$, 95% CI [0.89, 1.01], $p=0.081$).

In contrast, climate information effects on attention towards GHG emission were not reduced by a carbon tax (frequency: $b=0.54$, 95% CI [0.27, 0.81], $p<0.001$; evidence against H4), while a tax alone, in the absence of the information intervention, redirected attention from GHG emissions ($b=-0.33$, 95% CI [-0.537, -0.14], $p=0.001$). Combining tax and climate information increased the likelihood that GHG emissions were viewed first ($OR=1.13$, 95% CI [1.06, 1.21], $p<0.001$) compared to the information intervention alone. The effects on attention were small in magnitude which is consistent with process-tracing research showing that attention shifts are often subtle but systematic^{14,41,42}.

We then tested whether political orientation influenced attention allocation, but observed no significant interaction with the interventions (Supplementary Fig. S1). Information intervention effects on attention to GHG emissions varied significantly by country ($\chi^2(3)=16.86$, $p<0.001$), with the strongest effect in the UK ($b=1.38$, $p<0.001$), followed by South Africa ($b=1.16$, $p<0.001$), the USA ($b=0.73$, $p<0.001$), and no significant effect in Mexico ($b=0.09$, $p=0.53$). No interaction between country and carbon tax was found (Supplementary Table S2).

Figure 2: Attention allocation as a function of interventions



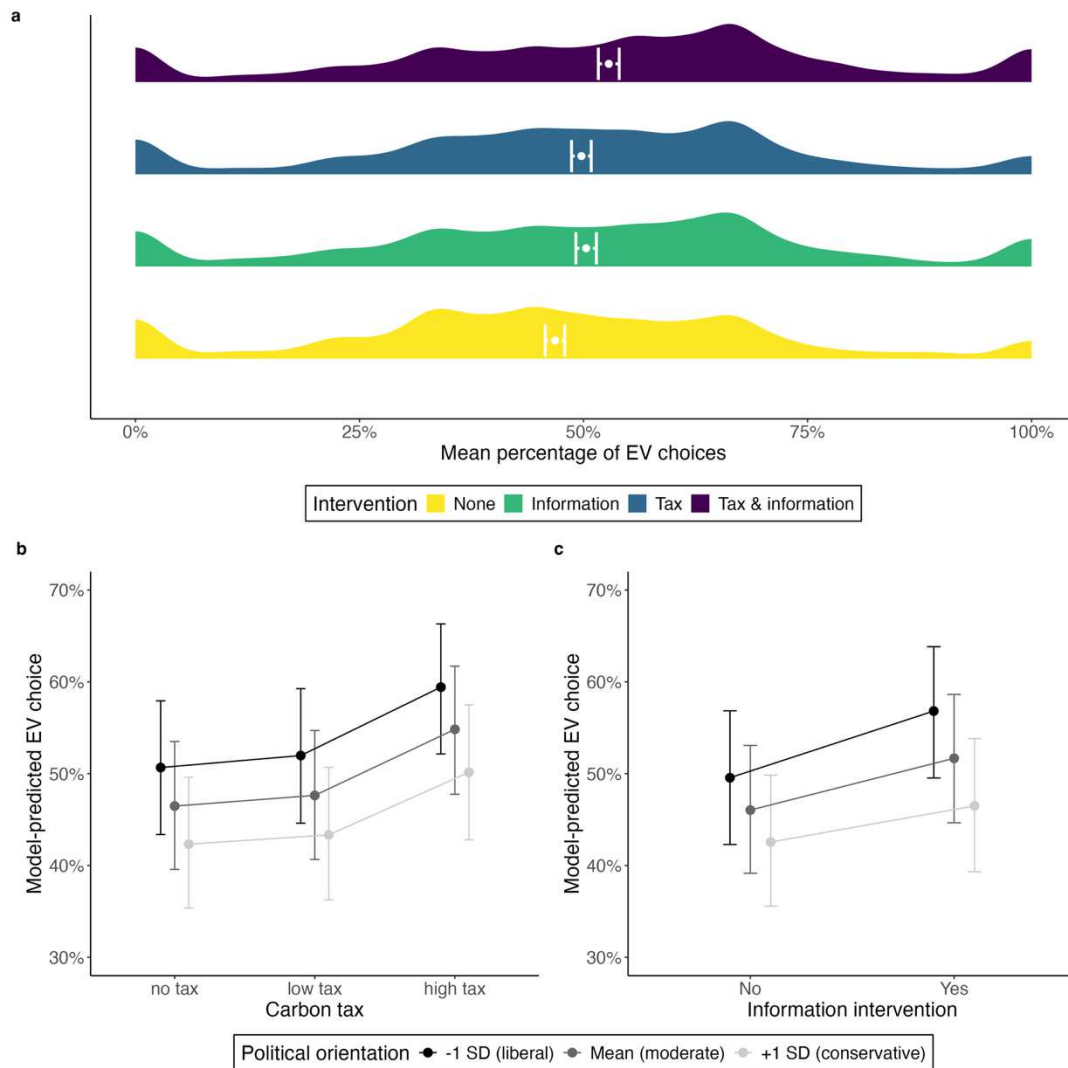
Note. **a** Boxplot showing the mean percentage of attention allocated to savings information per choice trial across conditions. Boxes represent the interquartile range (middle 50% of data), and whiskers extend to 1.5x the interquartile range from the box. More than 95% of individual observations fall within the range displayed and are represented in the figure. **b** As in **a**, but showing the mean percentage of attention allocated to emissions information per choice trial across conditions, with more than 95% of observations within the displayed range. $N=1,589$ participants, $N=110,978$ observations. Error bars represent 95% confidence intervals based on observed values.

Additive effects of policy coupling on individual EV decisions

We next examined effects of the carbon tax and information intervention on hypothetical EV adoption choices. A high carbon tax significantly increased EV choice ($OR=1.40$, 95% CI [1.34, 1.46], $p<0.001$; evidence for H5; smaller effect for low tax: $OR=1.05$, 95% CI [1.00, 1.09], $p=0.029$). The information intervention also increased EV choice ($OR=1.26$, 95% CI [1.22, 1.29], $p<0.001$; evidence for H6). As shown in Fig. 3a, effects were additive when interventions were combined, with no significant interaction (low tax: $OR=0.99$, 95% CI [0.92, 1.06], $p=0.753$; high tax: $OR=0.95$, 95% CI [0.89, 1.03], $p=0.225$). Effects of additional EV attributes (price/range/savings/social norm) and covariates (e.g., income) are reported in Supplementary Table S3.

