How Media Coverage and Elite Communication Shape Public Opinion on AI Regulation*

Tamar Mitts† and Shir Raviv‡

February 3, 2025

Draft: Comments Welcome Word count: 10,010

Abstract

As AI increasingly shapes society, policymakers face the challenge of crafting regulations that balance innovation with the public interest. While the technical and legal hurdles of AI governance are well-documented, its political feasibility remains understudied. We explore potential polarization in AI regulation by analyzing over 12,000 U.S. news articles, identifying the stakeholders involved and the primary issues discussed. Using a well-powered survey experiment with a behavioral component, we assess how media messaging shapes voter support for AI regulation. Our media analysis reveals an emerging partisan divide in AI coverage. However, experimental results suggest that this potential politicization is not inevitable. Rather than directly adopting elite positions, voters rely on trusted sources to determine which information deserves attention, which, in turn, shapes their policy preferences in an unbiased manner. The findings highlight the possibility of building cross-partisan coalitions for AI governance frameworks that prioritize the public interest over partisan agendas.

*This study was pre-registered on 06/01/2024 (https://doi.org/10.17605/OSF.IO/UQDXB) and approved by Columbia University's IRB (#AAAV0154).

†Assistant Professor, School of International and Public Affairs, Columbia University.

‡Post-Doctoral Researcher, Data Science Institute, Columbia University.

Introduction

Recent advances in Artificial Intelligence (AI) and large language models hold great promise for enhancing government efficiency, boosting human capabilities, and driving economic growth (Bommasani et al., 2021; Rotman, 2023). Yet, this rapid expansion of AI also introduces significant risks and ethical dilemmas, including reinforcing biases, spreading misinformation, causing widespread job displacement, and misuse in military applications (Eubanks, 2018; Bond, 2024; Swenson and Chan, 2024). As AI increasingly influences nearly every aspect of life—from the information voters receive to their interactions with public officials and the evolving job landscape—policymakers face the challenge of crafting regulations that harness AI's potential while protecting human rights and serving the public interest.

This is not an easy task. The dynamic nature of AI technologies and their diverse applications require adaptable regulatory frameworks that are both technically feasible and practically enforceable across various sectors (Cath, 2018; Engstrom and Haim, 2023). While the technical and legal hurdles in AI regulation are widely recognized (Büthe et al., 2022), the political feasibility of proposed measures has received much less attention. This oversight is surprising because effective regulations largely hinge on their political viability—namely, the ability to mobilize broad support from a diverse coalition of voters and stakeholders with varying interests and concerns (König, Wurster, and Siewert, 2023). In the polarized political environments that many countries face today, where partisan divides often overshadow substantive policy discussion, garnering broad support can be particularly challenging (Bullock, 2020; Slothuus and Bisgaard, 2021).

What do voters think about government intervention to regulate this powerful technology? To what extent are their views divided along partisan lines? And how influential are media narratives in shaping their perspectives on the issue? Although research on AI regulation is still emerging, recent U.S.-based studies suggest that this debate currently lacks strong partisan divides (Zhang and Dafoe, 2020; Margalit and Raviv, 2023). However, as seen in areas like environmental regulation or online content moderation, issues can become politicized over time, shaped by elite cues and partisan dynamics (Brenan and Saad, 2018; Mitts, 2025).[1] The trajectory of AI regulation may follow a similar pattern (Magistro et al., 2024). As AI grows more powerful and regulatory needs become more urgent, stakeholders—including tech companies, policymakers, and advocacy groups—are increasingly seeking to shape public opinion by highlighting both its benefits and risks.

In this article, we examine the potential politicization of AI regulation by analyzing how the media shapes public opinion on this emerging issue. Media serves as a key channel through which voters learn about new policy issues and stakeholders communicate their positions (McCombs and Valenzuela, 2020; Baum and Potter, 2008). We analyze U.S. media coverage of recent AI advances, identifying the stakeholders involved and the primary issues discussed. Leveraging data from a well-powered, pre-registered experiment embedded in a U.S. survey, we then assess the impact of different media messages, including elite quotes, on mobilizing public support for AI regulation.

Analyzing the content of 12,269 articles published in major U.S. news outlets between September 2022 and September 2024, we find that media coverage tends to depict AI positively —emphasizing productivity gains, economic growth, and technological advancement. While less common, negative coverage focuses on issues such as AI-induced misinformation, algorithmic bias, copyright infringement, and AI existential risks. Our analysis also shows that industry leaders and academic experts are the most frequently cited voices in AI coverage, though quotes from politicians—while less common—have grown increasingly

[1] For example, environmental regulation in the 1960s enjoyed bipartisan support in the U.S., but over time, it became highly polarized. By 2018, 91% of Democrats were concerned about climate change, compared to just 33% of Republicans (Hochschild, 2021). A similar pattern has occurred in the debate over online content moderation, which initially had broad support but later became a partisan issue, with conservatives and liberals polarized on the role of social media platforms in addressing harmful content (Appel, Pan, and Roberts, 2023; Buntain et al., 2023; Mitts, 2025).

prominent over time. Republicans emphasize AI's role in driving economic opportunity and market competition while raising concerns about intellectual property rights and content manipulation. Democrats, by contrast, display more skepticism, focusing on the need for regulatory oversight to address concerns ranging from labor market disruption to election integrity.

To systematically examine how these emerging patterns in media coverage shape public opinion toward AI regulation, we designed a survey experiment that isolates the effects of both information content and elite cues. Specifically, respondents completed editorial tasks involving news article paragraphs that varied along two dimensions: the content (risks, benefits, or placebo) and the source cited (tech leaders, experts, or politicians—either Democrats or Republicans). Drawing from our media analysis, we focused on three prominent themes where partisan narratives could emerge: fairness and bias in AI decision-making, automation in the labor market, and large language models (LLMs). This experimental design allows us to test competing theoretical predictions about how voters process information on complex technological issues: whether they engage substantively with the content regardless of source, default to partisan predispositions, or use elite cues to selectively determine which information merits their attention.

Our analysis shows that over 55% of Americans support immediate and stringent government oversight of AI, even at the expense of innovation. However, this broad support masks notable partisan differences: Republicans are generally less supportive of government intervention compared to Democrats. These divisions could hinder the implementation of effective regulations, despite widespread aggregate support. Importantly, our experimental results suggest that public opinions on AI regulation are not fixed. When respondents are exposed to concrete information about AI's implications, they adjust their views—even when the information challenges their prior beliefs. The extent of this attitudinal shift, however, depends heavily on the source of the message. Democrats are particularly responsive to messages from experts, whereas Republicans are more influenced by statements from co-partisan elites. Interestingly, when Republican politicians express concerns about AI risks, the partisan gap on regulation narrows significantly.

