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ABSTRACT

Perceptions of Artificial Intelligence and Environmental Sustainability*

Artificial intelligence (AI) technologies are increasingly viewed as both a potential driver of environmental sustainability and a contributor to global energy demand. Yet little is known about how the public interprets these dual narratives. We conducted a pre-registered online experiment (N = 2142) on a representative sample of the United States to examine how framing the environmental impacts of AI—as positive or negative—affects beliefs, policy preferences, and behavioral intentions. Positive messaging led to greater optimism about AI's environmental impact, lower support for regulation, increased support for government subsidies of AI-enabled technology adoption, and increased consumer preferences for AI-enabled appliances. Negative messaging increased support for regulation and decreased support for government subsidies. Consistent with previous evidence, the messenger (scientist vs journalist) had minimal impact. Our findings highlight the power of environmental framing in shaping public narratives around AI, with implications for science communication, sustainability governance, and technology acceptance.

JEL Classification: O3, Q4, Q5

Keywords: Artificial Intelligence, energy use, online experiment, energy conservation, behavior

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1 Introduction

Artificial Intelligence (AI) has rapidly emerged as a transformative force across sectors, promising unprecedented advancements in efficiency, decision-making, and innovation. Among the many areas where AI's impact is being felt, energy use and environmental sustainability stand out as two of significant potential and concern. As the global community grapples with the urgent need to combat climate change and transition towards more sustainable energy systems, AI offers both opportunities and challenges that need to be carefully examined (Nishant et al. 2020).

On the one hand, AI has the potential to revolutionize energy management and environmental protection (Aguilar et al. 2021, Antonopoulos et al. 2020, Singh and Kaunert 2024). Through predictive analytics, AI can improve grid stability (Shi et al. 2020), optimization system configuration, and energy control strategy (Abdalla et al. 2021). Furthermore, AI can contribute to environmental monitoring, providing valuable insights into for example, ecosystem health (Ditria et al. 2022) and pollution levels (Asha et al. 2022).

However, the deployment of AI is not without its drawbacks (Al-Sharafi et al. 2023). The computational power required to train and operate AI models often demands significant energy resources, which, paradoxically, can contribute to carbon emissions if not managed sustainably (De Vries 2023). Despite this tension, little is known about how laypeople perceive AI's environmental implications (Frank 2021, Görücü et al. 2025, Gherheș and Obrad 2018, Yeh et al. 2021). Public beliefs about AI's environmental impact may shape acceptance of new technologies, regulatory approaches, and even international climate governance, since perceptions shape public support for policies, particularly when impacts are ambiguous and mediated by expert or media narratives (Campbell 2011, Cockerill 2002, Drews and Van den Bergh 2016, Nabi et al. 2018).

This study investigates these perceptions through a pre-registered, randomized survey experiment on a large and representative sample of the United States population in 2025, and randomized both content and source of environmental messaging about AI ($N = 2142$ after exclusions for inattention). The experimental design included 4 treatment groups and a control group to which participants were randomly assigned. These conditions varied along two dimensions: the valence of the information (positive vs. negative) regarding AI's environmental impact, and the identity of the messenger delivering the information (a scientist vs. a journalist). The number of respondents in each treatment arm is shown in Appendix Table A1.

The results of our experiment extend a behavioral energy conservation literature older than the more recent conversations around AI. For example, Jessoe and Rapson (2014) provided information on household electricity usage in an RCT, finding evidence of reduced energy consumption from habit formation in the short and medium run. Andor and Fels (2018) provide a systematic review of 44 international studies (restricted to only those that allow for identification of causal effects e.g., RCT's) examining 105 non-price interventions for energy conservation; all four intervention categories (social comparison, commitment devices, goal setting, labeling) were found to reduce the energy consumption of households (with varying effect sizes). More generally, Khanna et al. (2021) conduct a 122 study (representing 25 countries) meta analysis of behavioral changes in reducing energy consumption emissions in households, finding that both monetary and non-monetary interventions reduce energy consumption (with monetary interventions slightly more effective). Further, Bergquist et al. (2023) found, in a pre-registered second-order meta analysis of over 430 primary studies, that pro-environmental behaviors increase by 2 to 12 percentage points compared to what is expected absent treatment (with monetary and social comparison interventions most effective and education and feedback as the least effective).

We combine lessons learned from these studies with two additional considerations. First, pro-environmental responses to behavioral interventions have been shown to be sensitive to gain versus loss framing; Homar and Cvelbar (2021) provide a systematic review of 47 studies to find that self-reporting constructs (including attitudes which we examine) are more affected by environmental harm (loss) framing. Second, van Valkengoed et al. (2022) note that despite these systematic reviews and meta-analyses, it is unclear which interventions designed to promote pro-environmental behavior will be effective; in response they characterize 13 determinants of behavior and their supporting theoretical frameworks. Our intervention, accordingly, is multi-determinant, and designed to touch upon respondents' (1) understanding of scientific facts (2) perceived likelihood of environmental change (3) concerns of environmental hazards (4) awareness of behaviors increasing environmental problems (5) personal responsibility for actions (6) attitudes towards a particular action of theirs (7) and the extent to which they perceive their behavior as effective in resolving environmental problems. Last, we examine the role of the messenger. Hafner et al. (2019) examine the efficacy of four different messenger types on non-student households for pro-environmental behaviors on heating choice. They found that the messenger (as varied by knowledge and trustworthiness) did not matter, whereas message content (framing) was found to have a substantial impact on behavior. Accordingly, we examine the role of two salient messengers of environmental information - scientists reporting on their findings, or news media reporting on scientists' findings while varying the content to be negative (loss-) or positive (gain-framed).

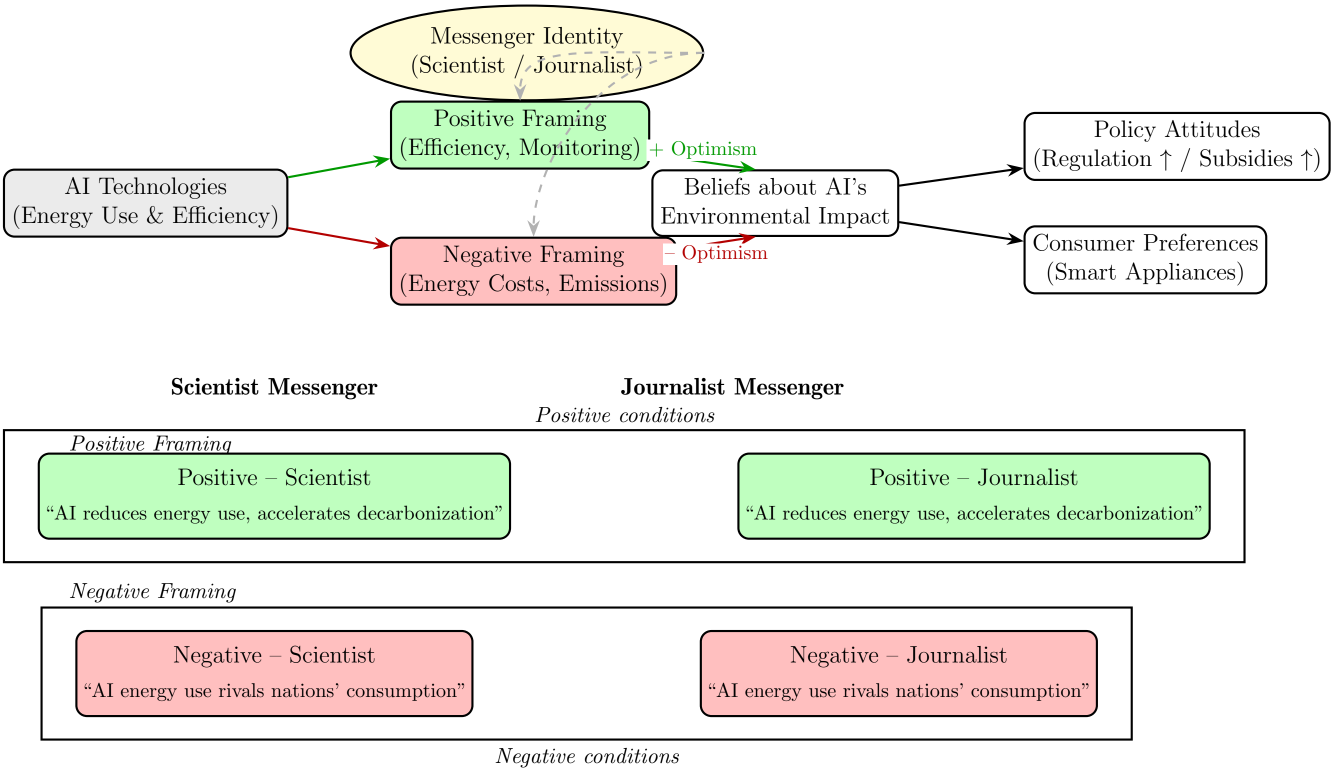


Figure 1: (a) Conceptual model illustrating how messaging about AI's environmental impacts (positive vs negative framing) influences public beliefs, which in turn shape policy attitudes and consumer preferences. The identity of the messenger (scientist vs journalist) is shown as a secondary influence with modest effects. (b) Experimental design showing the four treatment conditions: positive vs negative framing crossed with scientist vs journalist messengers, and the control group that received no messaging. Full treatment texts are provided in the Appendix.

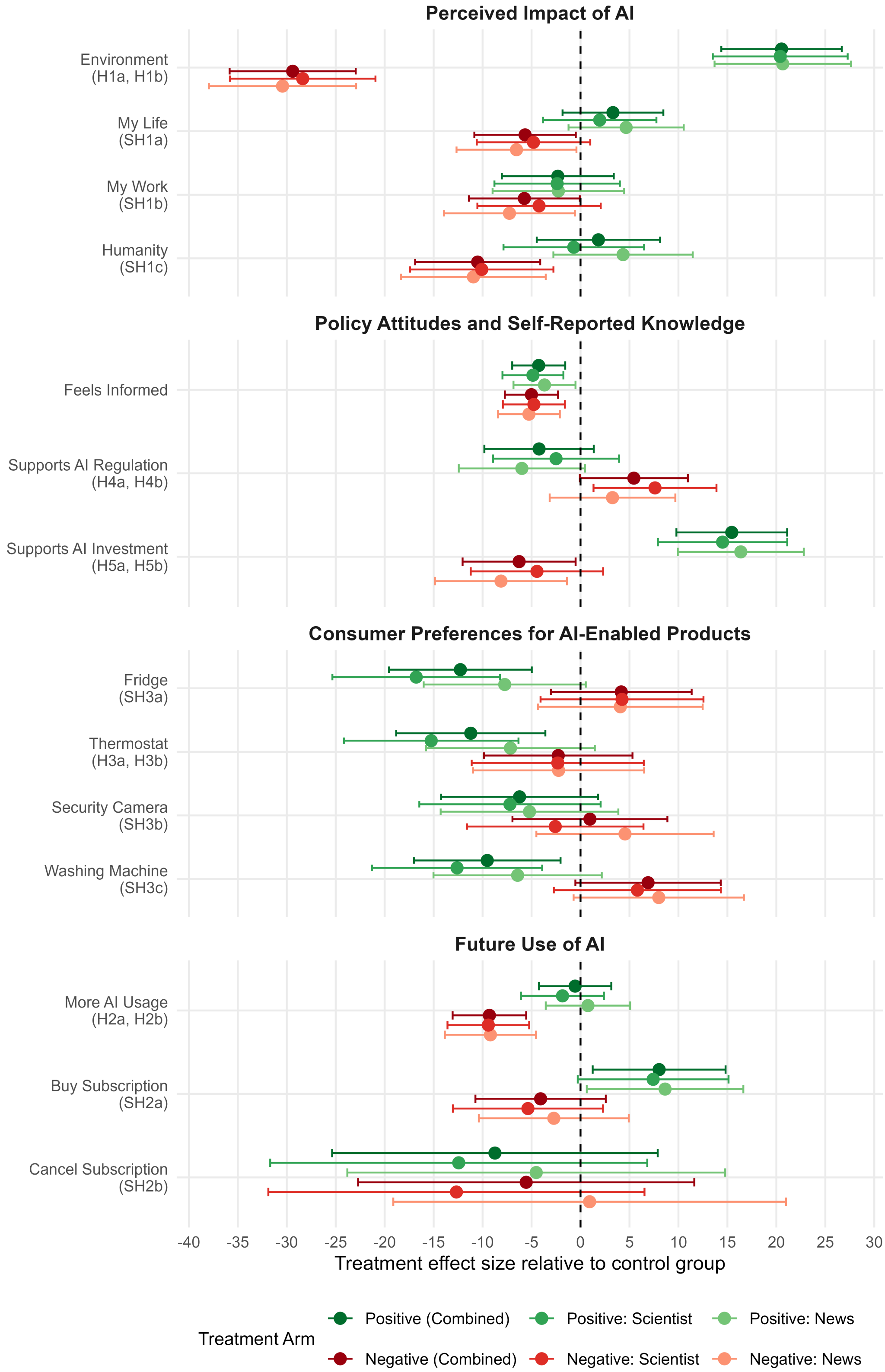
The experimental treatments consisted of short informational texts that either emphasized the potential environmental benefits of different AI technologies (e.g., improved energy efficiency, real-time environmental monitoring) or their drawbacks (e.g., carbon-intensive training processes, increased electricity consumption). These messages were carefully crafted to reflect real-world narratives and were attributed either to an academic researcher or to a news outlet, mirroring common channels through which the public encounters science communication (Figure 1).