More conservative participants were overall less likely to choose an EV ($OR=0.84$, 95% CI [0.78, 0.91], $p<0.001$; evidence for H7a) but the effectiveness of the carbon tax did not vary by political orientation (low tax: $OR=0.99$, 95% CI [0.96, 1.03], $p=0.766$; high tax: $OR=0.98$, 95% CI [0.94, 1.02], $p=0.306$; Fig. 3b; evidence against H7b). Exploratory analyses showed that the information intervention was more effective among liberals ($-1SD$; slope: $b=0.29$, 95% CI [0.25, 0.33], $p<0.001$) than conservatives ($+1SD$; slope: $b=0.16$, 95% CI [0.12, 0.20], $p<0.001$; interaction information-political orientation: $OR=0.94$, 95% CI [0.91, 0.96], $p<0.001$; Fig. 3c).

Figure 3: EV decisions as a function of interventions and political orientation.

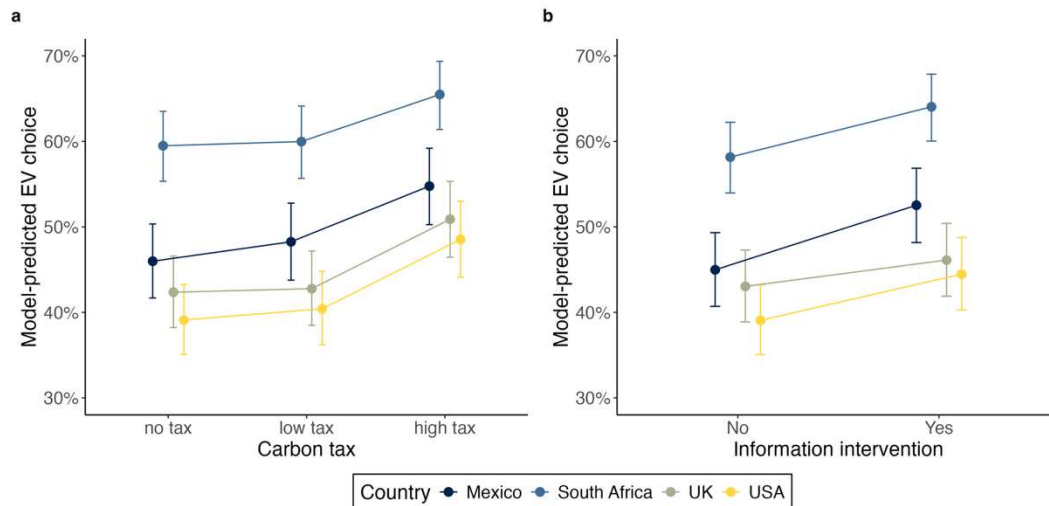


Note. **a** Half-violin plots showing the distribution of participants' mean EV choice rates for each intervention condition. The width of each shape reflects how frequently a given mean choice rate occurred among participants. White points indicate means; error bars show 95% confidence intervals based on observed values. **b** Predicted probability of EV choice as a function of the carbon tax and political orientation estimated from mixed-effects logistic regression models. No significant interaction was found between political orientation and tax. Error bars represent 95% confidence intervals based on predicted probabilities, accounting for repeated measures and between-country variation. **c** Predicted probability of EV choice as a function of the climate information intervention and political orientation estimated from mixed-effects logistic regression models. The significant interaction indicates that the information intervention had a stronger effect on EV choice for more liberal participants. Error bars represent 95% confidence intervals based on predicted probabilities, accounting for repeated measures and between-country variation. Group sizes political orientation (for visualisation): $n_{liberal}=310$; $n_{conservative}=274$, $n_{moderate}=1,005$. $N=1,589$ participants, $N=114,408$ observations.

We observed national heterogeneity in EV choices ($\chi^2(3)=52.09$, $p<0.001$; evidence for H8a). Adoption likelihood was highest in South Africa, followed by Mexico, and lowest in the UK and USA.

The carbon tax had similar effects across countries ($\chi^2(6)=8.34$, $p=0.214$; Fig. 4a), while the effect of the information intervention was moderated by national context ($\chi^2(3)=17.46$, $p<0.001$; partial support for H8b; Fig. 4b). Country-specific results are reported in Supplementary Table S4-S5.

Figure 4: EV decisions as a function of interventions and country.



Note. **a** Predicted probability of EV choice as a function of the carbon tax and country of residence estimated from mixed-effects logistic regression models. **b** Predicted probability of EV choice as a function of the information intervention and country of residence estimated from mixed-effects logistic regression models. Error bars represent 95% confidence intervals based on predicted probabilities, accounting for repeated measures. $N=1,589$ participants, $N=114,408$ observations.

Synergistic system-level effects of policy coupling on EV diffusion

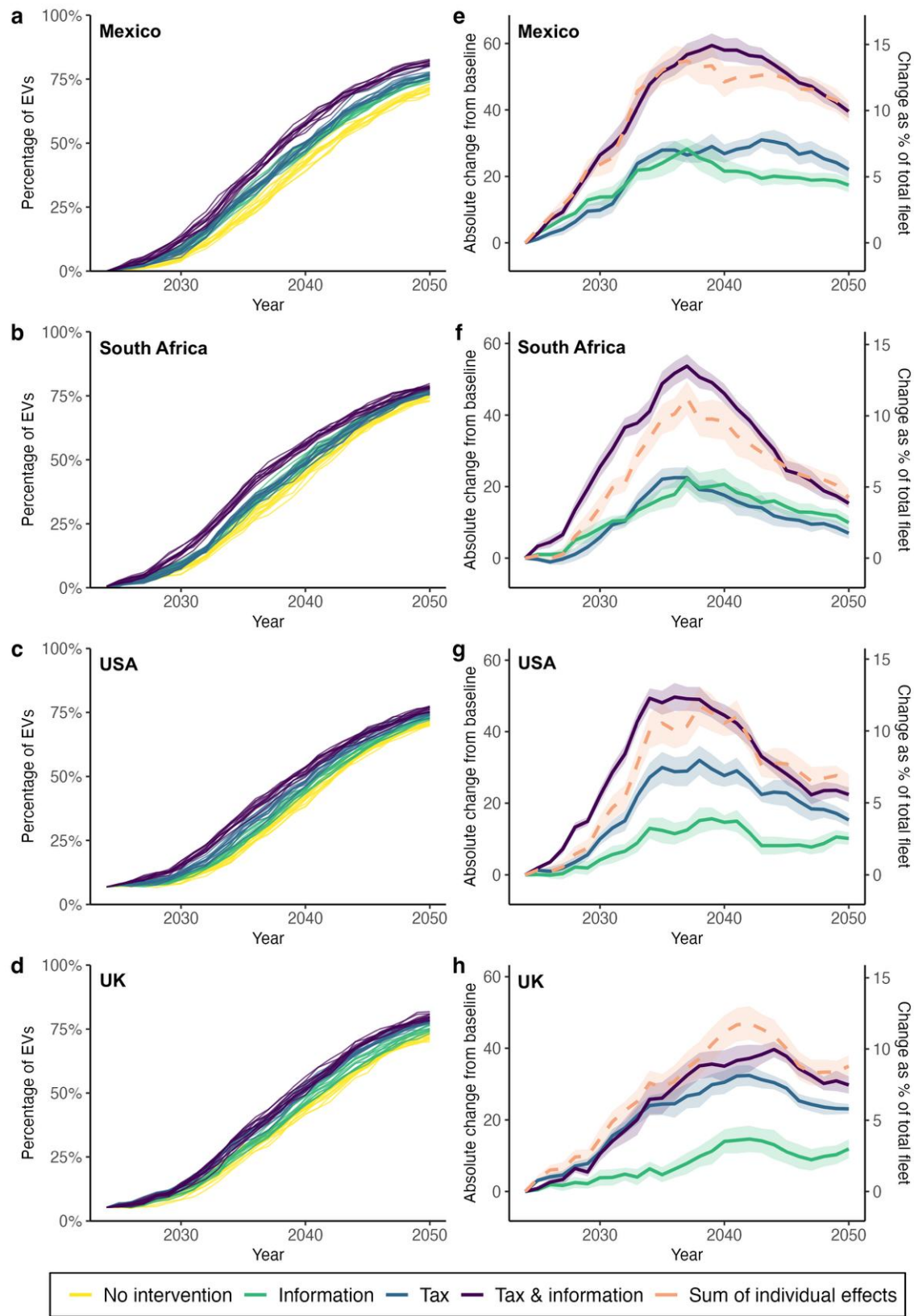
To examine long-term EV diffusion at the system level, we simulated effects of both policies considering technological and renewable energy development, and social dynamics using ABM. Based on the simulation results, we estimated the individual intervention effects and their interaction on EV adoption in 2030, 2040, and 2050 (Supplementary Table S6). As shown in Figs. 5a-d, EV diffusion increased in all countries over time due to technological development, social influence, and the effect of both interventions. Joint policy effects varied in size by country and diffusion stage (Fig. 5e-h).