To assess whether the attitudinal changes reflect mere cue-taking or genuine information-seeking behavior, we created and launched a blog, "AlgorithmStories," which covered key debates on AI's implications. The three most recent posts on the blog included the full articles from which we extracted the paragraphs used in our experiment. We invited respondents to visit the blog and tracked the traffic and clicks on the web. We find systematic variation across treatments, with the highest engagement among respondents exposed to alarming messages attributed to Republican sources. The findings support the conjecture that AI's technical nature and seemingly abstract consequences reduce motivation to engage with the issue. Rather than blindly adopting elite views, voters use these cues to decide which information deserves their attention.

Our analysis suggests that while public opinion on AI regulation could grow increasingly polarized, this outcome is not inevitable. These findings carry significant implications for AI governance: drafting robust regulations alone is insufficient if policymakers fail to communicate effectively about the issues at stake. Equally important is understanding that public attitudes towards AI are malleable; when confronted with specific information about AI's capabilities and risks, many individuals—especially when guided by sources they trust—adapt their views.

These insights advance the growing literature on how citizens develop opinions about emerging technologies like AI. Much of this work has taken a snapshot of attitudes formed under limited knowledge or experience (Wu, 2023; Schiff et al., 2023; Kuo, Manzano, and Gallego, 2024; Borwein et al., 2024). By examining how media narratives and elite cues can shift preferences, we show that views on AI are not fixed; they evolve as people gain more exposure and insight into the technology.

Moreover, our findings speak to the broader literature on partisan-motivated reasoning, particularly regarding the influence of partisan endorsements on opinion formation (Taber and Lodge, 2006; Druckman, Peterson, and Slothuus, 2013; Bayes et al., 2020). Recent work has identified two distinct motivations in information processing: a directional goal, where individuals seek to confirm pre-existing beliefs or align with their party's position, and an accuracy goal, where they strive to form correct opinions based on available evidence and might differ in the sources they perceive to be credible. However, empirical evidence distinguishing between these motivations has been scarce (Druckman and McGrath, 2019). Our behavioral data on blog visitation rates provides evidence consistent with the latter goal, showing that on questions related to AI, voters prioritize accuracy: they use elite cues as motivations for engaging with complex information rather than as shortcuts to opinion formation.

The article is organized as follows. We begin by reviewing the existing literature and presenting a series of competing theoretical predictions that motivate our study. Next, we analyze U.S. media coverage of artificial intelligence and provide an overview of our experimental design and results. The study concludes with a discussion of the potential politicization of AI regulation and suggestions for future research.

Polarization of AI Regulation: Three Possible Dynamics

Under what conditions does the public debate over AI regulation become polarized? We contend that the answer to this question largely depends on voters' ability and motivation to engage with the often-complex details of AI's implications when forming policy preferences.

Emerging Issues and Substantive Information Processing

Extensive research shows that under conditions of elite polarization, voters are more likely to rely on partisan endorsements rather than substantive arguments when forming policy opinions (Druckman, Peterson, and Slothuus, 2013). This process stimulates partisan-motivated reasoning, where individuals favor arguments that align with their core beliefs (Wolsko, Ariceaga, and Seiden, 2016) or affirm their social group identities (Kahan, 2017). This tendency has been well-documented in the United States for issues already aligned with partisan identities (Bolsen, Druckman, and Cook, 2014; Druckman and Lupia, 2016).

However, AI regulation is an emerging policy issue. Unlike well-established debates on topics such as immigration or healthcare reform, issues related to AI lack widely accepted elite positions that could serve as cues for public opinion formation (Druckman and Lupia, 2016). Voters have not yet learned to associate specific AI policy stances with particular political parties. In fact, some bipartisan legislative initiatives in the U.S. have sought to oversee AI development and implementation (Global Policy Watch, 2024; Schumer, 2024).

The lack of clear partisan cues on AI regulation may encourage voters to engage with the issue substantively. Instead of defaulting to partisan-motivated reasoning, they might take the time to understand the concrete aspects of AI policy, uncovering nuances and trade-offs that do not neatly fit into existing ideological categories. A debate focused on concrete policy issues could also clarify the personal stakes for voters, highlighting considerations of material self-interest that might bridge ideological divides. Recent evidence supports this possibility, showing that expert predictions about AI's risks and benefits can shape public preferences on AI in policy decision-making, even when this information challenges voters' prior beliefs (Margalit and Raviv, 2023). Therefore, information about the concrete risks or benefits of AI is likely to influence preferences for regulation, regardless of party or ideological leaning, potentially leading to greater convergence of opinions across the political spectrum.

Complexity and Ideological Simplification

On the other hand, AI is a complex topic that often requires technical knowledge to fully understand its implications, which can create cognitive barriers for voters. Unlike healthcare or taxation, which have immediate personal consequences, the potential risks or benefits of AI may seem distant or abstract to the average voter, making it a less salient policy issue (Krosnick, 1990). This perceived distance likely reduces voters' motivation to engage with substantive information about AI and its implications.

Without engaging with the specifics of AI, voters are likely to form judgments on its regulation based on stable predispositions tied to broader values and principles. They may interpret AI policies through the lens of larger ideological debates, reducing it to binary choices, as seen in other policy areas (Margalit and Raviv, 2024). In the U.S., this likely means Republicans will oppose AI regulation as an unnecessary expansion of government control, while Democrats will support it as part of their broader belief in government oversight to protect public interests.

Credibility of Elite Cues

Given these contrasting dynamics, we propose a third possibility that acknowledges the unique nature of AI regulation as an emerging yet complex policy issue. Without clear ideological markers on AI policy, voters may turn to trusted sources to determine which information warrants their attention and cognitive effort. Rather than using elite cues to form opinions directly, voters might rely on these cues to decide whether to engage with the issue. They are more likely to consider concrete information on AI risks and benefits when it comes from sources they deem credible. However, perceptions of credibility can vary significantly, particularly in polarized contexts where partisan affiliation often shapes these judgments (Druckman and McGrath, 2019). Voters often trust sources aligned with their political beliefs and dismiss those from the opposing side.