2 Results

2.1 Perceived Impact of AI

We begin by asking participants' perceptions of how AI will impact society, including the environment, their own lives, work, and humanity overall. Figure 2 reports our main regression estimates with control variables. (See Appendix Figure A1 for estimates without controls, with little qualitative difference. Tables A9 through A11 in the Appendix show the quantitative results for these models.) Our finding is that messaging valence had a strong and consistent effect on beliefs about AI's environmental impact. Consistent with our pre-registered primary hypotheses H1a and H1b, participants exposed to positive messages—regardless of source—expressed significantly greater belief that AI would have a positive effect on the environment compared to the control group ($\beta = 20.530$, one-sided $p < 0.0001$). Conversely, participants exposed to negative messages reported sizable and statistically significant decreases in perceived environmental benefit ($\beta = -29.398$, one-sided $p < 0.0001$). These beliefs are scaled from -100 ("I believe that AI will impact the environment negatively") to 100 ("I believe that AI will impact the environment positively"), with any integer value possible between these two extremes. The control group, on average, reported a score of 8.51, suggesting a *slight* inclination towards AI having a positive impact absent any information treatment. Figure 2 also displays each of the 4 treatments separately, where a positive message from news coverage increased beliefs by 20.653 points on this scale (one-sided $p < 0.0001$) while a positive message from scientists increased beliefs in a positive impact by 20.399 points (one-sided $p < 0.0001$). Conversely, a negative message from news media reduced beliefs in AI's environmental impact by 30.436 points (one-sided $p < 0.0001$) while a negative message from scientists reduced beliefs by 28.374 points (one-sided $p < 0.0001$).

Figure 2: AI-Treatments effects on outcomes - with control variables



Note: This figure displays treatment effects relative to the control group with 95% confidence intervals. The "Positive (Combined)" and "Negative (Combined)" estimates derive from an OLS models pooling positive and negative treatments. The remaining four estimates ("Positive: Scientist," "Positive: News," "Negative: Scientist," "Negative: News") come from separate models with four treatment arms. All models employ robust standard errors and control for demographic characteristics, Prolific hours, prior AI usage, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media. Corresponding tabular results appear in Appendix Tables A6, A7, and A8.

Interestingly, negative message effects spilled over into broader attitudes about how AI will impact the participants' life, work, and humanity in general, but positive effects did not significantly impact these perceptions (pre-registered secondary hypotheses SH1a–c). Participants in the combined negative conditions expressed more negative expectations about AI's impact on their own life ($\beta = -5.663$, two-sided $p = 0.032$), own work ($\beta = -5.737$, two-sided $p = 0.047$), and humanity in general ($\beta = -10.507$, two-sided $p = 0.001$). However, the first two results are not robust to exclusion of control variables. This was especially the case when the negative message source was a news outlet ($p = 0.036$, $p = 0.034$, and $p = 0.004$ respectively) as compared to directly from a scientist ($p = 0.104$, $p = 0.188$, and $p = 0.007$ respectively). While not all of these secondary outcomes reached statistical significance, the overall pattern aligns with SH1a–c, suggesting that negative environmental framing may generalize to broader views of AI. Positive treatments were not associated with significant change on believes about the impact of AI on own life ($\beta = 3.312$, two-sided $p = 0.207$) own work ($\beta = -2.319$, two-sided $p = 0.427$) and humanity ($\beta = 1.827$, two-sided $p = 0.570$). The difference between positive an negative messaging might arise from the details of the messages. The message regarding positive impact of AI was focused on technologies with regards to building energy efficiency, while the negative text was about AI technologies more in general. See detailed definitions of the treatment texts in Section 4.1.

2.2 Policy Attitudes and Self-Reported Knowledge

Framing effects were evident in participants' views on environmental governance and AI-related policy. Any information led to lower self-reported knowledge (against an average of the treatment group of 48.78, halfway between 0 corresponding to "not at all informed" and 100 corresponding to "very informed") about AI and the environment. Our results suggest that prior to this experiment, respondents may not have reconciled the dual narrative of AI energy consumption and its potential energy efficiencies. The largest effects were found for negative messages from news sources ($\beta = -5.270$, two-sided $p = 0.001$) followed by positive ($\beta = -4.861$, two-sided $p = 0.002$) and negative messages from scientists ($\beta = -4.762$, two-sided $p = 0.003$) with positive messages from news media having the smallest impact ($\beta = -3.680$, two-sided $p = 0.023$).

Consistent with our signed primary hypothesis H4a and H4b, participants who received positive environmental messaging were less likely to support stricter environmental regulation for AI companies, however, this effect is not significant at the 5% level ($\beta = -4.234$, one-sided $p = 0.069$), whereas participants who received negative messaging were significantly more likely to support environmental regulation for AI companies ($\beta = 5.447$, one-sided $p = 0.027$). The overall support for the regulation was relatively high with control group mean at 41.65, where -100 corresponds to "very unlikely to support" and 100 corresponds to "very likely to support" additional regulation on AI companies. The largest effects were found for negative scientist messages, which *increased* support for additional regulation of AI companies by 7.606 points on the scale (one-sided $p = 0.009$) and for positive messages from news, which *reduced* support for additional regulation on AI companies by -5.991 (one-sided $p = 0.034$).

Consistent with our signed primary hypothesis H5a and H5b, support for government subsidies for AI-enabled HVAC technologies rose significantly under the positive conditions ($\beta = 15.447$, one-sided $p < 0.0001$) as well as individually for positive science ($\beta = 14.509$, one-sided $p < 0.0001$) and positive news ($\beta = 16.371$, one-sided $p < 0.0001$). In contrast, negative treatments had a smaller effect on subsidy attitudes combined ($\beta = -6.272$, one-sided $p = 0.017$, this effect is not significant in the model without control variables). Individually this effect was statistically significant only for negative news (one-sided $p = 0.009$), but only in the model with control variables, the effect of negative scientist was not significant at 5% level ($p = 0.099$). This asymmetry suggests that supportive and restrictive policies may respond differently to positive and negative framings. This may be because the positive messaging overlapped with the focus of the subsidy, namely energy efficiency in buildings and HVAC technologies, while the negative messaging was framed in broader terms, leaning more toward AI technologies in general.

2.3 Consumer Preferences for AI-Enabled Products

Consistent with our signed primary hypothesis H3a and H3b, positive messaging about the environmental benefits of AI decreased preferences for traditional thermostats in favor of AI-enabled ones ($\beta = -11.210$, one-sided $p = 0.002$), on a scale where -100 is preference for AI-enabled version and +100 is preference for traditional version. This holds true especially for positive messaging from scientists ($\beta = -15.247$, one-sided $p = 0.0004$), the effect of news sources is somewhat weaker ($\beta = -7.157$, one-sided $p = 0.052$). This is in contrast again to negative messages, which did not have a statistically significant effect on preferences between an AI or traditional thermostat, either combined ($\beta = -2.274$, one-sided $p = 0.557$) or separately ($\beta = -2.240$, one-sided $p = 0.615$ for news, $\beta = -2.324$, one-sided $p = 0.604$ for scientists). These results suggest that optimism sells, but pessimism does not deter adoption.

Extending beyond preferences for traditional or AI enabled thermostats, we asked about other sources of residential energy usage that AI has been widely integrated;

fridges, security cameras, and washing machines. Consistent with SH3a–c, positive messaging found decreased preference for traditional (increased preference for AI-enabled) fridges ($\beta = -12.269$, two-sided $p = 0.001$) and washing machines ($\beta = -9.525$, two-sided $p = 0.013$). The effect for security cameras was in the same direction but is not statistically significant ($\beta = -6.226$, two-sided $p = 0.128$), Negative messaging, however, did not impact the stated preferences (two-sided $p = 0.257 for fridge, p = 0.812$ for security camera, and $p = 0.069$ for washing machine).

Overall, we find evidence supporting H3a and SH3a-c (positive messaging) and insufficient evidence to support H3b and SH3a-c (negative messaging), suggesting that stated consumer preferences for smart appliances are differentially affected by positive and negative framing.

2.4 Future Use of AI

Examining our signed primary hypothesis H2a and H2b, positive messaging about the environmental benefits of AI did not increase participants' stated future intentions to use AI more or less ($\beta = -0.552$, one-sided $p = 0.770$), however negative messaging had greatly reduced participants stated future AI use ($\beta = -9.307$, one-sided $p < 0.0001$). Secondary hypotheses, SH2a and SH2b examine future stated likelihoods to purchase a premium subscription to an AI service (or cancel if the participant already had one). Positive messaging about the environmental effects of AI increased the willingness to purchase a premium subscription to AI chatbots ($\beta = 8.029$, two-sided $p = 0.021$), whereas negative messaging did not have an appreciable effect ($\beta = -4.076$, two-sided $p = 0.230$). In terms of canceling their subscriptions, the sample size for this question is small ($N = 397$; very few people had a premium subscription at the time of the survey) leaving these estimates to be very imprecise and the effects are not statistically significant (two-sided $p = 0.303$ for positive and $p = 0.527$ for negative). The significantly positive effect of positive environmental messaging on reported subscription intent suggests that consumers may, at least to some extent, view diverse AI technologies as belonging to a single category. In particular, positive framing of AI applications aimed at building efficiency and HVAC carried over to increase consumers' stated willingness to subscribe to AI chatbots such as ChatGPT. Although these technologies differ in both purpose and potential environmental impact, consumers appear to group them together under the broader label of "AI."

2.5 The Role of the Messenger

Finally, we explored whether the identity of the messenger (scientist vs journalist) shaped the magnitude of treatment effects (SH4). Whether the message came from a scientist or journalist had little impact on perceptions or policy attitudes. The messenger only mattered for one of many outcomes we measured; preference for AI-enabled fridge, where scientist-delivered positive messages decreased preference for traditional version a bit more than news messages ($\beta = 9.039$, two-sided $p = 0.036$).

3 Discussion

Our findings suggest that public perceptions, beliefs, and support for policies can be shaped by how AI is framed: positive messages emphasizing sustainability benefits significantly increased optimism about AI's environmental role, while negative messages emphasizing energy costs reduced environmental expectations and heightened support for regulation. These results align with prior work on the salience of climate framing and the power of message valence to shape beliefs and preferences (Bertolotti and Catellani (2014); Li and Su (2018); Shah et al. (2022)). They also align with recent meta-analytical evidence that climate communication interventions can shift pro-environmental behavior by 2–12 percentage points (Bergquist et al. (2023)).

The fact that positively framed messages also increased support for government subsidies for AI-enabled HVAC technologies, while negatively framed messages increased support for environmental regulation, reflects a broader asymmetry in how people respond to technological optimism versus risk cues. This finding resonates with prior behavioral work on policy design and feedback effects (MacKinnon et al. (2022); Yang et al. (2025)) and highlights the importance of strategic messaging when promoting emerging climate technologies.

Interestingly, while beliefs and policy attitudes were highly sensitive to framing, consumer preferences for AI-enabled products were largely unaffected. This may suggest that people differentiate between abstract environmental narratives and tangible product decisions, or that they require more sustained exposure or experience to shift behavioral intentions. It may also reflect limitations in online survey environments for capturing real-world tradeoffs in household technology adoption (Haghani et al. 2021). While respondents reported shifts in support for policies and interest in AI-enabled appliances, these intentions may not fully translate into real-world adoption decisions, where financial costs, household dynamics, and practical constraints play a stronger role.

The identity of the messenger generally did impact the effect of the positive and negative messages.

As AI technologies become a key feature of the global energy landscape, understanding how they are perceived is essential to public information and discourse.

This study contributes to an emerging literature on the social perception of these technologies and provides a framework for responsible science communication in the era of digital climate solutions.

Future research should explore the durability of these framing effects, the role of repeated exposure, and how framing interacts with trust in specific institutions (e.g., tech companies vs governments). Additionally, as AI applications expand across sectors, the narratives surrounding their environmental footprint will likely evolve. Monitoring how these narratives are framed, transmitted, and received across diverse populations will be essential for anticipating public reactions and designing effective policy interventions.

As calls grow for responsible AI governance, our study contributes to the emerging literature documenting how public narratives shape technology acceptance and climate policy (Luers et al. 2024). By situating AI within these broader debates, our work highlights that communication is not just descriptive, but constitutive of sustainable technology pathways.

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4 Methods

4.1 Study Design and Experimental Framework

This study employs a randomized online experiment to examine how message framing and source credibility influence public perceptions of AI and its environmental implications. The experimental design included 4 treatment groups and a control group to which participants were randomly assigned. These conditions varied along two dimensions: the valence of the information (positive vs. negative) regarding AI's environmental impact, and the identity of the messenger delivering the information (a scientist vs. a journalist). Treated participants see one of the following texts, respectively.

Positive Message and Science Messenger (*positive_science*):

As we face the challenges of climate change, AI technologies are emerging as powerful tools to optimize energy consumption and reduce emissions, particularly in the building sector. According to a recent scientific study[a], artificial intelligence (AI) has the potential to significantly reduce energy consumption and carbon emissions in the U.S. building sector. It is estimated that AI could lower energy use by approximately 8% by 2050 in a business-as-usual scenario. Moreover, the scientists note, that when combined with energy efficiency policies and low-carbon power generation, AI-driven technologies could reduce energy consumption by 40% and carbon emissions by up to 90%. AI can help accelerate the timeline for peak energy use in buildings, moving it from 2040 to 2035. This highlights AI's crucial role in achieving substantial energy and emissions reductions, particularly when integrated with policy measures and advanced energy-saving technologies.