In the USA and South Africa, joint implementation led to higher adoption than expected from the sum of individual effects, indicating synergistic policy coupling in early diffusion stages. These interactions were substantially pronounced in 2030 (USA: $b=7.92$, 95% CI [3.99, 11.85]; South Africa: $b=11.33$, 95% CI [6.62, 16.04]) and declined over time. However, combined interventions continued to outperform single-implemented policies throughout most of the simulation period (Figs. 5e-h), increasing adoption up to nine percentage points. In Mexico, combined effects were largely additive

(2030: $b=1.67$, 95% CI [-3.78, 7.11]) and in the UK, positive effects of policy coupling compared to a carbon tax alone emerged only at later diffusion stages (e.g., a two percentage-point increase in 2044 compared to a carbon tax alone, and a six percentage points in 2045 compared to information alone), with no synergistic interactions in early diffusion (2030: $b=-4.25$, 95% CI [-8.61, 0.11]).

Results for a low carbon tax and a scenario with stronger renewable energy policies influencing lifetime GHG emissions⁴³ are reported in Supplementary Table S7 and Supplementary Fig. S2.

240 **Figure 5: Simulated EV diffusion over time under different policy scenarios**



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242 *Note.* ABM simulated EV diffusion. **a-d** Mean EV diffusion curves under different intervention scenarios: no
243 intervention, carbon tax only, information only, and both interventions combined. Each line represents one

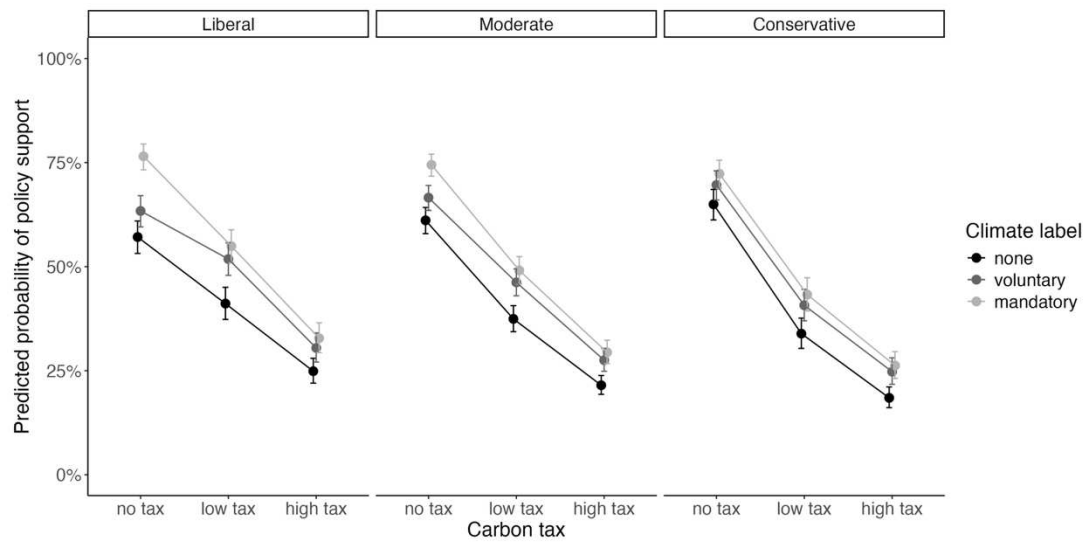
simulation, capturing stochastic variation (e.g., agent interactions). The initial share of EVs was based on participants' reported EV ownership in each country, ensuring realistic conditions: Mexico=0%, South Africa=0.51%, USA=6%, UK=4.36%. **e-h** Mean absolute change in EV adoption relative to the baseline (corresponding to the yellow lines in left panels). Deviations between observed (purple line) and expected additive effects (orange dashed line) highlight synergistic, additive, or sub-additive dynamics when interventions are combined. The left y-axis shows the absolute change in the number of EVs; the right y-axis translates this into a percentage of the total vehicle fleet in the agent population. Shaded areas represent the 95% range of simulated outcomes. Agent population sizes matched to survey sample (Mexico: $n=397$, South Africa: $n=392$, USA: $n=402$, UK: $n=398$).

Heterogeneous effects of policy coupling on public policy support

To evaluate how combining policies influences policy package support, we examined the effects of the two interventions and political orientation on support. Taxes reduced support (high tax: $OR=0.17$, 95% CI [0.16, 0.18], $p<0.001$; low tax: $OR=0.38$, 95% CI [0.36, 0.41], $p<0.001$; evidence for H9), and labels increased it (mandatory label: $OR=1.65$, 95% CI [1.54, 1.76], $p<0.001$; voluntary label: $OR=1.36$, 95% CI [1.27, 1.45], $p<0.001$; evidence for H10). Results for additional policy mix attributes are provided in Supplementary Table S8. Conservatives were generally less supportive of the policy mixes than liberals ($OR=0.90$, 95% CI [0.86, 0.95], $p<0.001$; evidence for H11a).