In the context of climate change, for example, Zhou (2016) shows that Republicans were more likely to reject messages advocating for governmental action on climate change, especially when those messages came from a Democratic source. Conversely, when a Republican delivered the message, it was more likely to be accepted. Similarly, Pink et al. (2021) shows that Republicans were more likely to support vaccination when cued by their party elites, even if they had previously been hesitant about the vaccine. Another potential driver of skepticism towards elite messaging is anti-intellectualism, which has long been cited as an important force in American politics (Shogan, 2007). Studies suggest that Republicans are increasingly skeptical of intellectual elites (Motta, 2018).

Thus, voters may engage in a form of motivated reasoning that differs from the typical partisan-driven process. Instead of seeking to confirm prior beliefs, voters' motivation may be driven by an appraisal of credibility (Bayes et al., 2020). While partisanship may influence which sources voters trust, it does not necessarily predetermine their policy positions on AI regulation. Motivated by a desire for accuracy, once voters engage with relevant information and understand the complex trade-offs in regulating AI, they might process the information more "objectively," potentially altering their opinions regardless of their predispositions.

We therefore hypothesize that the effect of information about AI regulation on voter attitudes depends on the perceived credibility of the source. When voters receive information from trusted elites, they are likely to update their views accordingly, even if it contradicts their ideological predispositions. However, if the information comes from a source they distrust, voters are expected to disregard it and rely on their existing beliefs. This dynamic implies that the polarization of preferences on AI regulation may either be reinforced or reduced, depending on the source's credibility.

Coverage of Artificial Intelligence in U.S. Media

Before testing how media messages influence voter attitudes, we first examine how recent developments in AI technologies have been covered in U.S. media over the past few years. Media coverage offers a window into both the substantive information voters receive about AI's implications and the emerging role of elite voices in framing the debate. If AI regulation remains primarily a technical issue, we would expect coverage to focus on concrete risks and benefits, with expert and industry voices dominating. However, if the issue is becoming politicized, we should see increasing involvement of political elites and emerging partisan narratives.

We compiled a corpus of 12,269 articles from major U.S. news outlets published between September 2022 and September 2024, analyzing their content to assess sentiment, topic prevalence, and the presence of quotes from various elites.[2] Figure 1A shows the average sentiment of media coverage of AI over time. Media coverage of artificial intelligence has generally been more positive than negative, with a notable increase in positive stories following the public release of ChatGPT on November 30, 2022. Although this trend has since tapered off, overall sentiment toward AI has remained positive in subsequent months.[3] Panel B shows that the topics receiving the most positive coverage include the development of hardware to support AI technologies, explanations of how AI tools like LLMs can enhance productivity, and discussions of economic growth. By contrast, the issues receiving the most negative coverage include election misinformation caused by AI, bias in AI algorithms—particularly in criminal justice applications—and existential risks that AI may pose to humanity.[4]

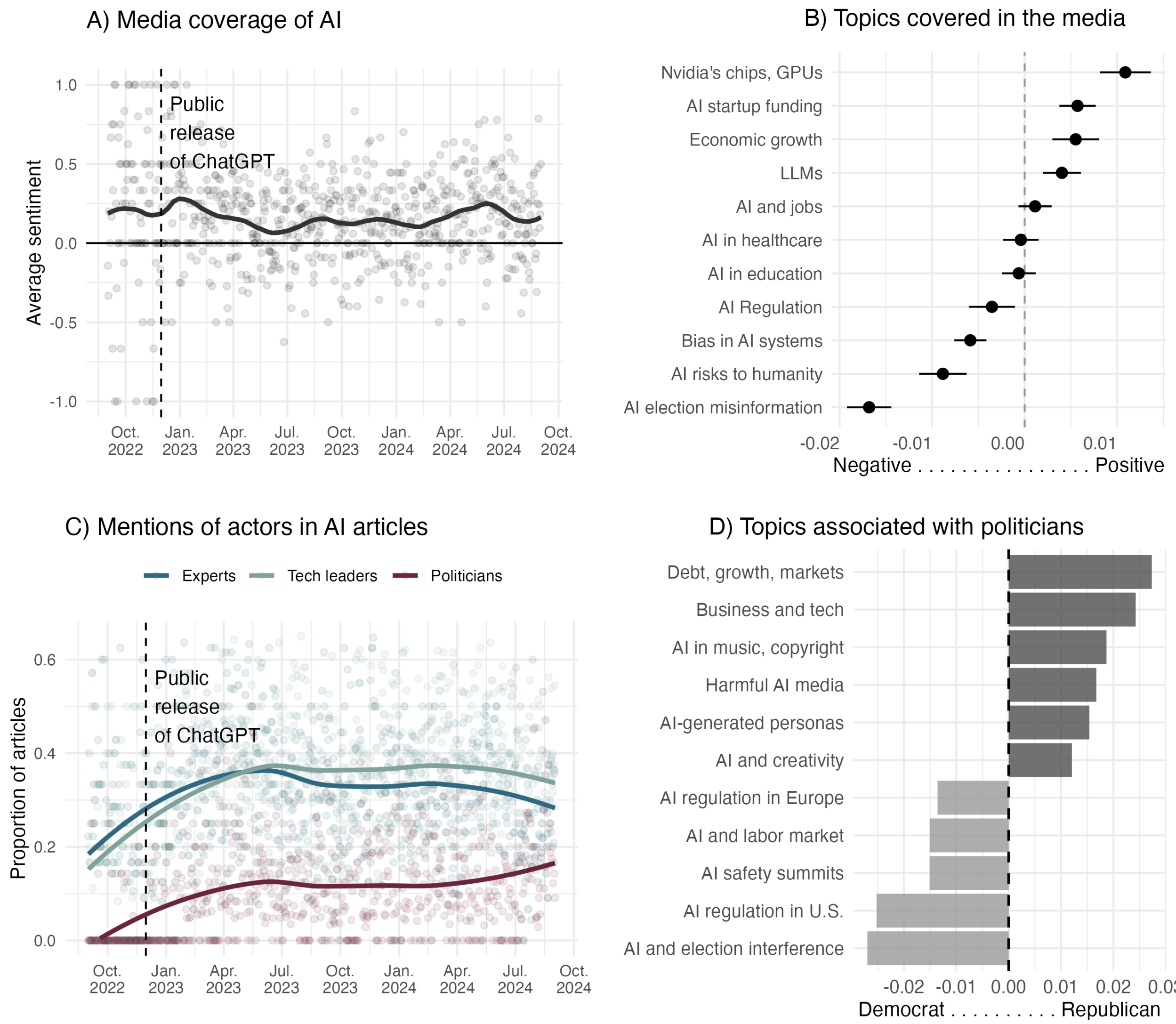
When examining the representation of elites in the media, we find that experts and tech

[2] Appendix section 1 provides details on the data collection and measurement methods.