[a]The text linked to the following source: https://www.nature.com/articles/s41467-024-50088-4

Positive Message and News Messenger (*positive_news*):

As we face the challenges of climate change, AI technologies are emerging as powerful tools to optimize energy consumption and reduce emissions, particularly in the building sector. According to a recent news article[a], artificial intelligence (AI) has the potential to significantly reduce energy consumption and carbon emissions in the U.S. building sector. It is estimated that AI could lower energy use by approximately 8% by 2050 in a business-as-usual scenario. Moreover, the news notes, that when combined with energy efficiency policies and low-carbon power generation, AI-driven technologies could reduce energy consumption by 40% and carbon emissions by up to 90%. AI can help accelerate the timeline for peak energy use in buildings, moving it from 2040 to 2035. This highlights AI's crucial role in achieving substantial energy and emissions reductions, particularly when integrated with policy measures and advanced energy-saving technologies.

[a] The text linked to the following source: https://www.utilitydive.com/news/ai-adoption-energy-use-emissions-reductions-potential-lawrence-berkeley/723271/

Negative Message and Science Messenger (*negative_science*):

As we face the challenges of climate change, concerns are growing about the negative environmental impact of emerging AI technologies, such as ChatGPT, particularly their significant energy consumption and related carbon emissions. According to an analysis recently published by a scientist[a], the energy demands of AI could rival those of entire nations. For instance, if AI were integrated into all Google searches, it would consume 29.2 terawatt-hours (TWh) of electricity a year—equivalent to Ireland's annual consumption. The scientist further notes that, based on a projection of AI server production, worldwide AI-related annual electricity consumption could increase even more, by 85 to 134 TWh. Under such a scenario, the negative environmental impact of AI would be even greater, with annual electricity needs comparable to those of countries like the Netherlands, Argentina, or Sweden, posing a serious challenge for climate change mitigation efforts.

[a] The text linked to the following source: https://www.cell.com/joule/fulltext/S2542-4351(23)00365-3

Negative Message and News Messenger (*negative_news*):

As we face the challenges of climate change, concerns are growing about the negative environmental impact of emerging AI technologies, such as ChatGPT, particularly their significant energy consumption and related carbon emissions. According to a recent news article[a], the energy demands of AI could rival those of entire nations. For instance, if AI were integrated into all Google searches, it would consume 29.2 terawatt-hours (TWh) of electricity a year—equivalent to Ireland's annual consumption. The news further notes that, based on a projection of AI server production, worldwide AI-related annual electricity consumption could increase even more, by 85 to 134 TWh. Under such a scenario, the negative environmental impact of AI would be even greater, with annual electricity needs comparable to those of countries like the Netherlands, Argentina or Sweden, posing a serious challenge for climate change mitigation efforts.

[a]The text linked to the following source: https://www.euronews.com/next/2023/10/10/demand-for-ai-could-mean-technology-consumes-same-energy-as-a-country-analysis-shows

To verify that participants correctly understood the intended framing of the experimental messages, we included a manipulation check asking: "According to the text, what is the impact of AI on the environment?" Responses were recorded on a scale from –100 (very negative) to +100 (very positive). As shown in Figure A3, the results confirm successful treatment delivery. Participants in the two positive message conditions (Pos. Sci., Pos. News) reported strongly positive perceived environmental impacts (mean scores $> +70$), while those in the negative conditions (Neg. Sci., Neg. News) reported strongly negative impacts (mean scores < -70), with minimal overlap across groups. These large, precisely estimated differences validate the effectiveness of the framing manipulation.

We test whether the treatment groups are balanced in Appendix Tables A2-A5. We rely on baseline data (i.e., responses prior to the treatment) on AI use and trust, and demographics for our baseline tests. Overall, we find that the randomization process effectively balanced participant characteristics across treatment groups. The vast majority of the estimates are not statistically significant for the four treatment groups (control group is the omitted category). For our three AI use variables, we find no differences between the treatment groups and the control group. Turning to trust, we also find no differences in how much respondents trust information from scientists and social media across the treatment groups and control group. There are statistically significant ($p < 0.10$) differences for trust in news media, but this is likely due to randomness and the large number of regressions that we estimate.

4.2 Hypotheses

4.2.1 Primary Hypotheses (All Signed / Directional)

H1a: Exposure to **positive messaging** about the environmental impacts of AI increases stated beliefs that AI will impact the environment positively.

H1b: Exposure to **negative messaging** about the environmental impacts of AI increases stated beliefs that AI will impact the environment negatively.

H2a: Positive messaging increases stated likelihood of future use of AI chatbots.

H2b: Negative messaging decreases stated likelihood of future use of AI chatbots.

H3a: Positive messaging increases preference for AI-enabled thermostats.

H3b: Negative messaging decreases preference for AI-enabled thermostats.

H4a: Positive messaging decreases beliefs that AI companies should face stricter environmental regulations.

H4b: Negative messaging increases beliefs that AI companies should face stricter environmental regulations.

H5a: Positive messaging increases beliefs that governments should financially support the use of AI-enabled HVAC technologies.

H5b: Negative messaging decreases beliefs that governments should financially support the use of AI-enabled HVAC technologies.

4.2.2 Secondary Hypotheses (All Non-directional / Exploratory)

SH1a: Messaging about AI's environmental impacts affects beliefs that AI will impact the respondent's **life**.

SH1b: Messaging affects beliefs that AI will impact the respondent's **work**.

SH1c: Messaging affects beliefs that AI will impact **humanity** more broadly.

SH2a: Messaging affects the stated likelihood of **purchasing** a premium AI subscription.

SH2b: Messaging affects the stated likelihood of **cancelling** an existing premium AI subscription.

SH3a: Messaging affects preference for AI-enabled **fridges**.

SH3b: Messaging affects preference for AI-enabled **security cameras**.

SH3c: Messaging affects preference for AI-enabled **washing machines**.

SH4: The identity of the **information source** (scientist vs news outlet) moderates the impact of positive and negative messages on outcomes stated in H1–H5.

4.3 Measured Variables

AI Usage and Access

Frequency of AI chatbot use: In the past 30 days, how often did you use AI chatbots like ChatGPT or similar? (1–7 scale: Never to Multiple times per day)

Paid AI chatbot subscription: Do you currently have a paid subscription to an AI chatbot like ChatGPT or similar? (Yes/No)

Devices at home: At home, do you have any of the following devices? (Multiple select from 7 options, including "None of the above")

Trust Measures (0–100 Scale)

Trust in scientists

Trust in social media

Trust in news media

Treatment Comprehension (Treatment Group Only)

Perceived environmental impact of AI: According to the text, what is the impact of AI on the environment? (–100 to +100 scale)

Information source recall: Who was mentioned in the text as the information source? (Single choice: one of 3 options)

Beliefs and Perceptions (–100 to +100 Scale)

Self-reported knowledge: How informed would you say you are about the relationship between AI and the environment?

Perceived impact of AI: On the environment / On your life / On your work / On humanity

Anticipated future use: Compared to your current usage, how do you anticipate your use of AI chatbots will change in the next 6 months? (Includes "Not applicable")

Subscription intent:

- For non-subscribers: Likelihood of purchasing a paid AI chatbot subscription within the next 6 months
- For current subscribers: Likelihood of cancelling a paid subscription within the next 6 months

Policy Preferences and Consumption Intentions

AI environmental regulation: AI companies should face stricter environmental regulation. (–100 to +100 scale, includes "Not applicable")

Government subsidies: The government should financially support AI-enabled HVAC technologies. (–100 to +100 scale)

Consumer preferences (–100 to +100 scale):

- Fridge: Preference between AI-enabled vs traditional version
- Thermostat
- Security camera

- Washing machine

Demographics

State of residence: Dropdown list of U.S. states

Age: Integer

Marital status: Single choice (Married, Widowed, Divorced, Separated, Never married, Prefer not to say)

Sex: Single choice (Male, Female, Intersex, Prefer not to say)

Hispanic origin: Single choice (Yes, No, Prefer not to say)

Race: Multiple select (White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Pacific Islander, Other, Prefer not to say)

Education level: Single choice (From "Less than high school diploma" to "Doctorate degree", including "Prefer not to say")

Employment status: Single choice (e.g., Employed – at work, Retired, Student only, Prefer not to say)

Prolific hours: In the last 12 months, how many hours per week did you usually work on Prolific? (Integer)

Non-Prolific hours: In the last 12 months, how many hours per week did you usually work for pay (not including Prolific)? (Integer)

Household income: Single choice (Less than $60,000, $60,000 or more, Prefer not to say)

Treatment Text, and Attention and Retention Check

Treatment text: According to the text, what is the impact of AI on environment (–100 to +100 Scale)

Treatment text: Who was mentioned in the text as the information source? (single choice one of 3)

Study topic recall: Finally, what are the two things this study examined? (Multiple select: Environment, Artificial Intelligence, Media Bias, Employment, Politics, Education)

4.4 Participants and Sampling

Participants were recruited through the online platform Prolific, which offers a diverse pool of adult internet users. To achieve sufficient statistical power for detecting small effects, we calculated the required sample size using a two-tailed t-test for the difference of independent means, assuming an effect size of Cohen's d = 0.20 and a power of 80%. This resulted in a minimum target of 394 participants per group in any 2 group contrast. Anticipating around 15% potential dropouts and attention failures, we aimed to recruit enough in order to retain approximately 2,000 participants in total.

Participants were screened to ensure English fluency and location within the United States, with an approval rating of between 80-100. Participants were randomly assigned to conditions via Prolific's built-in randomization tool, and the final sample was balanced across all four treatment arms. Participants were recruited through the Prolific platform. They were offered 0.75 USD upon completion of the survey.

We also have the following exclusion criteria. First, we excluded participants based on time taken to answer the survey. More precisely, respondents below 5th percentile of total survey duration within their treatment group were excluded. Subsequently, we excluded participants that failed the comprehension check (i.e., Finally, what are the two things this study examined?).

4.5 Survey Instrument and Measures

Following exposure to the experimental treatment, respondents completed a structured survey measuring their beliefs, attitudes, and behavioral intentions concerning AI and environmental sustainability. Primary outcomes included perceived environmental impact of AI, trust in the information provided, and support for potential regulatory interventions. These outcomes were assessed on Likert-type scales and were pre-specified in the preregistration.

Secondary outcomes included perceived credibility of the messenger, likelihood of sharing the information, and changes in overall trust toward AI technologies. Moderator variables were collected to examine heterogeneity in treatment effects. These included political ideology, baseline familiarity with AI, trust in science, and media consumption patterns. Mediation pathways were explored by evaluating how messenger credibility may influence downstream outcomes such as support for regulation.

4.6 Statistical Methods

Treatment effects were estimated using ordinary least squares (OLS) regressions with robust standard errors. The main analysis regressed each outcome on indicator variables for treatment conditions and included controls for the following baseline covariates: demographic characteristics, Prolific hours, prior AI usage, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media. Additional analysis using models without control variables was also conducted.

Effect sizes are reported alongside 95% confidence intervals and p-values. We implemented one-tail tests for our primary hypotheses which were preregistered as directional. For unsigned secondary hypotheses we use two-tailed tests.

All analyses were pre-specified in a registered analysis plan and implemented using Stata 18.5 SE. Figures and tables were produced using R version 4.4.1. Power calculations were performed using G*Power version 3.1 and are visualized in Appendix Figures A1 and A2.

4.7 Power

This section describes the power calculations conducted during the design phase of this study. To achieve a power of 80% when comparing any two treatment arms using a two-tailed t-test[1] with significance level of 5% and assuming effect size of 0.2 standard deviations, we require 394 respondents per treatment arm (depicted in Figure A4). A total of 1970 respondents. Assuming up to 15% of respondents could be excluded based on the pre-registered exclusion criteria, we require 394/0.85=464 respondents per treatment arm. This gives us a total sample of 2320 respondents to be interviewed for the 5 treatment arms. The pooled specification where we make the comparison of the combined positive/negative messaging groups (2*394 respondents) to the control (394 respondents) yields power of 90%. All calculations done in G*Power version 3.1 and replicated in R using package *pwr*.

We proceeded to collect 2300 responses. After applying the exclusion criteria our final sample is 2142 respondents, 426 in control group, 431 in positive scientist, 427 in positive news, 430 in negative scientist, and 429 in negative news. All above the required 394 respondents.

4.8 Deviations from Pre-Analysis Plan

4.8.1 Control Variables We include total hours worked and question about frequency of AI use among control variables. These two variables were mentioned

[1] This results in under-estimation of power for our primary hypothesis with pre-registered hypothesis that are evaluated using a one-tailed test.

in section “Measured variables” in our PAP, but were accidentally omitted in the “Statistical models” section. Results are generally the same, see Section 4.8.3.

4.8.2 Exclusion Criteria We preregistered the following exclusion criterion:

> “Subsequently, we will exclude participants that fail the comprehension check:
>
> Finally, what are the two things this study examined? (multiple select: Environment, Artificial Intelligence, Media Bias, Employment, Politics, Education)
>
> Participants that did not select ‘Environment’ and ‘Artificial Intelligence’ will be excluded.”