Fig. 6 shows that labels attenuated the negative effects of carbon taxes on policy package support. Among liberals, predicted support was cut from 57% with no tax to 25% with a high tax, but fell only to 33% with a mandatory climate label in the policy package. Among conservatives, predicted support dropped more sharply from 65% with no tax to 18% with a high tax, but decreased only to 26% with a mandatory label. These results reflect stronger negative tax effects among conservatives (interaction political orientation-low tax: $OR=0.75$, 95% CI [0.71, 0.81], $p<0.001$; political orientation-high tax: $OR=0.78$, 95% CI [0.73, 0.84], $p<0.001$; evidence for H11b) and somewhat stronger positive label effects among liberals (political orientation-mandatory label: $OR=0.89$, 95% CI [0.84, 0.95], $p=0.001$; political orientation-voluntary label: $OR=0.97$, 95% CI [0.91, 1.13], $p=0.444$; exploratory analysis). While generally positive, the mandatory label's effect on support was weakened when combined with a high tax (interaction label-tax: $OR=0.81$, 95% CI [0.66, 1.00], $p=0.049$ evidence against H12a), especially among liberals (three-way interaction label-political orientation-low tax: $OR=1.22$, 95% CI [1.03, 1.43], $p=0.019$; high tax: $OR=1.36$, 95% CI [1.15, 1.61], $p<0.001$; evidence against H12b).

Figure 6: Policy package support as a function of interventions and political orientation

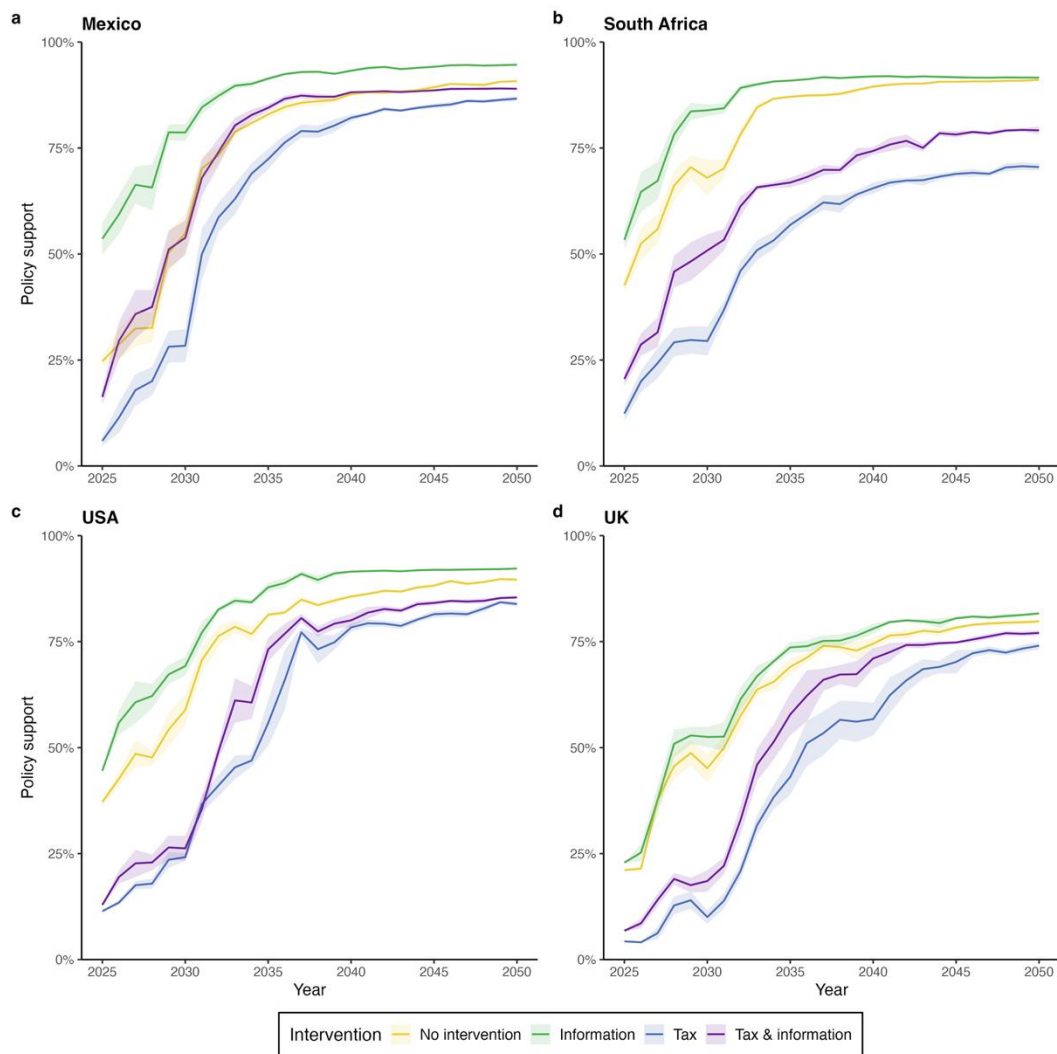


Note. Predicted probability of supporting climate policy mixes as a function of climate information label, carbon tax, and political orientation estimated from mixed-effects logistic regression models. Predicted policy support decreased with the introduction of a carbon tax, more strongly so among conservative participants. Predicted support increased with climate information label implementations, more strongly among liberal participants. Error bars represent 95% confidence intervals based on predicted probabilities, accounting for repeated measures and between-country variation. Group sizes political orientation (for visualisation): $n_{liberal}=310$; $n_{conservative}=274$, $n_{moderate}=1,005$. $N=1,589$ participants, $N=28,602$ observations.

We observed significant differences in policy support across the four national samples ($\chi^2(3)=16.55$, $p<0.001$; evidence for H13a) and interactions between country and intervention effects (tax: $\chi^2(6)=36.06$, $p<0.001$; label: $\chi^2(6)=43.07$, $p<0.001$; supporting H13b), although the direction of tax and label effects was consistent (Supplementary Table S9 and Fig. S3). The influence of political orientation varied across countries (Supplementary Table S10).

To examine how policy support evolves over time, we simulated policy support dynamics conditional on EV diffusion in the ABM. Across countries, support for tax-inclusive policy packages started off low but increased as EV adoption advanced (Fig. 7). In the early years of the simulations, support for combined tax-and-information packages rose more strongly than support for tax-only measures, particularly in Mexico, South Africa, and the USA (Fig. 7), suggesting that policy coupling can enhance public support by promoting faster EV diffusion. The study results revealed that support is influenced by the share of newly registered EVs (Supplementary Table S8), thus, faster adoption in the ABM translates into higher public acceptance of policies. As a result, the strongest gains in support occurred during periods when coupling effects on diffusion were most pronounced.