[3] This pattern aligns with prior research on media discourse about AI, which finds that media outlets tend to emphasize the benefits of the technology over its drawbacks (Fast and Horvitz, 2017).

[4] These results come from a structural topic model analysis. See section 1 in the Appendix for details. Figure SI-3 in the Appendix shows full results for all topics.

Figure (1) Media Coverage of Artificial Intelligence



Note: Panel A shows the average sentiment of media coverage of AI over time. Panel B illustrates the prevalence of topics by article sentiment. Panel C depicts the proportion of AI-related articles that mention or quote different types of elites on a daily basis. Panel D highlights the topics that significantly differ in how Republicans and Democrats discuss AI in the media.

leaders have been mentioned most frequently (see Figure 1C). In the media, experts often provide insights on the potential impact of AI on different industries, ethical concerns, and the various technical aspects of AI development. For example, in an interview with CNN, a professor at Cornell University's engineering school said, "Efficiencies is one thing that AI is very good at ... it's a system that has very strong predictive capabilities that could be tremendously helpful in many domains."[5] Other experts, discussing the effects of AI on the job market, predicted that AI will "close gaps between entry-level workers and superstars" and allow "people with less formal education to do more things."[6]

Tech leaders, on the other hand, are frequently cited in the media in discussions about AI innovations and regulatory challenges, often advocating for policies that align with industry interests. For instance, Alphabet CEO Sundar Pichai emphasized Google's leadership in AI development, saying, "We'll do everything that is needed to make sure we have the leading AI models and infrastructure in the world."[7] Similarly, OpenAI CEO Sam Altman warned against adopting strict AI regulations, stating that such regulations would "slow down American industry in such a way that China or somebody else makes faster progress."[8]

Although media coverage of AI featuring political elites is less common than coverage involving experts and tech leaders, the frequency of quotes from politicians on AI has increased over time. Politicians often focus on the regulatory implications of AI, expressing concerns about its potential impact on jobs, privacy, and national security. For example, former Secretary of Homeland Security Alejandro Mayorkas stated in an interview, "a failure to deploy AI in a safe and secure and responsible manner when it comes to critical infrastructure can be devastating."[9] Senator Chris Coons voiced similar concerns, adding, "we cannot afford to be as late to responsibly regulating generative A.I. as we have been to social media."[10] There have also been numerous calls by politicians for bipartisan initiatives to address the potential harms posed by AI. For instance, Senator Chuck Schumer remarked, "Harnessing the potential of AI demands an all-hands-on-deck approach, and that's exactly what our bipartisan AI working group has been leading," following the publication of a roadmap to

[5] Source: https://edition.cnn.com/2023/11/26/tech/ai-climate-solutions/index.html
[6] Source: https://www.nytimes.com/2023/08/24/upshot/artificial-intelligence-jobs.html
[7] Source: https://www.wsj.com/tech/alphabet-google-googl-q3-earnings-report-2023-103907cf
[8] Source: https://www.wsj.com/articles/openai-ceo-calls-for-collaboration-with-china-to-counter-ai-ris
[9] Source: https://www.wsj.com/tech/ai/openais-sam-altman-and-other-tech-leaders-to-serve-on-ai-safety-
[10] Source: https://transcripts.cnn.com/show/es/date/2023-05-17/segment/01

guide AI policy in the Senate.[11]

To systematically examine what politicians tend to emphasize when talking about AI in the media, we estimated a structural topic model with a prevalence covariate that accounts for the party of the politician mentioned in the text. While there are many topics that Republicans and Democrats are similarly associated with, such as the semiconductor race with China, AI-driven innovations in healthcare and retail, and AI and academic integrity in education,[12] there are notable differences in how political elites frame AI-related issues in the media.

Figure 1D highlights the topics that significantly differ between Republicans and Democrats. We find that Republicans tend to emphasize issues related to economic growth and innovation, such as debt, growth, and financial markets; business and technology; and AI in creative sectors like music, voice, and copyright debates. In addition, Republican discourse also focuses on harmful applications of AI, including deepfake pornography and AI-generated personas. By contrast, Democrats tend to prioritize issues tied to regulation and societal impacts, including AI's influence on labor markets, AI regulation, and concerns over election interference.

These framing differences reflect broader partisan priorities: Republicans often present AI as a tool for economic opportunity and technological advancement, while Democrats focus on its societal challenges and the need for oversight. This growing involvement of political elites in media discourse, coupled with variations in how they frame AI-related issues, suggests that the technical complexity of the technology could either lead voters to rely on ideological shortcuts or engage selectively with trusted elite cues to make sense of the debate.

[11] Source: https://edition.cnn.com/2024/05/15/tech/schumer-ai-framework/index.html

[12] See Figure SI-4 in the Appendix.

Experimental Design

To systematically examine whether and how patterns in media coverage influence polarization in public attitudes toward AI regulation, we conducted a well-powered experiment in which respondents were randomly exposed to different types of information about AI's implications from various sources. We contend that the potential for polarization in the debate over AI regulation depends on voters' motivation to engage with substantive information regarding AI risks and benefits rather than relying on broader ideological predispositions or partisan heuristics when forming policy preferences. Our experimental design allows us to test the competing theoretical predictions about how voters process information on complex technological issues: whether they engage substantively with the content regardless of source, default to partisan predispositions, or use elite cues to selectively determine which information merits their attention.