However, this criterion is not balanced across the treatment arms, likely due to the treatments themselves. Control group participants were more likely to answer “Artificial Intelligence” and “Employment’ than the other four treatment groups. Similarly, control group and the two ‘news’ treatments were more likely to answer ‘Artificial Intelligence’ and ‘Media Bias’.

Therefore, we decided not to exclude those who answered “Artificial Intelligence” and ‘Employment” or ‘Artificial Intelligence” and “Media Bias” for any of the treatment groups.

The pre-registered exclusion criteria result in exclusion of 111 more respondents than the alternative we use. Results are generally the same, see Section 4.8.3.

4.8.3 If PAP is exactly followed In Figures A5 and A6 and Tables A12 through A17 we report results no a sample constructed using the pre-registered exclusion criteria and, where applicable, using control variables as listed in the pre-registration. The results are generally similar when using this alternative specification. However, there are a few differences. In our preferred specification with control variables, the coefficients for combined negative treatment for impact on “My Life” and “My Work”, and “Supports AI Investment”, and preference for “Washing Machine” are no longer statistically significant at 5% level. And the effect of “Positive: News” treatment on feeling informed is no longer significant, but its effect on “Supports AI regulation” and preference for AI “Thermostat” and “Washing Machine” all become statistically significant at 5% level. Similarly, the effects of “Positive: Scientist” on “Buy Subscription” becomes significant at 5% level.

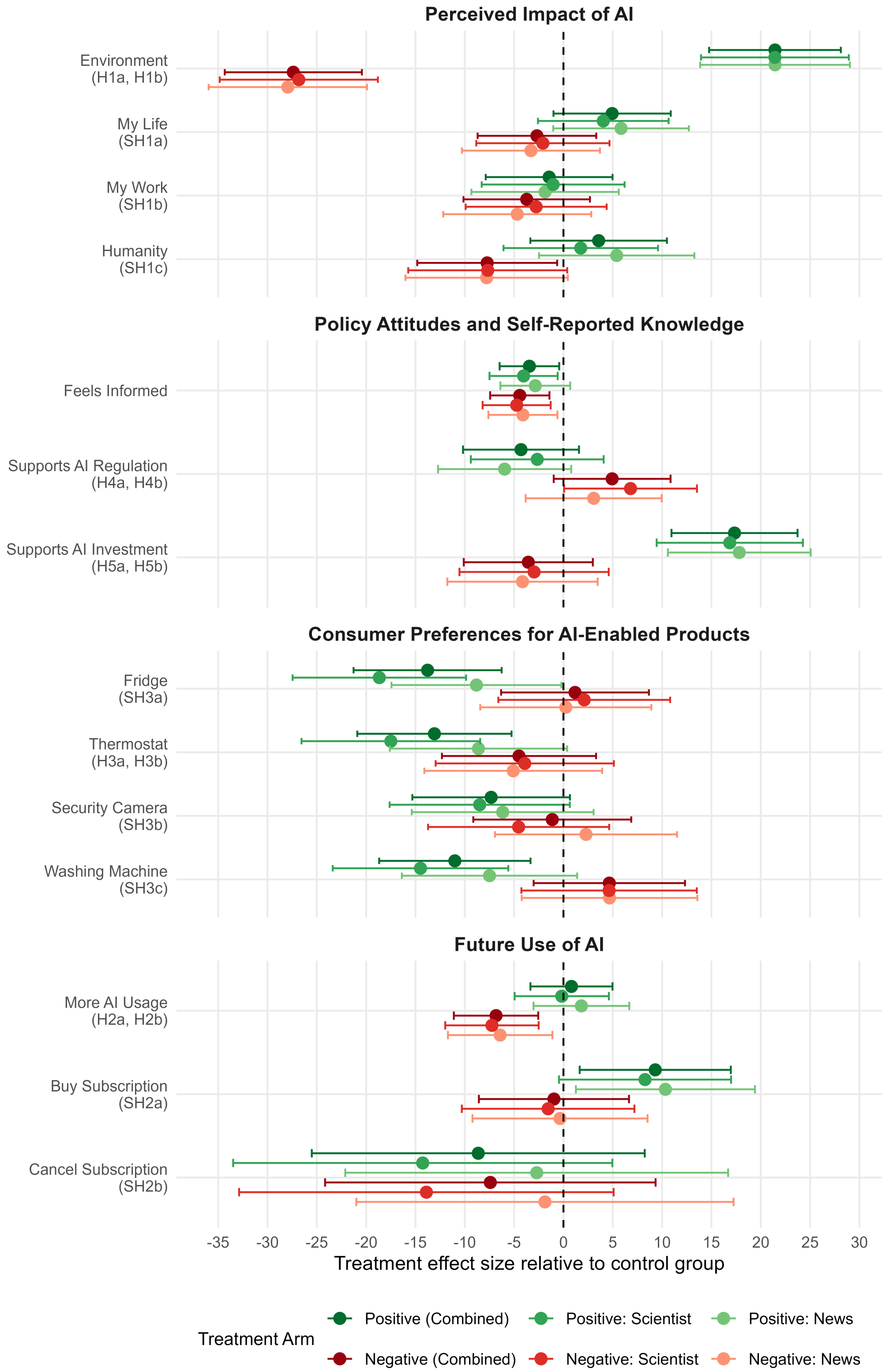
We preregistered exploratory heterogeneity analyses by prior usage of AI chatbots, paid subscription to AI chatbots, ownership of AI-enabled/smart devices, and levels of trust in scientists, social media, and news media. These analyses were not conducted and are left for future work.

5 Ethics and Preregistration

The study protocol was approved by the Research Ethics Board of Wilfrid Laurier University. All participants provided informed consent prior to participation. The preregistration, analysis scripts, and survey materials are publicly available on the Open Science Framework (OSF) at https://osf.io/wk8zu ensuring full transparency and reproducibility.

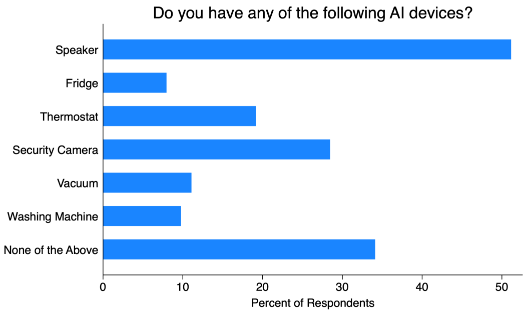
6 Appendix Figures

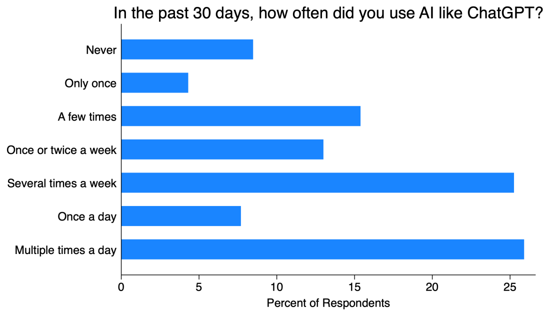
Figure A1: AI-Treatments effects on outcomes (no controls



Note: This figure displays treatment effects relative to the control group with 95% confidence intervals. The "Positive (Combined)" and "Negative (Combined)" estimates derive from an OLS models pooling positive and negative treatments. The remaining four estimates ("Positive: Scientist," "Positive: News," "Negative: Scientist," "Negative: News") come from separate models with four distinct treatment arms. All models employ robust standard errors. No control variables are included in these models. Corresponding tabular results appear in Appendix Tables A9, A10, and A11.

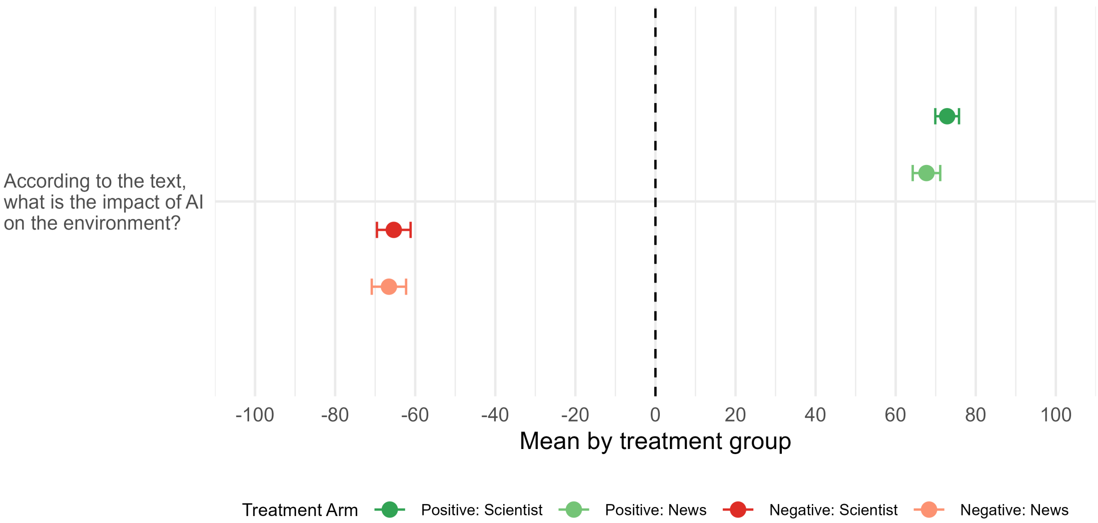
Figure A2: AI Device and Usage in Sample





Notes: Percent of respondents.

Figure A3: Treatment Check



Notes: This figure shows the mean and 95% confidence interval answers by treatment group for the question "According to the text, what is the impact of AI on the environment?" with a scale of -100 for very negative to 100 for very positive, where we expect to see a negative value for negative (loss) messaging and a positive value for positive (gain) messaging if respondent engages with the content of the message.

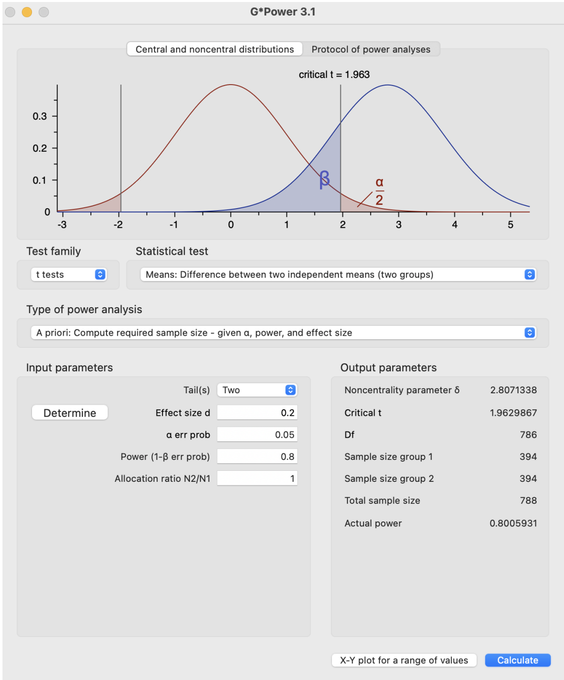
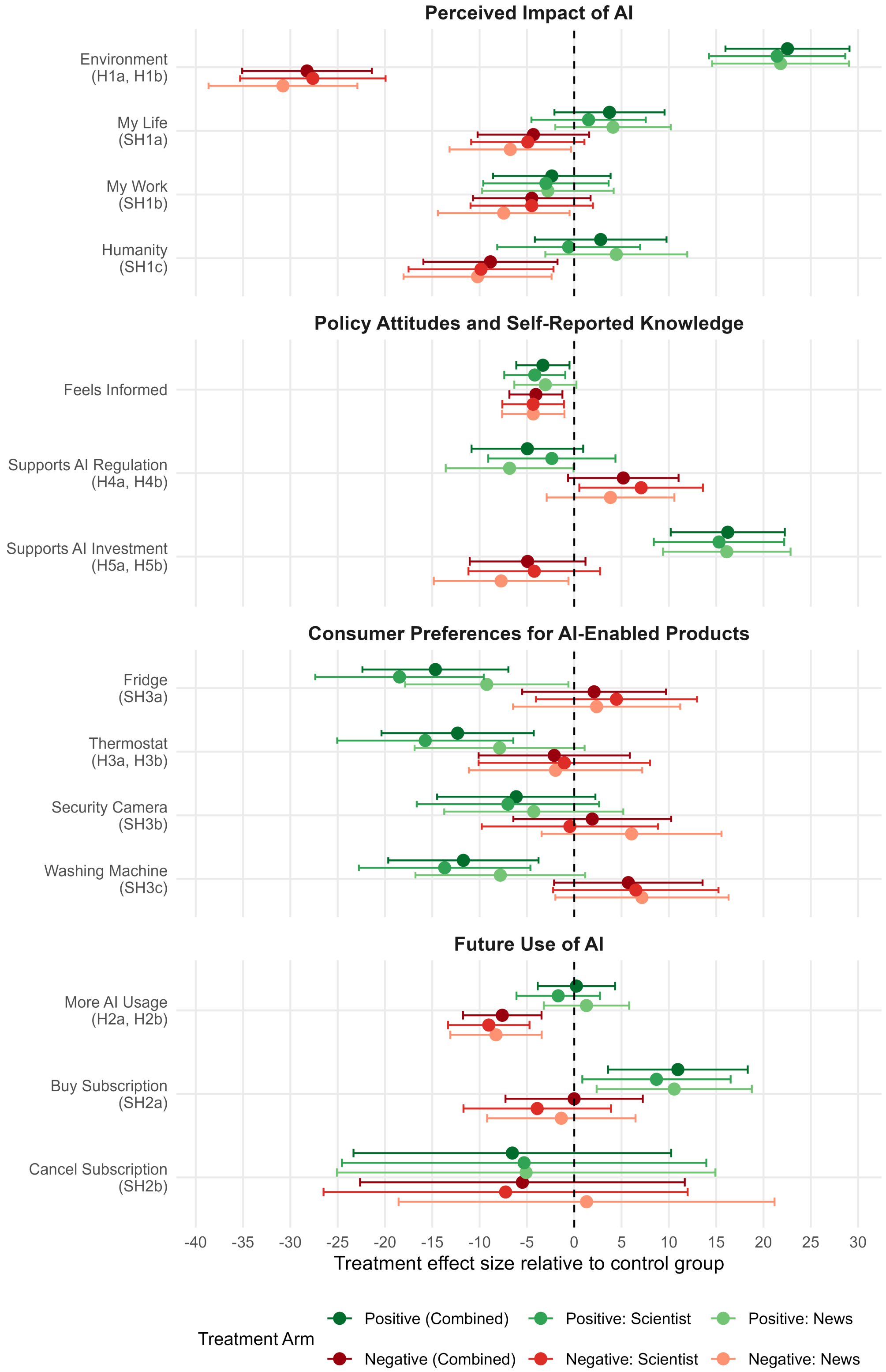