Figure 7: Simulated policy support over time under different policy scenarios



Note. a-d Simulated mean support for policy packages under different scenarios from 2025 to 2050. Policy support is modelled to begin in the year following policy implementation (electric vehicle adoption simulation starts in 2024). Scenarios include no intervention, high carbon tax only, information intervention only, and both interventions combined. Shaded areas represent the 95% empirical confidence interval of simulated outcomes. Agent population sizes matched to survey sample (Mexico: $n=397$, South Africa: $n=392$, USA: $n=402$, UK: $n=398$).

Discussion

This research examined how combining an economic intervention, a carbon tax, and a climate information intervention influences EV adoption decision-making and policy support across four countries. By integrating choice experiments with process tracing and ABM, we conducted a holistic analysis of intervention effects. Our study advances energy transition research by showing how individual-level responses to energy policies can scale into change at the societal level.

At the individual level, our findings underscore the importance of attentional mechanisms in choice processes. When confronted with multiple pieces of information, people often focus on salient and easy-to-understand information. Making GHG emissions information comprehensible increased attention to it (see also refs.^{14,15}), whereas the carbon tax drew attention to financial savings, both affecting EV choice. When combined, the information intervention reduced attention to savings, but tax information did not divert attention away from emissions when these were translated. This pattern suggests that more information is not always better and that multiple cues can compete for attention. Simplified formats like labels can help maintain attention, and influence behaviour even when looked at only briefly⁴¹.

Our insights into cognitive mechanisms can help explain the effects of the two interventions on EV adoption decisions. Additive intervention effects are a common finding in behavioural research, showing that policy mixes perform better than single interventions but rarely interact synergistically^{7,8}. The observed attentional trade-offs may limit behavioural synergies, highlighting the importance of investigating not only whether interventions work, but how they influence decision processes¹⁴.

Moving from individual to system dynamics, the ABM simulations demonstrate that small, additive individual-level effects can scale into meaningful, potentially synergistic outcomes when behavioural heterogeneity, technological progress, and social influence are accounted for. Combined policies that encourage adopters can catalyse the formation of social norms, which, together with increasingly favourable technological conditions, facilitate broader diffusion^{21,22}. In our simulations, combined interventions produced synergistic effects in South Africa and USA, particularly in the early stages of EV diffusion when unfavourable technological and market conditions may be offset by combined policies. In Mexico and UK, effects remained largely additive or sub-additive. In later years of the simulated time period, the marginal benefit of policy coupling declined, likely due to improved contextual conditions. These findings highlight the value of coupling behavioural research with system modelling such as ABM in pinpointing critical windows for interventions.

Implementing ambitious policy ultimately depends on public support. We found that while carbon taxes lowered support for policy packages (see also refs.^{28,32,33}), support was higher when a tax was paired with a climate information label. One explanation could be that, unlike some nudges that inadvertently reduce support for carbon taxes³⁴, an information intervention might be perceived as reinforcing the tax's goals rather than being an alternative. Our simulation results further suggest that not only the design of policies determines public support, but also how effective they prove to be. In the ABM simulations, policy coupling accelerated EV adoption, which in turn increased support for tax-inclusive policies. This pattern might reflect self-interest, with fewer people being negatively affected by fuel taxes as adoption rises, and social dynamics, whereby wider diffusion enhances perceived legitimacy of energy policies. Climate labels could thus be a pragmatic complementary measure of taxes, increasing both EV adoption and public support.

Across outcomes, we observed heterogeneity in intervention effects. The information intervention was more effective and supported among ideologically liberal participants, suggesting a "signpost" effect¹⁵, where translated information helps align decisions with personal goals. The carbon

tax increased EV adoption regardless of political orientation, however, support for policy mixes including taxes was significantly lower among conservatives (see also refs.^{28,44}). Tax aversion seems to shape public opinion without impeding behavioural responses; an important finding in light of research showing that opposition to system-level policies tends to decline after implementation²⁹. Ideological effects on adoption and policy support (Supplementary Tables S5 and S10) were strongest in the USA, where climate policy is politically polarised⁴⁵. In the UK these effects were less pronounced, and in Mexico and South Africa, we observed nearly no ideological differences, likely reflecting a weaker link between political orientation and climate-related beliefs³⁹, and emphasising the importance of accounting for contextual influences on intervention effects^{20,37}.

Our study has limitations. The use of hypothetical decisions in an online setting cannot fully reflect real-world behaviour (but note that incentivised and hypothetical decisions are often remarkably similar^{46,47}). Information intervention effects may be overestimated, as they are often stronger in online compared to offline contexts^{48,49}. Tax effects may be underestimated, because we embedded the tax within operating cost savings, which is less intuitive than direct fuel price increases that consumers monitor closely⁵⁰. Additionally, integrating experimental data into an ABM introduces uncertainty because it maps hypothetical decisions to future real-world behaviour, and should be seen as a complement to traditional modelling methods using historical data. Samples in Mexico and South Africa were more educated than average (Supplementary Table S11), limiting the generalizability. Finally, our design does not establish a causal pathway from attention to behaviour. This remains a direction for future research.

Taken together, we demonstrate the benefits of integrating individual choices and underlying cognitive mechanisms, contextual dynamics, and public support for evaluating the effectiveness of energy policies. Our results suggest that the combination of carbon taxes and climate information can promote EV adoption, especially in early stages of diffusion, while simultaneously improving policy acceptability. Future work should extend this integrative approach, coupling experimental decision research with system modelling, to other behaviours, such as mode choice or EV charging, and test more policy combinations, including regulatory interventions such as mandates. For behavioural scientists, ABM captures emergent effects of individual decisions in context⁵¹. For energy and climate modelers, considering behavioural heterogeneity increases model plausibility¹⁸. Given the importance of demand-side measures across various contexts, such interdisciplinary strategies are necessary for the design of effective energy policy.

Materials & Methods

Ethics information

This research was approved by the Ethics Committee of the Faculty of Psychology, University of Basel, Switzerland (approval no. 033-23-1). Online study participants provided informed consent and received a flat payment for their participation.

Sample

Pilot study

We conducted a pilot study on January 10, 2024, with 400 participants from the United States via the online participant recruitment platform Prolific. The primary aims were to test the experimental procedure, extract effect sizes for sample size calculations, and ensure successful data integration into the ABM. The pilot study followed a design largely identical to the main study and was implemented in *oTree*⁵². The preregistration for the pilot study is available online (<https://osf.io/3m4wf>).

Sampling plan

For the main study, we collected data in Mexico, South Africa, the UK, and the USA. These countries were selected to represent a mix of economic, geographical and cultural variability, and differing policy contexts. Additional practical considerations guided their selection, as these countries have high internet penetration rates, which facilitated data collection.