The experiment was embedded in a large scale survey of 3,350 American adults, administered in June 2024 through CloudResearch.[13] To minimize concerns about experimenter demand effects (Mummolo and Peterson, 2019), we indirectly communicated the information as part of a survey on journalism involving simple editorial tasks. Respondents were asked to complete a simple task that involved reading paragraphs from popular media sources and identifying the appropriate headings and subheadings for each article by highlighting sentences in the text. The paragraphs focused on key themes related to AI that have been

[13] We used CloudResearch's Connect Panel, employing quota sampling to ensure representation across key demographics: gender, age, ethnicity, and education level. We also over-sampled Republican voters to enable a robust analysis by political party affiliation. Previous research has shown that this approach yields high response quality while maintaining demographic representativeness (Stagnaro et al., 2024). Table SI-2 in Appendix compares our sample characteristics to those of the general US population. While our sample broadly reflects U.S. demographics, we replicate the main analyses using post-stratification weights to match U.S. Census benchmarks for gender, age, education, and race and to match the Pew Research Center's benchmarks for political party affiliation. Table SI-4 shows the results remain substantively similar. Full details of the sampling procedure and survey instrument are available in Appendix 2.1. A pre-analysis plan detailing the design and hypotheses was preregistered prior to fielding the survey.

widely covered in the media: (1) the potential for racial bias in decision-making, (2) The impact of AI automation on the labor market, and (3) The societal consequences of LLMs (such as ChatGPT). All respondents received all three themes but in a random order. We also added two additional paragraphs on unrelated issues to blur the focus of the study.[14] Another was presented at the end after respondents had engaged with the three AI-related paragraphs. Appendix section 2.1 provides the instructions for the task, the wording of the paragraphs, and a screen capture of the user interface.

Treatments

The experiment consisted of two manipulations. We examine the effect of relevant information on AI by manipulating the content of AI-related articles to cover either a positive or negative perspective. For instance, the article that covered racial bias with a negative tone highlighted the risk that AI-based decision-making will perpetuate existing biases. The positive treatment, in contrast, emphasized AI's potential to uncover past discrimination and make biases more transparent than human decision-making. We also included a control group that received placebo information on unrelated topics.

To assess whether and how voters leveraged elite cues in processing the new information and formulating their opinions on government responses to the recent advances in AI technology, the second manipulation varied the elites quoted in the article. Each paragraph cited one of the following actors: AI experts, tech leaders, or politicians—either Democrats or Republicans. We cited sources in three different ways to increase external validity. References to elites included either quotes byspecific individuals (e.g., Senator Chuck Schumer or Satya Nadella, Microsoft's chief executive), general groups (Democratic senators or Tech leaders), or collective references (a letter signed by 45 Democrats or 45 AI industry lead-

[14] One paragraph was used as a pre-test example to allow respondents to practice highlighting sentences in the interface. Only those who completed this pre-test correctly were allowed to proceed, ensuring that all participants understood the task.

ers). Therefore, the experiment included 2 (tone) × 4 (source) treatment conditions and one control..[15]

We used block randomization and grouped the sample according to respondents' party identification to further increase comparability across treatments. This approach allowed us to examine whether people were more receptive to information from sources aligned with their political orientation.[16]

All paragraphs in our study were adapted from real news stories published in major outlets to accurately reflect how AI issues are discussed in the media. We revised them to maintain symmetry across treatments, ensuring the core information remained consistent while isolating the effects of the information and elite cues. For instance, when discussing LLMs, both positive and negative treatments began with "A letter signed by 45 [AI industry leaders/House Democrats/House Republicans/AI experts from leading universities]." The letter then either "called for more investment in developing AI-based applications that can empower human skills, such as ChatGPT" in the positive message or "called for an immediate pause of at least six months in the training of AI systems more powerful than GPT-4" in the negative framing. The paragraph then elaborated on the rationale behind these positions, emphasizing either the key promises or risks associated with this specific AI application, depending on the treatment.[17]

To further engage respondents with the information treatment, participants were presented with a follow-up task that involved ranking the headlines they chose earlier based on

[15] A balance test, reported in Table SI-3, indicates that our treatment groups are balanced on a series of key socio-demographic covariates.

[16] We measured party ID prior the treatment assignment, using two questions. First, we asked respondents to choose between Democrat, Republican, Independent, or Other. For those who chose Independent or Other, we then asked them to indicate whether they leaned more towards the Democratic or Republican party. This approach is based on evidence suggesting that most independent voters tend to lean towards one of the major parties, and these "leaners" often have political views and behaviors similar to those who explicitly identify with the party they lean towards (Pew Research Center, 2019). In our analysis, we control for respondents who initially identified as Independent or Other.

[17] We debriefed all respondents about the study's objectives and the nature of the experimental manipulations several days after completing the survey.

their perceived importance. Specifically, we asked respondents to determine which article they think is the most important to the public and should be featured on the newspaper's front page, which one is of moderate importance, and which is of lesser importance and can be placed towards the back of the newspaper. We also presented them with the titles selected from the pre-test and placebo paragraphs to minimize the possibility of demand effects, in which respondents may alter their responses after realizing that the research focuses on AI.[18] As pre-registered, we use answers to this follow-up task as an additional outcome to assess the perceived importance of the issue covered in the news. Figure 2 shows the full experimental design.[19]

Outcome Measurement

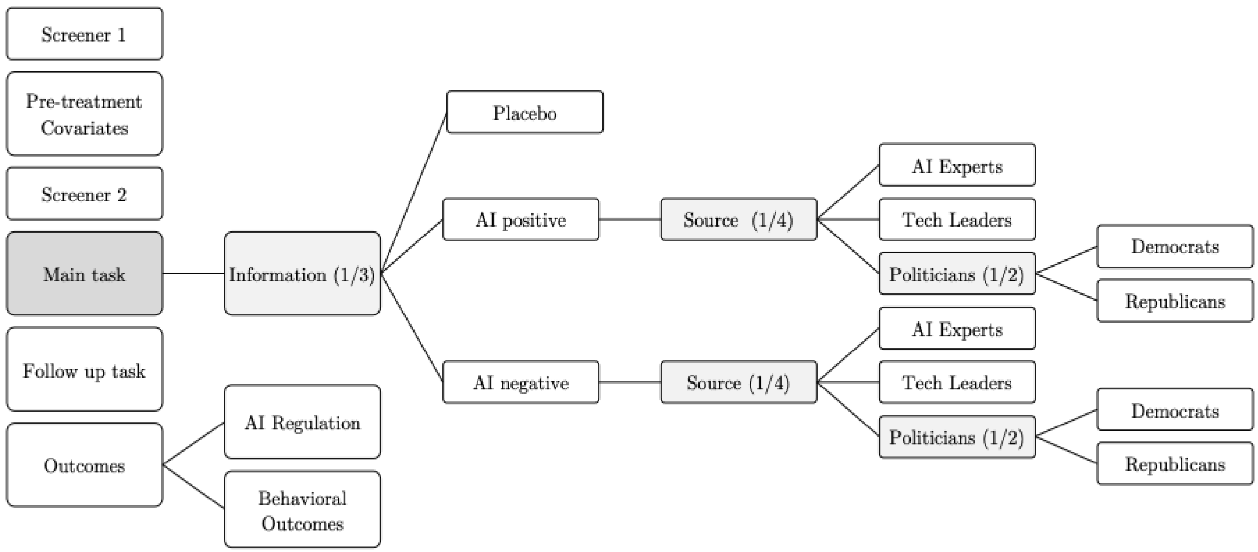
Our primary dependent variable measures support for stricter government regulation of AI. We use three questions, each addressing a distinct aspect of the current debate over regulating AI technology: the scope, timing, and the appropriate authority for leading regulatory efforts. Each question presented respondents with two contrasting viewpoints on a specific regulatory issue and asked them to indicate their position on a 7-point scale, where higher values indicate stronger support for AI regulation.