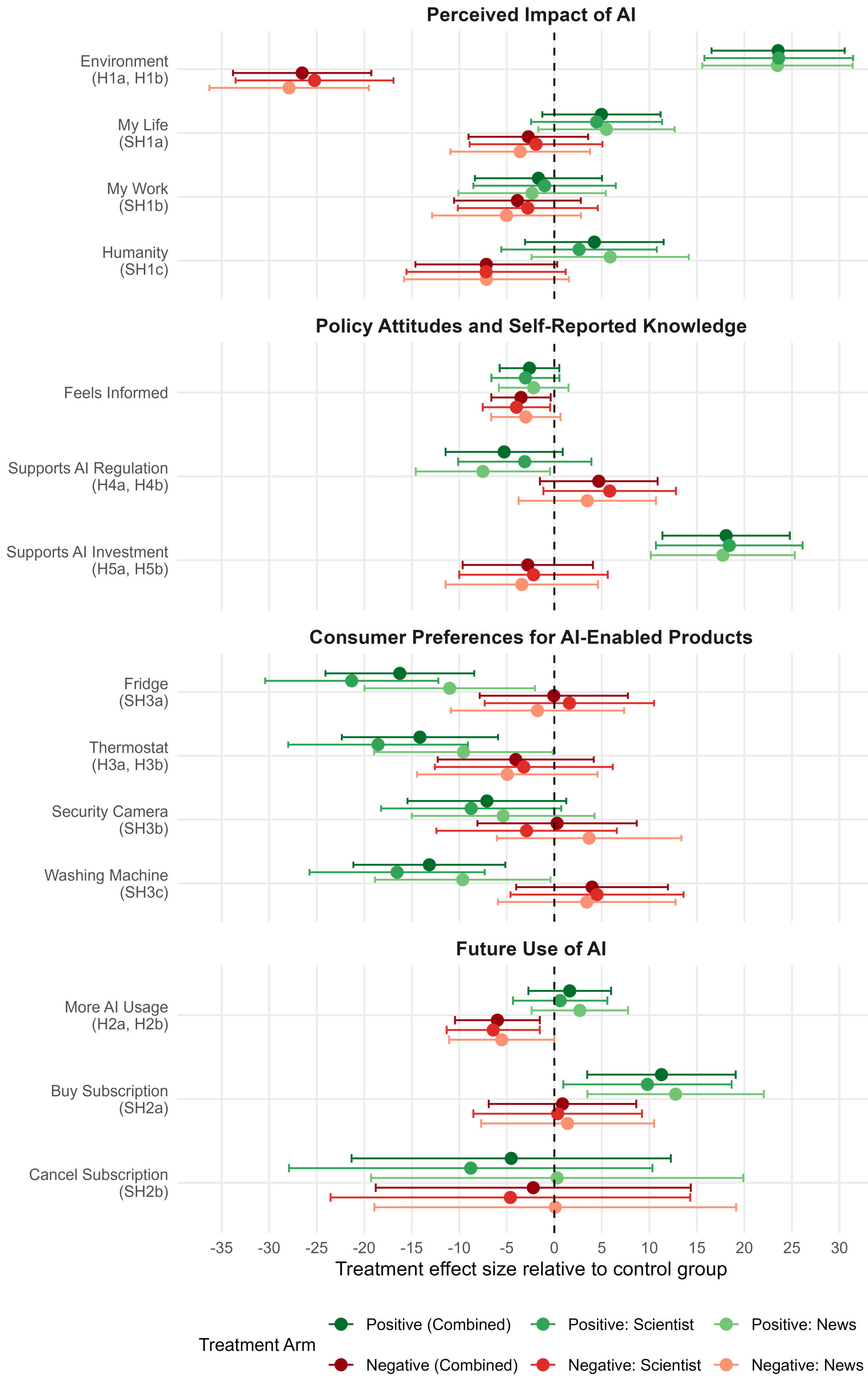
Figure A4: Minimum Sample Size Between Conditions

Figure A5: PAP specification: AI-Treatments effects on outcomes (with controls)



Note: This figure displays treatment effects relative to the control group with 95% confidence intervals. The "Positive (Combined)" and "Negative (Combined)" estimates derive from an OLS models pooling positive and negative treatments. The remaining four estimates ("Positive: Scientist," "Positive: News," "Negative: Scientist," "Negative: News") come from separate models with four distinct treatment arms. All models employ robust standard errors. No control variables are included in these models. All models control for demographic characteristics, Prolific hours, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media as preregistered in the PAP. The sample restriction for inattention was applied as described in the PAP.

Figure A6: PAP specification: AI-Treatments effects on outcomes (no controls)



Note: This figure displays treatment effects relative to the control group with 95% confidence intervals. The "Positive (Combined)" and "Negative (Combined)" estimates derive from an OLS models pooling positive and negative treatments. The remaining four estimates ("Positive: Scientist," "Positive: News," "Negative: Scientist," "Negative: News") come from separate models with four distinct treatment arms. All models employ robust standard errors. No control variables are included in these models. The sample restriction for inattention was applied as described in the PAP.

7 Appendix Tables

Table A1: Number of Respondents by Treatment Arm

Treatment Arm	Number of Respondents
Control	426
Positive: Scientist	431
Positive: News	427
Negative: Scientist	430
Negative: News	429
Total	2143

Note: This table shows the number of respondents by treatment arm after the exclusion criteria for speed and inattention were applied.

Table A2: Baseline Test: AI Use

	Baseline AI Use		
	(1)	(2)	(3)
	How Often Use AI	Paid For AI	Num AI Devices
Pos. Sci.	0.030	0.008	-0.083
	(0.810)	(0.754)	(0.340)
Pos. News	0.085	-0.004	0.021
	(0.498)	(0.869)	(0.809)
Neg. Sci.	0.121	-0.018	-0.126
	(0.341)	(0.496)	(0.151)
Neg. News	0.072	-0.001	0.075
	(0.570)	(0.956)	(0.396)
Constant	4.601***	0.184***	1.291***
	(0.000)	(0.000)	(0.000)
Observations	2,171	2,171	2,171
r2	0.001	0.000	0.003

These questions were asked pre-intervention. Dependent variable differs by column. (1) Likert score of how often respondent used AI in the last 30 days, where 1 is 'never', 4 is 'once or twice a week', and 7 is 'multiple times a day'. (2) Indicator variable for whether respondent has a paid subscription to an AI. (3) Count of the number of owned AI devices respondent has from the following list: speaker, fridge, thermostat, security camera, vacuum, washing machine. Primary independent variables are indicators for treatment group - for example 'Pos. Sci.' takes a value of one if the respondent is randomized into the positive science-based messaging. The omitted group is the control group. Model estimated using Ordinary Least Squares. *p*-values in parentheses where (* $p<0.10$, ** $p<0.05$, *** $p<0.01$).

Table A3: Baseline Test: Trust

	How much do you trust information from...		
	(1)	(2)	(3)
	Scientists	Social Media	News Media
Pos. Sci.	1.708	-0.524	3.200*
	(0.242)	(0.728)	(0.070)
Pos. News	0.582	-0.530	3.042*
	(0.693)	(0.727)	(0.087)
Neg. Sci.	1.357	-2.208	0.277
	(0.360)	(0.149)	(0.877)
Neg. News	1.924	-1.276	2.011
	(0.197)	(0.407)	(0.265)
Constant	74.315***	34.627***	46.540***
	(0.000)	(0.000)	(0.000)
Observations	2,171	2,171	2,171
r2	0.001	0.001	0.003

These questions were asked pre-intervention. Dependent variable differs by column. (1) Score from 0 to 100 of how much respondent trusts information from scientists (2) social media (3) news media. Primary independent variables are indicators for treatment group - for example 'Pos. Sci.' takes a value of one if the respondent is randomized into the positive science-based messaging. The omitted group is the control group. Model estimated using Ordinary Least Squares. *p*-values in parentheses where (* $p<0.10$, ** $p<0.05$, *** $p<0.01$).

Table A4: Baseline Test: Demographics I

	Demographics Balance 1				
	(1)	(2)	(3)	(4)	(5)
	Age	Married	Female	Hispanic	White
Pos. Sci.	1.834*	0.021	-0.044	-0.005	0.077**
	(0.082)	(0.519)	(0.188)	(0.827)	(0.012)
Pos. News	0.052	0.010	-0.021	-0.008	0.031
	(0.961)	(0.776)	(0.529)	(0.731)	(0.313)
Neg. Sci.	0.892	-0.033	-0.012	-0.020	0.045
	(0.405)	(0.330)	(0.713)	(0.360)	(0.145)
Neg. News	0.750	-0.005	-0.027	-0.008	0.023
	(0.487)	(0.880)	(0.434)	(0.724)	(0.452)
Constant	45.262***	0.469***	0.531***	0.132***	0.659***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,171	2,171	2,171	2,171	2,171
r2	0.002	0.001	0.001	0.000	0.003

Dependent variable differs by column. (1) respondent age (integer) (2) indicator for married (3) indicator for female (4) indicator for Hispanic (5) indicator for white. Primary independent variables are indicators for treatment group - for example 'Pos. Sci.' takes a value of one if the respondent is randomized into the positive science-based messaging. The omitted group is the control group. Model estimated using Ordinary Least Squares. p-values in parentheses where (* p<0.10, ** p<0.05, *** p<0.01).

Table A5: Baseline Test: Demographics II

	Demographics Balance 2				
	(1)	(2)	(3)	(4)	(5)
	Employed	B.A./B.Sc.	Income 60+	Hours Prolific	Hours Work
Pos. Sci.	-0.002	0.001	0.017	0.732	-0.539
	(0.936)	(0.978)	(0.597)	(0.468)	(0.695)
Pos. News	-0.017	-0.019	0.011	0.486	-0.293
	(0.592)	(0.561)	(0.749)	(0.632)	(0.833)
Neg. Sci.	-0.045	-0.017	-0.005	0.275	-0.123
	(0.148)	(0.603)	(0.879)	(0.788)	(0.930)
Neg. News	-0.029	0.004	-0.018	-0.879	-0.050
	(0.355)	(0.900)	(0.584)	(0.394)	(0.972)
Constant	0.707***	0.386***	0.557***	13.304***	28.499***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,171	2,171	2,171	2,171	2,171
r2	0.001	0.000	0.001	0.001	0.000

Dependent variable differs by column. (1) indicator for employed (other than Prolific) (2) indicator for Bachelor's degree (3) indicator for household income above \$60,000 per year (4) hours spent on Prolific per week in the last 12 months (5) hours spent working (not on Prolific) per week in the last 12 months. Primary independent variables are indicators for treatment group - for example 'Pos. Sci.' takes a value of one if the respondent is randomized into the positive science-based messaging. The omitted group is the control group. Model estimated using Ordinary Least Squares. p-values in parentheses where (* p<0.10, ** p<0.05, *** p<0.01).