The target sample size was calculated a priori using the R package *mixedpower*⁵³ based on 100 simulation runs and informed by the effect sizes from our pilot study. We determined the smallest effect sizes of interest (SEOI) by reducing our observed effect sizes by 15%⁵³. The simulations indicated that 400 participants would provide a power of 0.80 to detect effects with the SEOI for the tax intervention and 0.97 for the information intervention. We thus aimed for 400 participants per country.

Data collection and exclusion criteria

We collected data between May 7, 2024, and May 24, 2024 via Prolific. A total of 1,786 participants started the study. During data collection, participants who did not provide informed consent ($n=10$), attempted to participate via a mobile device ($n=49$), or did not complete the study ($n=135$) were automatically excluded and replaced with new participants to ensure the target sample size was met. Of the 1,592 participants who completed the study, mouse movement data were successfully recorded for 1,589 participants. The missing data for three participants were due to an unknown connection error. To ensure data integrity, all analyses were conducted using the 1,589 complete cases, which included both choice and attention data.

The final sample was nearly equally distributed across the four countries: USA ($n=402$), Mexico ($n=397$), South Africa ($n=392$), and UK ($n=398$). The overall gender distribution was balanced, with 48.33% identifying as women, 51.04% as men, and 0.63% identifying as another gender (see Supplementary Table S11 for demographic details per country). In the US and UK, we used quotas

for age and political orientation (liberal, moderate, conservative). In Mexico and South Africa, we used quotas for age but the final samples were older than the general population (see Supplementary Table S11 for comparison to general population).

Design

The online study employed a within-subjects design with two experimental tasks: an EV adoption choice experiment and a policy support experiment. Participants evaluated scenarios, deciding whether to purchase EVs or support policy packages, respectively. Attribute levels used in the choice tasks were selected based on prior research²⁷, projections of GHG emissions from climate models⁴³, and real-world price data by governmental agencies such as the electricity price monitoring of the US Energy Information Administration⁵⁴, and were adapted to country-specific contexts (see Supplementary Tables S12-13 for all attribute levels per country). During the choice tasks, we assessed participants' attention allocation using a MouselabWEB design⁴⁰. Attribute information was hidden behind interactive boxes and revealed when hovered over, allowing us to track the frequency and sequence of information acquisitions.

Electric vehicle choice experiment

Participants completed 18 unique choice trials, repeated across four blocks covering the four policy scenarios: no intervention, tax only, information intervention only, and both interventions, resulting in 72 trials. In each trial, participants evaluated one EV offer which included five attributes with one of three possible levels (low, medium, high): purchase price, battery range, savings compared to a gasoline car, lifetime GHG emissions, and the number of EV drivers in the neighbourhood, representing a descriptive social norm (see Supplementary Table S12 for all attribute levels per country). In blocks featuring the carbon tax, a tax was introduced with two levels (low, high). The tax was operationalised as a levy on gasoline, increasing the financial savings attribute, for example, "Savings compared to gasoline car: \$13.4 per 100 miles (\$7.4 + \$6 due to gasoline tax)". In blocks without a tax, the savings attribute read, for example, "Savings compared to gasoline car: \$7.4 per 100 miles." In blocks with the information intervention, the lifecycle GHG emissions attribute was translated, providing information about emissions saved over the lifecycle of the EVs (assumed 120,000 miles) compared to a gasoline car, for example, "70% of emissions saved compared to gasoline car". In blocks without the information intervention, the GHG emissions were presented as absolute emissions (e.g., "11 metric tons of emissions"). The outcome variable was EV choice, operationalised as a binary yes-/no-question for each EV offer ("Would you buy this electric vehicle?"). A full factorial design with all possible attribute-level combinations would have required 486 trials, which we reduced to a fractional design with 18 trials using the R packages *ExpertChoice*⁵⁵ and *DoE.base*⁵⁶. This design achieved a D-efficiency of 100%, ensuring sufficient variability to detect main effects and the interaction between the interventions while minimizing participant burden⁵⁷.

Policy support experiment

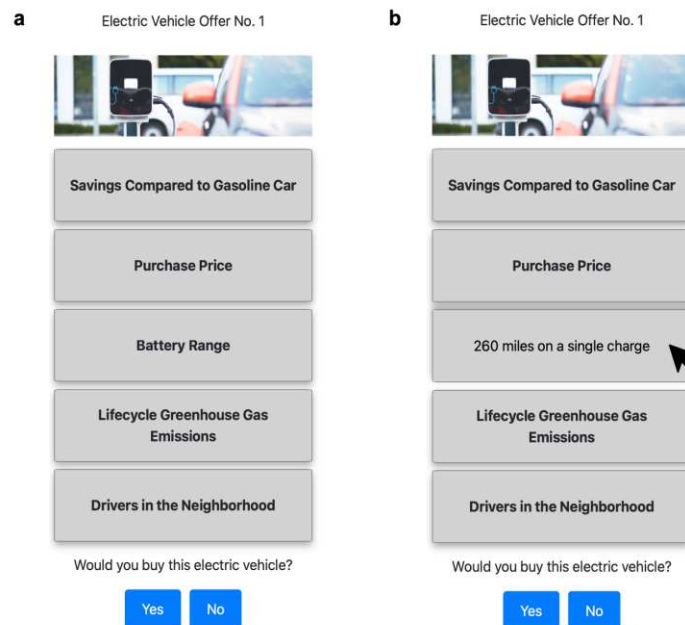
Participants decided for 18 policy mixes which aimed at promoting the uptake of EVs whether or not they would support them. The policy packages consisted of four attributes, each with three levels

(low, medium, high): carbon tax, subsidy, climate impact label, and adopters in the neighbourhood, which provided an estimate of how many people would be affected by the policy (see Supplementary Table S13 for all attribute levels per country). The outcome variable was policy support, operationalised as a binary yes-/no-question for each policy mix (“Would you support this policy package?”). The number of trials was reduced from 81 (full factorial design) to a fractional factorial design with 18 trials, achieving a D-efficiency of 100%⁵⁷.

Assessment of attention processes

In both tasks, attribute levels were concealed behind interactive boxes that participants revealed by hovering over them (Fig. 8). Using this MouselabWEB design⁴⁰, we recorded participants’ attribute acquisitions, including box opening and closing times, as well as the order of box openings. These data provided insights into participants’ attention allocation, specifically whether participants opened the GHG emissions or savings information box first and the frequency of opening the respective boxes. We defined the attention allocated to the respective boxes by the relative frequency of opening the boxes within a choice trial and whether the respective boxes were the first to be opened.

Figure 8: Screenshots of an example product choice trial



Note. **a** The attribute levels are concealed behind boxes. **b** Boxes open and reveal information when participants hover their mouse over them (here: “Battery range: 260 miles on a single charge”). The attribute list format reflects how consumers often encounter information in online comparison tools, whereas offline contexts typically present vehicle information in a more descriptive or promotional way.