In the first question, we gauged respondents' views on the balance between regulation and innovation, with one end of the 7-point scale calling for no intervention, prioritizing

[18]Respondents were instructed as follows: "Below are the headlines you selected from the news articles we asked you to review. Please rank the headlines by their importance. Assign 1 to the article that is the most significant for the public and should be featured on the newspaper's front page, and 5 to the article you think is the least important and can be placed towards the back of the newspaper."

[19]To ensure that respondents in both the control and treatment conditions have a similar understanding of AI while minimizing potential experimenter demand effects, we began the survey with three relevant definitions, including one for AI. We used the definitions as an attention screener, presenting respondents on the next page with four definitions and asking them to identify which one did not appear on the previous page. Those who answered incorrectly were immediately removed from the study before randomizing the information treatments. To ensure that respondents were attentive to the treatment information and carefully evaluated the policy questions, we further followed Read, Wolters, and Berinsky (2021) by using response time per question as a measure of inattentiveness, accounting for both those who rushed through the survey and those who may have been distracted. We controlled for this indicator in our analyses.

Figure (2) Experimental Design - Flow Chart



technological progress and economic growth, and the other end advocating for strict oversight to address potential negative consequences of AI. In the second question, we asked about the urgency of regulation, contrasting immediate action with a slower, more gradual approach. Finally, the third question examined who should lead regulatory efforts. One perspective favored private sector self-regulation, where companies establish their own safety protocols and supervisory bodies. The alternative view called for government agencies to take the lead in imposing regulations.

We created dichotomous measures for each of the three items, coding those who supported a regulatory approach (responses of 5–7 on the scale) as one and all others, including those who were indifferent, as zero. Additionally, we constructed a combined standardized index using the first component from a factor analysis of the three questions and dichotomized it to create a binary measure: "support for urgent government oversight on AI," by splitting respondents at the median factor score.

Results

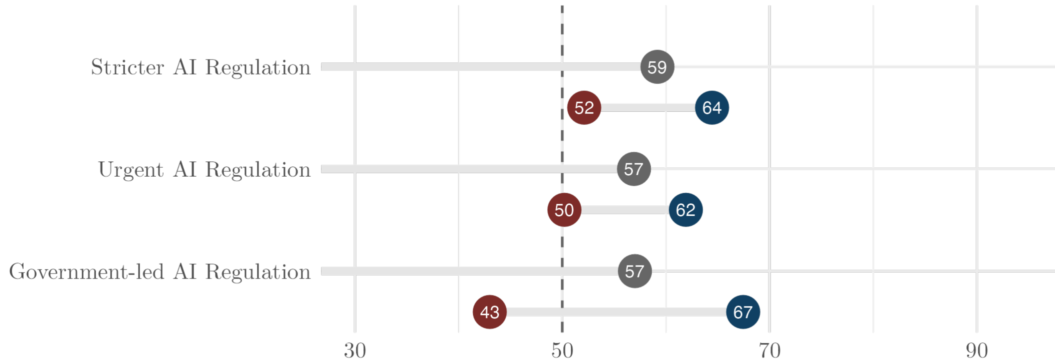
Before describing the results of our experimental study, we first examine baseline support for various approaches to regulating AI. Figure 3a shows the share of respondents in the control group ($N = 1,113$) who support AI regulation. These individuals were not exposed to AI-related articles; instead, they read articles on topics such as travel and fashion. We find that a majority of voters (indicated by gray dots) support the urgent implementation of more stringent regulations on AI technologies by government agencies. The data shows that 59% of respondents support stricter AI regulation, 57% support urgent regulatory action, and a similar share favors regulation led by government agencies. This widespread support is notable, indicating a public demand for more active intervention.

However, this aggregate support for AI regulation may mask divisions along partisan lines, which could pose challenges to adopting effective regulation, even with majority support in aggregate. As explained earlier, in the absence of information about the specific risks and benefits associated with AI development and use, voters are likely to form policy preferences based on pre-existing beliefs and broader predispositions that have little to do with AI—such as their views on the government's role in the market and attitudes toward large corporations.

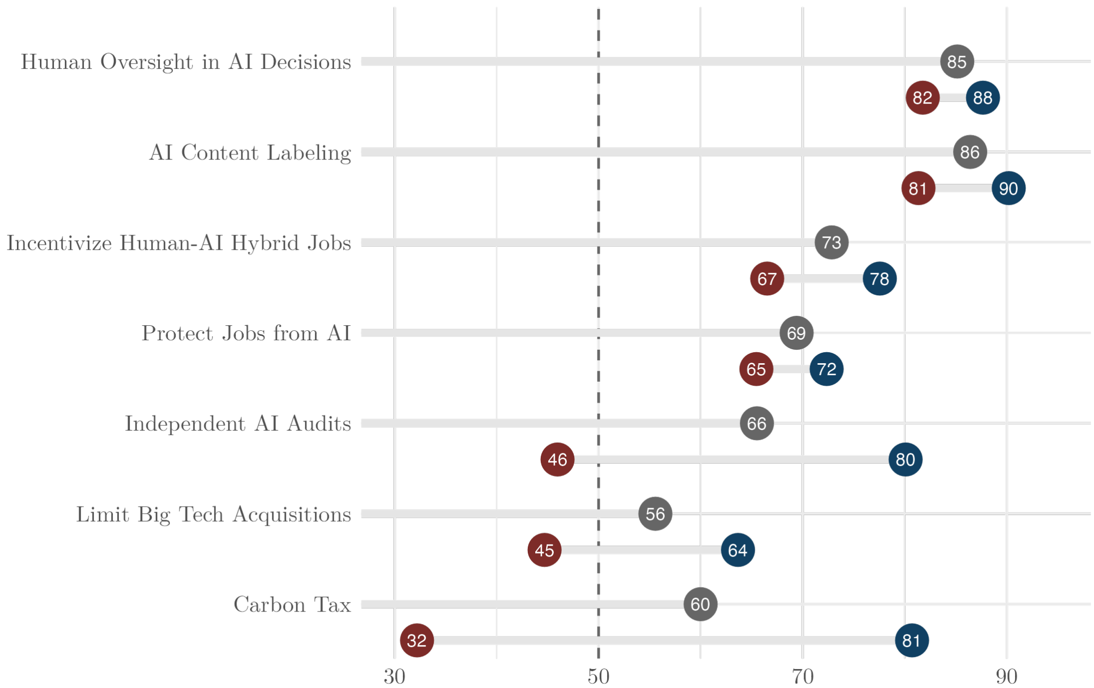
Indeed, the figure shows partisan differences in views on AI regulation, where Democrats (blue dots) generally express stronger support than Republicans (red dots) for regulating AI across all three measures. The most notable difference appears in opinions on government-led regulation of AI, where 67% of Democrats favor this approach, compared to only 43% of Republicans. This gap likely reflects long-standing ideological differences between the two parties regarding the government's role in markets (Shapiro and Jacobs, 2011). However, despite their general skepticism toward government interventions, a majority of Republican voters (52%) still support strict oversight of AI, even if it comes at the potential cost of innovation. Moreover, 50% believe that urgent action is necessary, further indicating the