Table A6: Treatment Effects of Combined Treatments (With Controls)

Panel A: AI Attitudes

	Environment (1)	My Life (2)	My Work (3)	Humanity (4)
Positive Treatment	20.530	3.312	-2.319	1.827
	(3.138)	(2.626)	(2.916)	(3.213)
	[0.000]	[0.207]	[0.427]	[0.570]
Negative Treatment	-29.398	-5.663	-5.737	-10.507
	(3.286)	(2.644)	(2.890)	(3.260)
	[0.000]	[0.032]	[0.047]	[0.001]
Controls	Yes	Yes	Yes	Yes
p-value (pos. = neg.)	0.000	0.000	0.140	0.000
Control group mean	8.51	36.78	31.44	32.82
Observations	2142	2142	2142	2142

Panel B: Information and Policy Support

	Feels Informed (1)	Supports AI Reg. (2)	Supports AI Invest. (3)
Positive Treatment	-4.270	-4.234	15.447
	(1.381)	(2.852)	(2.886)
	[0.002]	[0.138]	[0.000]
Negative Treatment	-5.013	5.447	-6.272
	(1.385)	(2.815)	(2.945)
	[0.000]	[0.053]	[0.033]
Controls	Yes	Yes	Yes
p-value (pos. = neg.)	0.527	0.000	0.000
Control group mean	48.78	41.65	6.69
Observations	2142	2142	2142

Panel C: Smart Device Preferences

	Fridge (1)	Thermostat (2)	Security Camera (3)	Washing Machine (4)
Positive Treatment	-12.269	-11.210	-6.226	-9.525
	(3.720)	(3.887)	(4.090)	(3.820)
	[0.001]	[0.004]	[0.128]	[0.013]
Negative Treatment	4.162	-2.274	0.961	6.899
	(3.668)	(3.868)	(4.037)	(3.788)
	[0.257]	[0.557]	[0.812]	[0.069]
Controls	Yes	Yes	Yes	Yes
p-value (pos. = neg.)	0.000	0.005	0.025	0.000
Control group mean	36.10	19.60	7.85	30.62
Observations	2141	2136	2142	2136

Panel D: AI Usage and Subscriptions

	More AI Usage (1)	Buy Subscription (2)	Cancel Subscription (3)
Positive Treatment	-0.552	8.029	-8.743
	(1.885)	(3.463)	(8.483)
	[0.770]	[0.021]	[0.303]
Negative Treatment	-9.307	-4.076	-5.551
	(1.916)	(3.397)	(8.760)
	[0.000]	[0.230]	[0.527]
Controls	Yes	Yes	Yes
p-value (pos. = neg.)	0.000	0.000	0.647
Control group mean	25.92	-47.28	-32.00
Observations	2067	1697	397

Note: This table reports estimated treatment effects from OLS models that pool the two positive treatments into one group and the two negative treatments into another, across all outcomes. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. All models control for demographic characteristics, Prolific hours, prior AI usage, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media.

Table A7: Treatment Effects (Panels A and B, With Controls)

Panel A: AI Attitudes

	Environment (1)	My Life (2)	My Work (3)	Humanity (4)
Positive: News	20.653	4.659	-2.264	4.345
	(3.553)	(3.001)	(3.426)	(3.631)
	[0.000]	[0.121]	[0.509]	[0.232]
Positive: Scientist	20.399	1.960	-2.387	-0.690
	(3.513)	(2.954)	(3.269)	(3.661)
	[0.000]	[0.507]	[0.465]	[0.851]
Negative: News	-30.436	-6.540	-7.259	-10.942
	(3.834)	(3.125)	(3.413)	(3.770)
	[0.000]	[0.036]	[0.034]	[0.004]
Negative: Scientist	-28.374	-4.803	-4.235	-10.088
	(3.792)	(2.955)	(3.214)	(3.736)
	[0.000]	[0.104]	[0.188]	[0.007]
Controls	Yes	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.000	0.000	0.147	0.000
p (pos. news = neg. news)	0.000	0.016	0.550	0.009
Control group mean	8.51	36.78	31.44	32.82
Observations	2142	2142	2142	2142

Panel B: Information and Policy Support

	Feels Informed (1)	Supports AI Reg. (2)	Supports AI Invest. (3)
Positive: News	-3.680	-5.991	16.371
	(1.616)	(3.287)	(3.283)
	[0.023]	[0.069]	[0.000]
Positive: Scientist	-4.861	-2.500	14.509
	(1.588)	(3.283)	(3.369)
	[0.002]	[0.446]	[0.000]
Negative: News	-5.270	3.266	-8.122
	(1.613)	(3.273)	(3.440)
	[0.001]	[0.319]	[0.018]
Negative: Scientist	-4.762	7.606	-4.450
	(1.616)	(3.204)	(3.449)
	[0.003]	[0.018]	[0.197]
Controls	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.338	0.005	0.000
p (pos. news = neg. news)	0.952	0.002	0.000
Control group mean	48.78	41.65	6.69
Observations	2142	2142	2142

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. All models control for demographic characteristics, Prolific hours, prior AI usage, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media.

Table A8: Treatment Effects (Panels C and D, With Controls)

Panel C: Smart Device Preferences	Fridge	Thermostat	Security Camera	Washing Machine
	(1)	(2)	(3)	(4)
Positive: News	-7.741	-7.157	-5.212	-6.423
	(4.224)	(4.400)	(4.629)	(4.385)
	[0.067]	[0.104]	[0.260]	[0.143]
Positive: Scientist	-16.780	-15.247	-7.207	-12.609
	(4.369)	(4.547)	(4.725)	(4.434)
	[0.000]	[0.001]	[0.127]	[0.005]
Negative: News	4.064	-2.240	4.543	7.994
	(4.293)	(4.456)	(4.620)	(4.439)
	[0.344]	[0.615]	[0.326]	[0.072]
Negative: Scientist	4.238	-2.324	-2.579	5.807
	(4.245)	(4.485)	(4.597)	(4.351)
	[0.318]	[0.604]	[0.575]	[0.182]
Controls	Yes	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.006	0.263	0.030	0.001
p (pos. news = neg. news)	0.000	0.005	0.310	0.000
Control group mean	36.10	19.60	7.85	30.62
Observations	2141	2136	2142	2136

Panel D: AI Usage and Subscriptions	More AI Usage	Buy Subscription	Cancel Subscription
	(1)	(2)	(3)
Positive: News	0.759	8.634	-4.523
	(2.199)	(4.079)	(9.845)
	[0.730]	[0.034]	[0.646]
Positive: Scientist	-1.841	7.418	-12.439
	(2.160)	(3.928)	(9.824)
	[0.394]	[0.059]	[0.206]
Negative: News	-9.204	-2.727	0.930
	(2.372)	(3.908)	(10.231)
	[0.000]	[0.485]	[0.928]
Negative: Scientist	-9.416	-5.372	-12.676
	(2.128)	(3.909)	(9.800)
	[0.000]	[0.170]	[0.197]
Controls	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.000	0.005	0.592
p (pos. news = neg. news)	0.000	0.001	0.981
Control group mean	25.92	-47.28	-32.00
Observations	2067	1697	397

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. All models control for demographic characteristics, Prolific hours, prior AI usage, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media.

Table A9: Treatment Effects of Combined Treatments (Without Controls)

Panel A: AI Attitudes

	Environment (1)	My Life (2)	My Work (3)	Humanity (4)
Positive Treatment	21.442	4.934	-1.451	3.569
	(3.406)	(3.032)	(3.280)	(3.532)
	[0.000]	[0.104]	[0.658]	[0.312]
Negative Treatment	-27.383	-2.689	-3.724	-7.730
	(3.546)	(3.068)	(3.271)	(3.617)
	[0.000]	[0.381]	[0.255]	[0.033]
Controls	No	No	No	No
p-value (pos. = neg.)	0.000	0.001	0.375	0.000
Control group mean	8.51	36.78	31.44	32.82
Observations	2143	2143	2143	2143

Panel B: Information and Policy Support

	Feels Informed (1)	Supports AI Reg. (2)	Supports AI Invest. (3)
Positive Treatment	-3.450	-4.302	17.340
	(1.541)	(2.999)	(3.260)
	[0.025]	[0.152]	[0.000]
Negative Treatment	-4.427	4.935	-3.562
	(1.534)	(3.021)	(3.338)
	[0.004]	[0.103]	[0.286]
Controls	No	No	No
p-value (pos. = neg.)	0.439	0.000	0.000
Control group mean	48.78	41.65	6.69
Observations	2143	2143	2143

Panel C: Smart Device Preferences

	Fridge (1)	Thermostat (2)	Security Camera (3)	Washing Machine (4)
Positive Treatment	-13.770	-13.080	-7.329	-11.008
	(3.830)	(3.989)	(4.075)	(3.914)
	[0.000]	[0.001]	[0.072]	[0.005]
Negative Treatment	1.174	-4.505	-1.134	4.650
	(3.822)	(3.986)	(4.085)	(3.914)
	[0.759]	[0.259]	[0.781]	[0.235]
Controls	No	No	No	No
p-value (pos. = neg.)	0.000	0.008	0.058	0.000
Control group mean	36.10	19.60	7.85	30.62
Observations	2142	2137	2143	2137

Panel D: AI Usage and Subscriptions

	More AI Usage (1)	Buy Subscription (2)	Cancel Subscription (3)
Positive Treatment	0.812	9.306	-8.635
	(2.121)	(3.909)	(8.610)
	[0.702]	[0.017]	[0.317]
Negative Treatment	-6.831	-0.964	-7.412
	(2.183)	(3.882)	(8.547)
	[0.002]	[0.804]	[0.386]
Controls	No	No	No
p-value (pos. = neg.)	0.000	0.002	0.855
Control group mean	25.92	-47.28	-32.00
Observations	2068	1698	397

Note: This table reports estimated treatment effects from OLS models that pool the two positive treatments into one group and the two negative treatments into another, across all outcomes. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. These models did not include any control variables.

Table A10: Treatment Effects (Panels A and B, (Without Controls)

Panel A: AI Attitudes

	Environment (1)	My Life (2)	My Work (3)	Humanity (4)
Positive: News	21.448	5.839	-1.861	5.399
	(3.872)	(3.508)	(3.811)	(4.016)
	[0.000]	[0.096]	[0.625]	[0.179]
Positive: Scientist	21.435	4.037	-1.045	1.756
	(3.823)	(3.379)	(3.695)	(3.995)
	[0.000]	[0.232]	[0.777]	[0.660]
Negative: News	-27.941	-3.295	-4.684	-7.784
	(4.095)	(3.569)	(3.828)	(4.201)
	[0.000]	[0.356]	[0.221]	[0.064]
Negative: Scientist	-26.826	-2.084	-2.767	-7.675
	(4.090)	(3.445)	(3.645)	(4.111)
	[0.000]	[0.545]	[0.448]	[0.062]
Controls	No	No	No	No
p (pos. sci. = neg. sci.)	0.000	0.008	0.455	0.001
p (pos. news = neg. news)	0.000	0.055	0.620	0.015
Control group mean	8.51	36.78	31.44	32.82
Observations	2143	2143	2143	2143

Panel B: Information and Policy Support

	Feels Informed (1)	Supports AI Reg. (2)	Supports AI Invest. (3)
Positive: News	-2.854	-5.962	17.823
	(1.807)	(3.443)	(3.693)
	[0.114]	[0.083]	[0.000]
Positive: Scientist	-4.039	-2.657	16.862
	(1.763)	(3.435)	(3.781)
	[0.022]	[0.439]	[0.000]
Negative: News	-4.110	3.065	-4.149
	(1.786)	(3.519)	(3.887)
	[0.021]	[0.384]	[0.286]
Negative: Scientist	-4.742	6.801	-2.976
	(1.760)	(3.435)	(3.860)
	[0.007]	[0.048]	[0.441]
Controls	No	No	No
p (pos. sci. = neg. sci.)	0.490	0.009	0.000
p (pos. news = neg. news)	0.688	0.005	0.000
Control group mean	48.78	41.65	6.69
Observations	2143	2143	2143

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. These models did not include any control variables.

Table A11: Treatment Effects (Panels C and D, (Without Controls)

Panel C: Smart Device Preferences

	Fridge	Thermostat	Security Camera	Washing Machine
	(1)	(2)	(3)	(4)
Positive: News	-8.819	-8.612	-6.159	-7.494
	(4.393)	(4.585)	(4.703)	(4.534)
	[0.045]	[0.060]	[0.190]	[0.098]
Positive: Scientist	-18.662	-17.496	-8.488	-14.489
	(4.487)	(4.621)	(4.660)	(4.540)
	[0.000]	[0.000]	[0.069]	[0.001]
Negative: News	0.237	-5.089	2.285	4.672
	(4.424)	(4.598)	(4.709)	(4.543)
	[0.957]	[0.268]	[0.627]	[0.304]
Negative: Scientist	2.108	-3.922	-4.545	4.628
	(4.443)	(4.609)	(4.684)	(4.536)
	[0.635]	[0.395]	[0.332]	[0.308]
Controls	No	No	No	No
p (pos. sci. = neg. sci.)	0.041	0.441	0.070	0.008
p (pos. news = neg. news)	0.000	0.003	0.390	0.000
Control group mean	36.10	19.60	7.85	30.62
Observations	2142	2137	2143	2137

Panel D: AI Usage and Subscriptions

	More AI Usage	Buy Subscription	Cancel Subscription
	(1)	(2)	(3)
Positive: News	1.818	10.338	-2.711
	(2.477)	(4.631)	(9.900)
	[0.463]	[0.026]	[0.784]
Positive: Scientist	-0.172	8.271	-14.263
	(2.437)	(4.449)	(9.805)
	[0.944]	[0.063]	[0.147]
Negative: News	-6.416	-0.350	-1.876
	(2.700)	(4.528)	(9.755)
	[0.018]	[0.938]	[0.848]
Negative: Scientist	-7.250	-1.554	-13.895
	(2.416)	(4.463)	(9.685)
	[0.003]	[0.728]	[0.152]
Controls	No	No	No
p (pos. sci. = neg. sci.)	0.003	0.023	0.930
p (pos. news = neg. news)	0.003	0.027	0.969
Control group mean	25.92	-47.28	-32.00
Observations	2068	1698	397

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. These models did not include any control variables.