Procedure

After providing informed consent, participants answered demographic questions and provided car- and driving-related information. They then performed a practice task to familiarise themselves with the

box-opening procedure to reveal information on EV and policy attributes in the two choice tasks and completed a practice question to ensure they understood how to reveal the information from behind the boxes. Participants completed either the policy task or the product choice task first, in a randomised order. At the start of each block, participants received instructions and an overview of the relevant attributes and the two interventions. To minimise potential carry-over effects of the attribute translation that expressed GHG emissions as percentage savings we grouped the information intervention conditions into consecutive blocks. Tax conditions were randomised within this structure, as the tax was presented as a numerical savings amount and thus less likely to influence interpretation across blocks. Attribute order was randomised between blocks but remained consistent within blocks to avoid overwhelming participants and to be able to capture systematic information search effects. Participants were required to open and close at least one attribute box before the Yes/No-decision buttons appeared, ensuring they accessed at least one piece of information. After the experimental tasks, participants answered questions about the expected and perceived benefits and risks of EVs, political orientation (assessed on a scale from 1 *extremely left/liberal* to 10 *extremely right/conservative*), and social network-related factors. Upon completion, participants were thanked, given the opportunity to describe their decision strategy and to provide feedback, and redirected to the Prolific website.

Hypotheses and statistical analysis

All hypotheses and analyses were preregistered (<https://osf.io/hrzyf>). Deviating from the preregistration, not all hypotheses were reported in this article. A full list of preregistered expectations is provided in Supplementary Table S14. We focused the article on the hypotheses most central to our research questions. In particular, we additionally preregistered the use of an attentional race diffusion model; a cognitive model for estimating decision thresholds, drift rates, attention weights, and attribute weights for each product attribute. These analyses were conducted but are not reported due to space limitations and focus.

Hypotheses reported in the manuscript

H1: Individuals attend more and earlier to information on financial savings when deciding on an electric vehicle in the presence of a carbon tax than in the absence of a tax.

H2: Individuals attend more and earlier to information on GHG emissions when deciding on an electric vehicle when the information is translated (climate label) than when it is not translated.

H3: The effect of the carbon tax on attention is moderated by the translation of GHG information: Individuals allocate less attention to savings in the presence of the attribute translation (label) than in the absence.

H4: The effect of the attribute translation on attention is moderated by the presence of a carbon tax: Individuals allocate less attention to GHG information in the presence of a carbon tax than in the absence.

H5: The probability of deciding for an electric vehicle is higher when a carbon tax is implemented, compared to when there is no tax.

H6: The probability of deciding for an electric vehicle is higher when a climate label is implemented, i.e., when the environmental impact (GHG emission information) is presented as a translated attribute (EV relative emission reduction compared to a conventional vehicle), compared to when the attribute is not translated.

H7: A more pronounced liberal political orientation a) impacts the EV decision positively and b) moderates the effect of the carbon tax on EV decision (stronger effect of carbon tax for liberal orientation).

H8: Country of residence a) impacts the EV decision and b) moderates the effects of the carbon tax and the climate label on EV decision.

H9: Proposing a climate label increases support for a policy package.

H10: Proposing a carbon tax decreases support for a policy package.

H11: A more pronounced liberal political orientation a) increases policy support and b) moderates the effects of the carbon tax on policy support: For conservatives, the carbon tax has stronger negative effects on policy support than for liberals. Specifically, conservatives show a sharp decrease in support with the introduction of any tax level, while liberals demonstrate a more linear decline in support as the tax level increases.

H12: a) Proposing a climate label in addition to a carbon tax attenuates the negative effects of the carbon tax on policy support. b) This effect is stronger for individuals with a more liberal political orientation.

H13: Country of residence a) impacts policy support and b) moderates the effects of the carbon tax and the climate label on policy support.

Statistical analysis

Data analyses were conducted using *R* (version 4.4.2) and *RStudio* (version 2024.09.0+375). *R* packages used for the analyses are listed in the analysis code available online (<https://osf.io/rxd79/>). All statistical tests were two-sided with $\alpha = 0.05$. No adjustments for multiple comparisons were applied because analyses were confirmatory and preregistered. For attention analyses, we excluded data from box openings of less than 200 milliseconds, as preregistered, because these were likely due to accidentally hovering the mouse over a box. Choice trials with response times exceeding three median absolute deviations above the median were excluded for preregistered sensitivity analyses. Results patterns for analyses without these outliers do not differ from those with them which are reported in the main text (Supplementary Tables S15, S16).

EV choice and policy support hypotheses were tested using mixed-effects logistic regression models with the binary yes/no choice as dependent variable. To analyse attention allocation, we applied mixed-effects logistic regressions for the likelihood that a specific attribute was attended to first and mixed-effects linear regressions for the proportion of total attention allocated to each attribute. For linear models, visual inspection of residuals showed that assumptions were met. As preregistered, demographic variables that significantly improved model fit were included as covariates in the regression models, resulting in age and income being included in all models, while gender was excluded.

As preregistered, we determined the most appropriate random effects structure for the multilevel regression models, by comparing three structures. Model 1 included EV (or policy) attributes, tax, and information intervention as fixed effects with random intercepts for participant and choice task. Model 2 included all elements of Model 1, plus a random intercept for the country. Model 3 included all elements of Model 2, plus random slopes for those attributes that varied across countries due to contextual differences (e.g., currency values, energy mix). If a model was too complex to estimate, we applied stepwise reduction of the random effects structure. Model fits were compared using model fit indices AIC and BIC, and the best-fitting random effects structure was used for hypothesis testing. For the EV decision hypotheses, the best-fitting random effects structure was Model 3 with random slopes for price. For the policy choice hypotheses, the best-fitting random effects structure was Model 2 with random intercepts for the choice task and country. For attention analyses, the random intercept for country did not increase model fit but was kept for theoretical considerations.

For H1 and H3, the dependent variable was attention allocation to “Savings Compared to Gasoline Car” during EV decisions, specifically, the relative frequency of opening the respective box, and whether it was opened first. Fixed effects in the regression models were EV attributes as well as carbon tax and information intervention, and for the model analysing H3, the interaction of carbon tax and information intervention. Models for H2 and H4 were the same but with attention to “Lifetime GHG emissions” as dependent variable.

For the regression models for H5 and H6 the dependent variable was the EV adoption decision (yes/no), fixed effects were EV product attributes (price/savings/GHG emissions/battery range/adopters in the neighbourhood), vehicle size, as well as carbon tax and climate information intervention. As preregistered, we included the interaction of carbon tax and information intervention as a robustness check. To test the main and moderating effects of political orientation, we included political orientation as a fixed effect (H7a) and in a second model the interaction of political orientation and carbon tax (H7b). Exploratively, we fitted a model with the interaction of political orientation and the climate information intervention. To analyse country differences, we added country as fixed effect (H8a) as well as the interaction between country and the interventions as fixed effect (H8b).