Figure (3) Public Support for AI Regulation and Specific Regulatory Measures

(a) Panel A: Support for AI Regulation



(b) Panel B: Support for Specific Regulatory Measures



Note: This figure shows descriptive trends in public support for AI regulation. Panel a displays the main outcomes: support for stricter, urgent, and government-led AI regulation, while Panel b presents support for specific regulatory approaches. "Carbon Tax" and "Limit Big Tech Acquisitions" are included as placebo items. All outcomes are binary measures. Gray points indicate overall support among all voters; blue dots indicate support among Democrats, and red points indicate support among Republicans.

public's recognition of the issue's importance.

In addition to our primary measures, we asked respondents for their views on specific policies currently being promoted at the federal and state levels in the United States (Human-Centered Artificial Intelligence (HAI), 2024). These policies included labeling AI-generated content, mandating independent reviews of AI decision-making systems to guard against discrimination, and providing tax incentives for human-AI hybrid jobs. To establish a baseline for support of regulations unrelated to AI, we further asked respondents whether they supported policies to prevent large tech companies from acquiring small competitors or implementing carbon taxes based on emissions. These items help disentangle the effects of our treatments on support for AI regulation from broader attitudes toward government regulation or sentiment toward tech companies.[20]

We find strong public support for concrete policy proposals to regulate AI. Figure 3b shows that 85% support requiring human oversight when using AI to make decisions in the public sector, and 86% favor labeling content generated by AI systems—views that are consistent across party lines. Similar patterns emerge for policies incentivizing human-AI hybrid jobs (67% Republican vs. 78% Democrat support) and policies determining specific jobs that AI should not replace (65% vs. 72%). This widespread bipartisan support is unusual in the current polarized climate in the United States. It also contrasts with the more divided opinions on policies restricting large tech companies from acquiring small competitors (a 19 percentage point difference) or tax companies based on their carbon emissions (a 49 percentage point difference).

The strong public support for government oversight of AI technology is surprising, especially in light of our media coverage analysis, which shows that news stories about AI are generally more positive. Is media coverage of AI technology irrelevant in shaping public

[20]See Appendix 2.1 for the exact wording of all questions. We provide summary statistics for all original variables in Table SI-2.

opinion on regulation? While exposure to media stories highlighting the risks or benefits of AI could inform and influence public opinion, its impact may be limited if voters' opinions are constrained by deeply held predispositions about government regulation or technology. Indeed, as seen in other policy domains, the partisan gap in attitudes could widen over time, especially if voters do not substantively engage with the concrete issues underlying the debate. In the next section, we examine how media coverage of AI influences these views.

Effects of Media Coverage

As discussed earlier, we view media coverage as a channel through which voters learn about new policy issues, such as AI regulation. To explore whether and how information spread through the media shapes public opinion, we next discuss our findings on the effects of media stories about AI. Figure 4 presents the average effects of our information treatments compared to the placebo.[21]

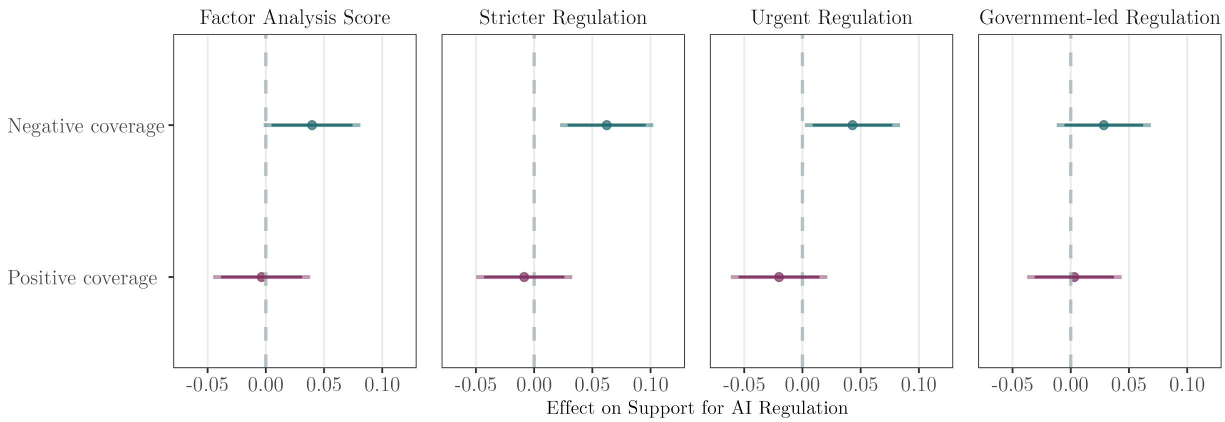
We find that people are more responsive to negative media coverage highlighting AI's potential risks and drawbacks than positive coverage focusing on its potential benefits. Negative information significantly increases public support for stricter regulation (at the expense of innovation), as well as for timely interventions to mitigate AI's negative consequences.[22] In contrast, the estimated effects of positive media coverage are substantively negligible and statistically indistinguishable from zero for all three outcomes.