Table A12: PAP specification: Treatment Effects of Combined Treatments (With Controls)

Panel A: AI Attitudes	Environment	My Life	My Work	Humanity
	(1)	(2)	(3)	(4)
Positive Treatment	22.536	3.725	-2.369	2.797
	(3.344)	(2.969)	(3.169)	(3.549)
	[0.000]	[0.210]	[0.455]	[0.431]
Negative Treatment	-28.240	-4.317	-4.486	-8.854
	(3.497)	(3.008)	(3.170)	(3.616)
	[0.000]	[0.151]	[0.157]	[0.014]
Controls	Yes	Yes	Yes	Yes
p-value (pos. = neg.)	0.000	0.000	0.387	0.000
Control group mean	6.15	36.71	31.49	31.95
Observations	2031	2031	2031	2031

Panel B: Information and Policy Support	Feels Informed	Supports AI Reg.	Supports AI Invest.
	(1)	(2)	(3)
Positive Treatment	-3.312	-4.953	16.225
	(1.435)	(3.010)	(3.075)
	[0.021]	[0.100]	[0.000]
Negative Treatment	-4.053	5.186	-4.927
	(1.430)	(2.980)	(3.121)
	[0.005]	[0.082]	[0.115]
Controls	Yes	Yes	Yes
p-value (pos. = neg.)	0.540	0.000	0.000
Control group mean	47.67	42.20	5.15
Observations	2031	2031	2031

Panel C: Smart Device Preferences	Fridge	Thermostat	Security Camera	Washing Machine
	(1)	(2)	(3)	(4)
Positive Treatment	-14.671	-12.324	-6.130	-11.714
	(3.934)	(4.105)	(4.268)	(4.051)
	[0.000]	[0.003]	[0.151]	[0.004]
Negative Treatment	2.100	-2.114	1.905	5.716
	(3.878)	(4.077)	(4.256)	(4.003)
	[0.588]	[0.604]	[0.654]	[0.153]
Controls	Yes	Yes	Yes	Yes
p-value (pos. = neg.)	0.000	0.002	0.015	0.000
Control group mean	38.16	19.93	6.91	32.38
Observations	2030	2025	2031	2026

Panel D: AI Usage and Subscriptions	More AI Usage	Buy Subscription	Cancel Subscription
	(1)	(2)	(3)
Positive Treatment	0.229	10.953	-6.540
	(2.086)	(3.766)	(8.564)
	[0.913]	[0.004]	[0.446]
Negative Treatment	-7.604	-0.010	-5.477
	(2.117)	(3.701)	(8.754)
	[0.000]	[0.998]	[0.532]
Controls	Yes	Yes	Yes
p-value (pos. = neg.)	0.000	0.000	0.885
Control group mean	24.93	-49.39	-41.50
Observations	1958	1629	356

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. All models control for demographic characteristics, Prolific hours, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media as preregistered in the PAP. The sample restriction for inattention was applied as described in the PAP.

Table A13: PAP specification: Treatment Effects (Panels A and B, With Controls)

Panel A: AI Attitudes	Environment (1)	My Life (2)	My Work (3)	Humanity (4)
Positive: News	21.804	4.097	-2.787	4.445
	(3.691)	(3.114)	(3.547)	(3.826)
	[0.000]	[0.188]	[0.432]	[0.245]
Positive: Scientist	21.438	1.519	-2.991	-0.589
	(3.674)	(3.083)	(3.380)	(3.853)
	[0.000]	[0.622]	[0.376]	[0.878]
Negative: News	-30.781	-6.757	-7.454	-10.219
	(4.013)	(3.276)	(3.550)	(3.991)
	[0.000]	[0.039]	[0.036]	[0.011]
Negative: Scientist	-27.623	-4.911	-4.493	-9.852
	(3.923)	(3.053)	(3.300)	(3.906)
	[0.000]	[0.108]	[0.174]	[0.012]
Controls	Yes	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.000	0.000	0.189	0.000
p (pos. news = neg. news)	0.000	0.023	0.631	0.011
Control group mean	6.15	36.71	31.49	31.95
Observations	2031	2031	2031	2031

Panel B: Information and Policy Support	Feels Informed (1)	Supports AI Reg. (2)	Supports AI Invest. (3)
Positive: News	-3.050	-6.830	16.118
	(1.673)	(3.445)	(3.440)
	[0.068]	[0.048]	[0.000]
Positive: Scientist	-4.172	-2.367	15.299
	(1.645)	(3.430)	(3.517)
	[0.011]	[0.490]	[0.000]
Negative: News	-4.331	3.832	-7.728
	(1.682)	(3.443)	(3.630)
	[0.010]	[0.266]	[0.033]
Negative: Scientist	-4.345	7.071	-4.223
	(1.661)	(3.334)	(3.548)
	[0.009]	[0.034]	[0.234]
Controls	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.456	0.002	0.000
p (pos. news = neg. news)	0.918	0.004	0.000
Control group mean	47.67	42.20	5.15
Observations	2031	2031	2031

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. All models control for demographic characteristics, Prolific hours, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media as preregistered in the PAP. The sample restriction for inattention was applied as described in the PAP.

Table A14: PAP specification: Treatment Effects (Panels C and D, With Controls)

Panel C: Smart Device Preferences	Fridge	Thermostat	Security Camera	Washing Machine
	(1)	(2)	(3)	(4)
Positive: News	-9.246	-7.887	-4.277	-7.812
	(4.402)	(4.583)	(4.826)	(4.576)
	[0.036]	[0.085]	[0.376]	[0.088]
Positive: Scientist	-18.463	-15.743	-7.008	-13.692
	(4.543)	(4.746)	(4.916)	(4.623)
	[0.000]	[0.001]	[0.154]	[0.003]
Negative: News	2.365	-1.978	6.058	7.157
	(4.508)	(4.675)	(4.850)	(4.670)
	[0.600]	[0.672]	[0.212]	[0.126]
Negative: Scientist	4.455	-1.048	-0.459	6.506
	(4.342)	(4.622)	(4.752)	(4.458)
	[0.305]	[0.821]	[0.923]	[0.145]
Controls	Yes	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.010	0.191	0.025	0.001
p (pos. news = neg. news)	0.000	0.001	0.155	0.000
Control group mean	38.16	19.93	6.91	32.38
Observations	2030	2025	2031	2026

Panel D: AI Usage and Subscriptions	More AI Usage	Buy Subscription	Cancel Subscription
	(1)	(2)	(3)
Positive: News	1.293	10.567	-5.081
	(2.300)	(4.183)	(10.205)
	[0.574]	[0.012]	[0.619]
Positive: Scientist	-1.694	8.691	-5.297
	(2.250)	(3.999)	(9.824)
	[0.452]	[0.030]	[0.590]
Negative: News	-8.269	-1.367	1.304
	(2.465)	(4.000)	(10.135)
	[0.001]	[0.733]	[0.898]
Negative: Scientist	-9.031	-3.913	-7.254
	(2.198)	(3.977)	(9.815)
	[0.000]	[0.325]	[0.460]
Controls	Yes	Yes	Yes
p (pos. sci. = neg. sci.)	0.000	0.003	0.551
p (pos. news = neg. news)	0.001	0.001	0.840
Control group mean	24.93	-49.39	-41.50
Observations	1958	1629	356

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. All models control for demographic characteristics, Prolific hours, AI device ownership, paid AI subscriptions, and trust in scientists, news, and social media as preregistered in the PAP. The sample restriction for inattention was applied as described in the PAP.

Table A15: PAP specification: Treatment Effects of Combined Treatments (Without Controls)

Panel A: AI Attitudes	Environment	My Life	My Work	Humanity
	(1)	(2)	(3)	(4)
Positive Treatment	23.546	4.958	-1.671	4.213
	(3.574)	(3.174)	(3.411)	(3.720)
	[0.000]	[0.118]	[0.624]	[0.258]
Negative Treatment	-26.534	-2.736	-3.881	-7.157
	(3.712)	(3.211)	(3.402)	(3.805)
	[0.000]	[0.394]	[0.254]	[0.060]
Controls	No	No	No	No
p-value (pos. = neg.)	0.000	0.001	0.400	0.000
Control group mean	6.15	36.71	31.49	31.95
Observations	2032	2032	2032	2032

Panel B: Information and Policy Support	Feels Informed	Supports AI Reg.	Supports AI Invest.
	(1)	(2)	(3)
Positive Treatment	-2.614	-5.277	18.076
	(1.601)	(3.143)	(3.419)
	[0.103]	[0.093]	[0.000]
Negative Treatment	-3.505	4.677	-2.791
	(1.594)	(3.159)	(3.497)
	[0.028]	[0.139]	[0.425]
Controls	No	No	No
p-value (pos. = neg.)	0.490	0.000	0.000
Control group mean	47.67	42.20	5.15
Observations	2032	2032	2032

Panel C: Smart Device Preferences	Fridge	Thermostat	Security Camera	Washing Machine
	(1)	(2)	(3)	(4)
Positive Treatment	-16.256	-14.137	-7.095	-13.149
	(3.992)	(4.193)	(4.261)	(4.077)
	[0.000]	[0.001]	[0.096]	[0.001]
Negative Treatment	-0.052	-4.058	0.292	3.970
	(3.979)	(4.188)	(4.277)	(4.072)
	[0.990]	[0.333]	[0.946]	[0.330]
Controls	No	No	No	No
p-value (pos. = neg.)	0.000	0.003	0.028	0.000
Control group mean	38.16	19.93	6.91	32.38
Observations	2031	2026	2032	2027

Panel D: AI Usage and Subscriptions	More AI Usage	Buy Subscription	Cancel Subscription
	(1)	(2)	(3)
Positive Treatment	1.622	11.273	-4.535
	(2.220)	(3.986)	(8.569)
	[0.465]	[0.005]	[0.597]
Negative Treatment	-5.989	0.862	-2.215
	(2.277)	(3.960)	(8.457)
	[0.009]	[0.828]	[0.794]
Controls	No	No	No
p-value (pos. = neg.)	0.000	0.002	0.731
Control group mean	24.93	-49.39	-41.50
Observations	1959	1630	356

Note: This table reports estimated treatment effects from OLS models that pool the two positive treatments into one group and the two negative treatments into another, across all outcomes. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. These models did not include any control variables. The sample restriction for inattention was applied as described in the PAP.

Table A16: PAP specification: Treatment Effects (Panels A and B, (Without Controls))

Panel A: AI Attitudes				
	Environment	My Life	My Work	Humanity
	(1)	(2)	(3)	(4)
Positive: News	23.479	5.487	-2.341	5.879
	(4.037)	(3.662)	(3.957)	(4.219)
	[0.000]	[0.134]	[0.554]	[0.164]
Positive: Scientist	23.611	4.447	-1.024	2.603
	(3.991)	(3.516)	(3.824)	(4.176)
	[0.000]	[0.206]	[0.789]	[0.533]
Negative: News	-27.905	-3.591	-5.027	-7.135
	(4.279)	(3.748)	(3.997)	(4.427)
	[0.000]	[0.338]	[0.209]	[0.107]
Negative: Scientist	-25.229	-1.921	-2.790	-7.178
	(4.237)	(3.564)	(3.757)	(4.274)
	[0.000]	[0.590]	[0.458]	[0.093]
Controls	No	No	No	No
p (pos. sci. = neg. sci.)	0.000	0.011	0.493	0.002
p (pos. news = neg. news)	0.000	0.049	0.616	0.013
Control group mean	6.15	36.71	31.49	31.95
Observations	2032	2032	2032	2032

Panel B: Information and Policy Support			
	Feels Informed	Supports AI Reg.	Supports AI Invest.
	(1)	(2)	(3)
Positive: News	-2.173	-7.517	17.733
	(1.870)	(3.603)	(3.859)
	[0.245]	[0.037]	[0.000]
Positive: Scientist	-3.040	-3.112	18.407
	(1.825)	(3.579)	(3.938)
	[0.096]	[0.385]	[0.000]
Negative: News	-3.000	3.471	-3.422
	(1.860)	(3.687)	(4.091)
	[0.107]	[0.347]	[0.403]
Negative: Scientist	-3.985	5.825	-2.189
	(1.810)	(3.557)	(3.987)
	[0.028]	[0.102]	[0.583]
Controls	No	No	No
p (pos. sci. = neg. sci.)	0.659	0.002	0.000
p (pos. news = neg. news)	0.596	0.009	0.000
Control group mean	47.67	42.20	5.15
Observations	2032	2032	2032

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. These models did not include any control variables. The sample restriction for inattention was applied as described in the PAP.