For regression models testing H9 and H10, the dependent variable was policy support (yes/no) with fixed effects being the two interventions and additional policy package attributes (subsidy/adopters in the neighbourhood). To test the main (H11a) and interaction effect of political orientation with the tax (H11b) and exploratively the interaction with the climate information label, we added political orientation and the interactions with the interventions to the regression model. H12a was analysed by adding the interaction between tax and climate label to the regression model, and H12b by adding the interaction between tax, climate label, and political orientation. To analyse country-level differences, we added country (H13a) as well as the interaction between country and the interventions as fixed effects (H13b).

Due to contextual variations across countries, we additionally analysed all hypotheses (except for those including country as a fixed effect) separately for each country. We preregistered to

standardise political orientation but did not specify how. In practice, we standardised political orientation within each country to account for country-specific distributions.

Agent-based modelling

To explore how the individual-level effects of carbon taxes and climate information interventions on EV adoption scale to long-term EV diffusion and policy support, we developed country-specific ABMs in *NetLogo*⁵⁸, building on a validated ABM of consumer adoption of low-carbon technology²⁷. Our models simulate EV adoption trajectories from 2024 to 2050 by integrating individual-level decision data with broader social and technological dynamics. Model code and Overview, Design Concepts and Details (ODD) protocol⁵⁹ are available online (<https://osf.io/rxd79/>). Each agent represents one of the 1,589 participants from our online study, inheriting their demographic, psychological, car-related factors, and individual decision preferences for EVs and policy acceptance.

We simulated EV diffusion under four policy scenarios: no intervention, tax only, information only, both interventions. Because such policy interventions would likely be embedded in a broader policy context, we additionally simulated all scenarios under stronger renewable energy policies consistent with the 2°C target of the Paris Agreement resulting in lower lifecycle GHG emissions of EVs⁴³. To evaluate policy effects, we fitted linear regression models to the simulated outcomes, focusing on 2030, 2040, and 2050, representing typical reference years in policy analyses. Model robustness was tested through sensitivity, stability, and uncertainty analyses (Supplementary Figs. S4–S6).

Empirical inputs

ABM parameters were informed by the choice experiment as well as the survey. Participants were asked about car ownership, the size of the car they would consider buying in the future (small, medium, large), typical car replacement time, and current car age. Additionally, participants rated subjective probabilities for beneficial outcomes of EV adoption, such as financial savings, as well as risky outcomes like low returns on investments. Affect toward EVs was assessed using one item “Overall, how do you feel about electric cars?” answered on a scale from 1 *very negative* to 10 *very positive*.

To initialise the social network, participants reported the number of people with whom they discuss cars and how similar their network members are to them in terms of home region, education, income, and political orientation, using a scale from 1 *very different* to 5 *very similar*. Agents form links to others based on their homophily preferences. Additionally, participants reported how often they hear positive or negative comments about EVs, serving as a proxy for word-of-mouth communication.

Agents’ decision preferences were operationalised as participant-specific weights for vehicle attributes (i.e., price, range, savings, emissions, social norm) and the policy interventions (i.e., carbon tax and information intervention), estimated from mixed logistic regression models with random slopes for participants. The extracted coefficients capture how strongly each participant valued each attribute in their decisions and were implemented as utility weights in the agents’ decision functions.

Adoption decision model

Agents make adoption decisions in a dynamic social and technological environment. After adopting, agents share opinions about EVs, which influences peers' affect toward EVs. The magnitude of this shift in affect was estimated from the survey data using linear regression analyses. Within the social network, agents observe others' adoption (neighbourhood effect/social norm) that enters the utility function through the empirically estimated coefficient from the choice experiment. In the technological context, EV purchase prices decline over time, lifetime emissions decrease, and battery ranges increase (see Supplementary Tables S18-S20 for ABM parameters).

In each simulated year, agents whose car reaches their replacement age decide whether to adopt an EV. Decisions follow a threshold adoption model, theoretically grounded in the established risks-as-feelings framework⁶⁰, which integrates economic utility, affective and cognitive factors. Agents evaluate the utility of adoption an EV using a logit function. The evaluation score is a linear combination of weighted attributes, derived from the choice experiment. The utility function includes the economic and technical attributes of the EV (e.g., price, battery range), a social norm (i.e., the share of EV adopters in the agent population), the policy interventions, subjective outcome probabilities for benefits and risks associated with EV adoption, affect towards EVs, and psychological characteristics (i.e., political orientation and climate change concern). The model computes a probability like score, which is compared to an empirically calibrated adoption threshold. Adoption occurs when an agent's utility exceeds this threshold (otherwise the agent adopts an internal combustion engine vehicle):

$$\frac{1}{1+e^{-(\alpha+\beta_1x_1+\beta_2x_2+\beta_ix_i)}} \geq threshold,$$

where α is the agent-specific intercept and β_i the coefficient for the independent variable x_i (out of i variables). We calibrated the adoption thresholds separately for each country and vehicle size by comparing observed choices from the experiment with predicted choices from the regression models. We generated confusion matrices for a range of cut-off values and computed Matthews correlation coefficients (MCC). The thresholds that maximise MCC were selected (Supplementary Table S17).

Policy support decision model

In addition to deciding on EV adoption, agents evaluate the currently implemented policy packages in each simulation year, generating public policy support trajectories conditional on the stage of EV diffusion. The policy support decision model mirrors the adoption model, evaluating agents' support for implemented policy packages. The model calculates for each agent an individual policy package evaluation score based on a linear combination of main effects of tax and climate information labels, their two-way and three-way interactions with political orientation, and the main effect of political orientation itself. Additional predictors capture a potential subsidy, the agent's climate change concern, and the perceived social norm, represented by the share of newly registered vehicles that are electric. To reflect the framing of the experiment while reducing volatility from small numbers of new registrations in early simulation years, the market share variable is exponentially smoothed,

687 giving more weight to the current year than the previous one. The resulting evaluation score is
688 compared to the empirically calibrated policy support threshold. If an agent's policy evaluation score
689 exceeds this threshold, they support the currently implemented policy package.

Author contributions

A.G.: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing - Original draft; M.V.D.K.: Conceptualization, Methodology, Software, Supervision, Writing - Review & Editing; A.H.H.R.: Methodology, Writing - Review & Editing; S.G.: Methodology, Writing - Review & Editing; U.J.J.H.: Conceptualization, Methodology, Funding acquisition, Supervision, Writing - Review & Editing.

Competing interest statement

The authors declare no competing interests.

Data and code availability

All data and code to reproduce results are available in a publicly accessible repository on OSF (<https://osf.io/rxd79/>).

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