Table A17: PAP specification: Treatment Effects (Panels C and D, (Without Controls))

Panel C: Smart Device Preferences				
	Fridge	Thermostat	Security Camera	Washing Machine
	(1)	(2)	(3)	(4)
Positive: News	-11.010	-9.561	-5.383	-9.638
	(4.575)	(4.798)	(4.906)	(4.713)
	[0.016]	[0.046]	[0.273]	[0.041]
Positive: Scientist	-21.314	-18.550	-8.749	-16.543
	(4.650)	(4.822)	(4.835)	(4.706)
	[0.000]	[0.000]	[0.070]	[0.000]
Negative: News	-1.771	-4.950	3.663	3.417
	(4.651)	(4.843)	(4.951)	(4.766)
	[0.703]	[0.307]	[0.459]	[0.473]
Negative: Scientist	1.585	-3.208	-2.919	4.494
	(4.547)	(4.775)	(4.843)	(4.645)
	[0.727]	[0.502]	[0.547]	[0.333]
Controls	No	No	No	No
p (pos. sci. = neg. sci.)	0.046	0.331	0.061	0.006
p (pos. news = neg. news)	0.000	0.001	0.210	0.000
Control group mean	38.16	19.93	6.91	32.38
Observations	2031	2026	2032	2027

Panel D: AI Usage and Subscriptions			
	More AI Usage	Buy Subscription	Cancel Subscription
	(1)	(2)	(3)
Positive: News	2.680	12.762	0.303
	(2.590)	(4.732)	(9.992)
	[0.301]	[0.007]	[0.976]
Positive: Scientist	0.614	9.798	-8.793
	(2.534)	(4.519)	(9.754)
	[0.808]	[0.030]	[0.368]
Negative: News	-5.531	1.403	0.097
	(2.823)	(4.642)	(9.709)
	[0.050]	[0.763]	[0.992]
Negative: Scientist	-6.430	0.354	-4.622
	(2.498)	(4.527)	(9.653)
	[0.010]	[0.938]	[0.632]
Controls	No	No	No
p (pos. sci. = neg. sci.)	0.004	0.018	0.983
p (pos. news = neg. news)	0.004	0.035	0.657
Control group mean	24.93	-49.39	-41.50
Observations	1959	1630	356

Note: This table reports estimated treatment effects from OLS models with four treatments. Robust standard errors are reported in parentheses and double-sided p-values in square brackets. These models did not include any control variables. The sample restriction for inattention was applied as described in the PAP.

8 Survey Instrument

LAUREIR WILFRID LAURIER UNIVERSITY

intro

Hello, I am a researcher at Wilfrid Laurier University and this study looks at the relationship between artificial intelligence (AI) use and the environment.

The study lasts approximately 5 minutes.

Your participation is voluntary, and you are not required to complete it.

Questions about this study may be directed to: Professor Nikolai Cook, Wilfrid Laurier University, ncook@wlu.ca

If you would like to proceed, please continue to the next page.

Informed Consent Statement "Survey Experiment of AI and Energy Use"

Principal Investigator: Dr Nikolai Cook

You are invited to participate in a research study. The purpose of this study is to examine the relationship between artificial intelligence (AI) use and the environment. The researcher is a Laurier professor in the department of Economics.

Information: In this study, you will be asked about your use of AI, technologies that use AI, and views on some environmental policies. The study will take about 5 minutes to complete. Data from approximately 2000 research participants on Prolific will be collected for this study. The study will be conducted via Prolific.

Risks: You are free to discontinue the study at any time and to choose not to respond to any question without loss of compensation. There are no anticipated risks associated with participating in the research study.

Benefits: You may directly benefit from the participation in this research project via Prolific compensation. The research will contribute to the body of literature/knowledge on sustainable AI use.

Privacy and confidentiality: No identifying information will be collected, and participation will remain anonymous. Only aggregate results will be published. Please Note: We do not collect or use internet protocol (IP) addresses or other information which could link your participation to your computer or electronic device. The data will be stored on a password protected computer will only be accessed by authorized research team members. The anonymous data will be kept for a minimum of 7 years and will then be destroyed by the principal investigator.

Incentives: For participating in this study, you will receive 0.75 USD. If you withdraw from the study prior to its completion, you will still receive this amount.

Contact: If you have questions related to this study or the procedures, or you experience adverse effects as a result of participating in this study, you may contact the researcher, Nikolai Cook, at ncook@wlu.ca. This project has been reviewed and approved by the University Research Ethics Board (REB#9058). If you feel you have not been treated according to the descriptions in this form or your rights as a participant in research have been violated during the course of this project, or if you have any questions for the board, you may contact Jayne Kalmar, PhD, Chair, University Research Ethics Board, Wilfrid Laurier University, +1 548 889 3518 or rebchair@wlu.ca.

Participation: Your participation in this study is voluntary; you may decline to participate without penalty. If you decide to participate, you may withdraw from the study at any time without penalty. You have the right to refuse to answer any question or participate in any activity you choose. Due to the anonymity of the data if you withdraw from the study, it is not possible to have your data removed/destroyed.

Feedback and publication: The results of this research might be published/presented in a journal article and conference presentation. You can request the executive summary by e-mailing ncook@wlu.ca by 2025-12-31.

Consent: It is advised that you print or save this consent form and/or record the researcher contact information in the case that you have any questions or concerns. If you do not want to participate in this study, please return to prolific in your browser.

If you read and understand the above information and agree to participate in this study, please complete the captcha.

I'm not a robot

reCAPTCHA
Privacy - Terms

What is your Prolific ID?
(Please note that this response should auto-fill with the correct ID)

${e://Field/PROLIFIC_PID}

In the past 30 days, how often did you use AI chatbots like ChatGPT or similar?

- ○ Multiple times a day
- ○ Once a day
- ○ Several times a week
- ○ Once or twice a week
- ○ A few times
- ○ Only once
- ○ Never

Do you currently have a paid subscription to an AI chatbot like ChatGPT or similar?

- ○ Yes
- ○ No

At home, do you have any of the following devices? (select all that apply)

- ☐ Smart Speaker (e.g. Echo, Nest, HomePod)
- ☐ Smart/AI-enabled fridge
- ☐ Smart/AI-enabled thermostat
- ☐ Smart/AI-enabled security camera
- ☐ Smart/AI-enabled vacuum
- ☐ Smart/AI-enabled washing machine

☐ None of the above

How much do you trust information from...

	Not at all							Trust Fully				
	0	10	20	30	40	50	60	70	80	90	100	
Scientists												
Social Media												
News Media												

pos_science

The following page will present you with information about the relationship between AI and the environment.

As we face the challenges of climate change, AI technologies are emerging as powerful tools to optimize energy consumption and reduce emissions, particularly in the building sector. According to a recent scientific study, artificial intelligence (AI) has the potential to significantly reduce energy consumption and carbon emissions in the U.S. building sector. It is estimated that AI could lower energy use by approximately 8% by 2050 in a business-as-usual scenario. Moreover, the scientists note, that when combined with energy efficiency policies and low-carbon power generation, AI-driven technologies could reduce energy consumption by 40% and carbon emissions by up to 90%. AI can help accelerate the timeline for peak energy use in buildings, moving it from 2040 to 2035. This highlights AI's crucial role in achieving substantial energy and emissions reductions, particularly when integrated with policy measures and advanced energy-saving technologies.

	Negative					Neutral				Positive		
	-100	-80	-60	-40	-20	0	20	40	60	80	100	
According to the text, what is the impact of AI on the environment?												

Who was mentioned in the text as the information source?

- ◯ Scientists
- ◯ Social Media
- ◯ News Media

pos_news

The following page will present you with information about the relationship between AI and the environment.

As we face the challenges of climate change, AI technologies are emerging as powerful tools to optimize energy consumption and reduce emissions, particularly in the building sector. According to a recent news article, artificial intelligence (AI) has the potential to significantly reduce energy consumption and carbon emissions in the U.S. building sector. It is estimated that AI could lower energy use by approximately 8% by 2050 in a business-as-usual scenario. Moreover, the news notes, that when combined with energy efficiency policies and low-carbon power generation, AI-driven technologies could reduce energy consumption by 40% and carbon emissions by up to 90%. AI can help accelerate the timeline for peak energy use in buildings, moving it from 2040 to 2035. This highlights AI’s crucial role in achieving substantial energy and emissions reductions, particularly when integrated with policy measures and advanced energy-saving technologies.

	Negative					Neutral			Positive		
	-100	-80	-60	-40	-20	0	20	40	60	80	100
According to the text, what is the impact of AI on the environment?											

Who was mentioned in the text as the information source?

- ◯ Scientists

○ Social Media
○ News Media

neg_science

The following page will present you with information about the relationship between AI and the environment.

As we face the challenges of climate change, concerns are growing about the negative environmental impact of emerging AI technologies, such as ChatGPT, particularly their significant energy consumption and related carbon emissions. According to an analysis recently published by a scientist, the energy demands of AI could rival those of entire nations. For instance, if AI were integrated into all Google searches, it would consume 29.2 terawatt-hours (TWh) of electricity a year—equivalent to Ireland's annual consumption. The scientist further notes that, based on a projection of AI server production, worldwide AI-related annual electricity consumption could increase even more, by 85 to 134 TWh. Under such a scenario, the negative environmental impact of AI would be even greater, with annual electricity needs comparable to those of countries like the Netherlands, Argentina, or Sweden, posing a serious challenge for climate change mitigation efforts.

	Negative				Neutral				Positive		
	-100	-80	-60	-40	-20	0	20	40	60	80	100
According to the text, what is the impact of AI on the environment?											

Who was mentioned in the text as the information source?

○ Scientists
○ Social Media
○ News Media

neg_news

The following page will present you with information about the relationship between AI and the environment.

As we face the challenges of climate change, concerns are growing about the negative environmental impact of emerging AI technologies, such as ChatGPT, particularly their significant energy consumption and related carbon emissions. According to a recent news article, the energy demands of AI could rival those of entire nations. For instance, if AI were integrated into all Google searches, it would consume 29.2 terawatt-hours (TWh) of electricity a year—equivalent to Ireland's annual consumption. The news further notes that, based on a projection of AI server production, worldwide AI-related annual electricity consumption could increase even more, by 85 to 134 TWh. Under such a scenario, the negative environmental impact of AI would be even greater, with annual electricity needs comparable to those of countries like the Netherlands, Argentina or Sweden, posing a serious challenge for climate change mitigation efforts.

	Negative					Neutral					Positive
	-100	-80	-60	-40	-20	0	20	40	60	80	100
According to the text, what is the impact of AI on the environment?											

Who was mentioned in the text as the information source?

- ○ Scientists
- ○ Social Media
- ○ News Media

control block

post_block

	Not at all informed			Somewhat informed			Very informed				
	0	10	20	30	40	50	60	70	80	90	100
How informed would you say you are about the relationship between AI and the environment?											

Please evaluate the following phrases.

	Negatively			No Effect			Positively				
	-100	-80	-60	-40	-20	0	20	40	60	80	100
I believe that AI will impact the environment...											
I believe that AI will impact my life...											
I believe that AI will impact my work...											
I believe that AI will impact humanity...											

	Much less			The same			Much more					Not Applicable
	-100	-80	-60	-40	-20	0	20	40	60	80	100	
Compared to your current usage of AI Chatbots and Conversational Agents (such as ChatGPT, Copilot, Claude, or Gemini), how do you anticipate your usage will change in the next 6 months?												

	Very Unlikely	Very Likely	Not Applicable
	-100 -80 -60 -40 -20 0 20 40 60 80 100		
How likely are you to purchase a paid subscription to an AI chatbot like ChatGPT or a similar service within the next 6 months?			

	Very Unlikely	Very Likely	Not Applicable
	-100 -80 -60 -40 -20 0 20 40 60 80 100		
How likely are you to cancel your paid subscription to an AI chatbot like ChatGPT within the next 6 months?			

policy_block

How do you feel about the following statements?

	Disagree	Agree
	-100 -80 -60 -40 -20 0 20 40 60 80 100	
AI companies should face stricter environmental regulation.		

	Disagree									Agree
	-100	-80	-60	-40	-20	0	20	40	60	80	100
The government should financially support the use of AI-enabled HVAC (Heating, Ventilation, and Air Conditioning) technologies.											

For each of the following products, please indicate your preference between purchasing an AI-enabled version or a traditional (non-AI) version.

	Smart/AI-enabled									Traditional
	-100	-80	-60	-40	-20	0	20	40	60	80	100
Fridge											
Thermostat											
Security Camera											
Washing Machine											

demo_block

Which state do you reside in?

What is your age?

What is your marital status?

- ◯ Married
- ◯ Widowed
- ◯ Divorced
- ◯ Separated
- ◯ Never married
- ◯ Prefer not to say

What is your sex?

- ◯ Male
- ◯ Female
- ◯ Intersex
- ◯ Prefer not to say

Are you of Hispanic, Latino, or Spanish origin?

- ◯ No
- ◯ Yes
- ◯ Prefer not to say

What is your race (select all that apply)?

- ☐ White
- ☐ Black or African American
- ☐ American Indian or Alaska Native
- ☐ Asian
- ☐ Native Hawaiian or Pacific Islander
- ☐ Other
- ☐ Prefer not to say

What is the highest degree or level of school you have completed?

- ◯ Less than high school diploma
- ◯ Regular high school diploma
- ◯ GED or alternative
- ◯ Some college, but less than 1 year
- ◯ 1 or more years of college credit, no degree

- Associate's degree (e.g. AA, AS)
- Bachelor's degree (e.g. BA, BS)
- Master's degree (e.g. MA, MS, MEng, MEd, MSW, MBA)
- Professional degree beyond a bachelor's degree (e.g. MD, DDS, DVM, LLB, JD)
- Doctorate degree (e.g. PhD, EdD)
- Prefer not to say

What is your current employment status?

- Employed - at work
- Employed - with job but absent (e.g vacation, leave, training)
- Unemployed - layoff
- Unemployed - looking
- Not in labor force - retired
- Not in labor force - disabled
- Not in labor force - student only
- Not in labor force - other
- Prefer not to say

In the last 12 months, how many hours per week did you usually work on Prolific?

In the last 12 months, how many hours per week did you usually work for pay (not including Prolific)?

What is your household income per year?

- Less than $60,000
- $60,000 or more
- Prefer not to say

(Optional) Would you like to share any comments?

Finally, what are the two things this study examined?

- ☐ Politics
- ☐ Employment
- ☐ Education
- ☐ Media Bias
- ☐ Artificial Intelligence
- ☐ Environment

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