While negative coverage increases support for stricter and more urgent regulation, it has little effect on preferences regarding whether the government or the tech industry should lead regulatory efforts (see rightmost panel in Figure 4). Although the coefficient on government-

[21] We used linear probability models, controlling for demographic characteristics and the type of elites cited in the paragraphs while clustering standard errors at the respondent level. Table SI-5 shows the results in tabular form.

[22] The estimated effect on these two outcomes is statistically significant and substantively large. For instance, the effect for stricter regulation (D=6.2, se=0.021) is greater than the differences observed between respondents with higher and lower levels of education (D=5.3, se=0.018).

Figure (4) Treatment Effects of Media Coverage on Support for AI Regulation



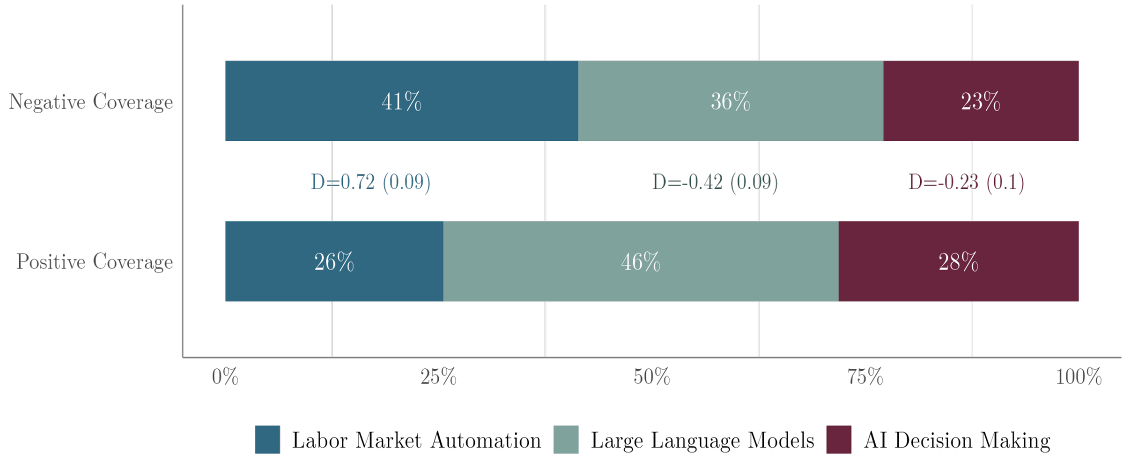
Note: This figure shows the average treatment effects of positive and negative AI coverage (relative to placebo coverage) on four measures of support for government regulation of AI. Points represent coefficient estimates from linear probability models, which also control for demographics to increase the precision of the estimates. Thick and thin bars represent 90% and 95% CIs. Full results are reported in Table SI-5.

led regulation is positive, it is small and statistically insignificant. This aligns with the patterns shown in Figure 3a, which points to a large partisan divide in support for government-led regulation, suggesting that views on this topic are more closely tied to one's broader ideological stance on government intervention in markets and are, therefore, less flexible.

To further understand how different types of media coverage shape preferences, we examine which AI-related issues respondents considered most important. After interacting with the media treatments, respondents were asked to rank the issues based on their perceived importance. Figure 5 reports the share of respondents in each treatment group who ranked each issue as the most important.

Our analysis of respondents' rankings of AI-related issues reveals notable differences in perceived importance between those exposed to negative versus positive media coverage. Respondents exposed to negative information about AI's risks were significantly more likely to rank labor market automation as the most critical issue, with 41% selecting it for the front page. In contrast, only 26% of those exposed to positive AI coverage rated this issue as the most important. This suggests that when AI's risks are emphasized, voters are more

Figure (5) AI Issue Salience, by Tone of Coverage



Note: The figure shows the proportion of respondents who ranked each issue as most salient for each treatment group.

concerned about its potential to disrupt employment. At the same time, positive coverage led 46% of respondents to prioritize LLMs, such as ChatGPT, underscoring the public's interest in AI's benefits when portrayed favorably. These results indicate that the tone of media coverage can significantly shift which aspects of AI voters consider most pressing.[23]

Interestingly, issues related to bias and fairness in AI decision-making remained low in salience across both the positive and negative information treatment conditions. This aligns with our analysis of U.S. media coverage, which shows that AI bias issues were rarely highlighted in the news (see Appendix Figure SI-5). This is notable given the strong emphasis on AI bias in initiatives such as the White House's "Blueprint for an AI Bill of Rights" (The White House, 2022), President Biden's Executive Order on Artificial Intelligence (The White House, 2023), and corporate policies from Google, Microsoft, and IBM (U.S. Congress, 2022; Google, 2018; Microsoft, 2022; IBM, 2021).

[23] To precisely estimate the differences, we used logistic regression models to assess the treatment effect of positive (relative to negative) coverage on the likelihood of ranking each issue as most important. The results, shown in Appendix 3.2, indicate significant differences: positive coverage decreased the odds of prioritizing labor market automation (D = -0.716, p<0.001) and increased the likelihood of viewing LLMs as most important (D = 0.423, p<0.001). The effect on perceptions of algorithmic bias was not statistically significant (D = 0.109, p = 0.283).

These results indicate that concrete information indeed influences voters' opinions on AI regulation, but there is a notable difference between the effects of positive and negative news stories. While negative media coverage of AI's risks increases support for regulation and heightens the salience of labor market automation, positive coverage does not significantly alter views on regulation; instead, it shifts focus toward the latest AI innovations, such as LLMs. The null effect of positive news stories contrasts with our pre-registered expectations, which hypothesized that positive media coverage would decrease support for regulation. We discuss possible explanations for this asymmetry in the conclusion.

Effects of Elite Cues in Media Messaging

The effects of media coverage, however, may be moderated by the messenger. As discussed in the theoretical section, we conjecture that AI's complex, technical, and uncertain implications make it more cognitively costly for voters to engage with the information. In such context, cues from elites can serve as heuristics for assessing the credibility and relevance of the information, with the influence of these cues varying depending on voters' partisan affiliation. Media messages referencing elites whom voters trust are more likely to be taken seriously. However, if the source is perceived as untrustworthy or having interests that conflict with the voter's identities or values, voters are more likely to disregard the concrete information. In this section, we analyze how the source of information interacts with partisanship to shape their attitudes toward AI regulation.

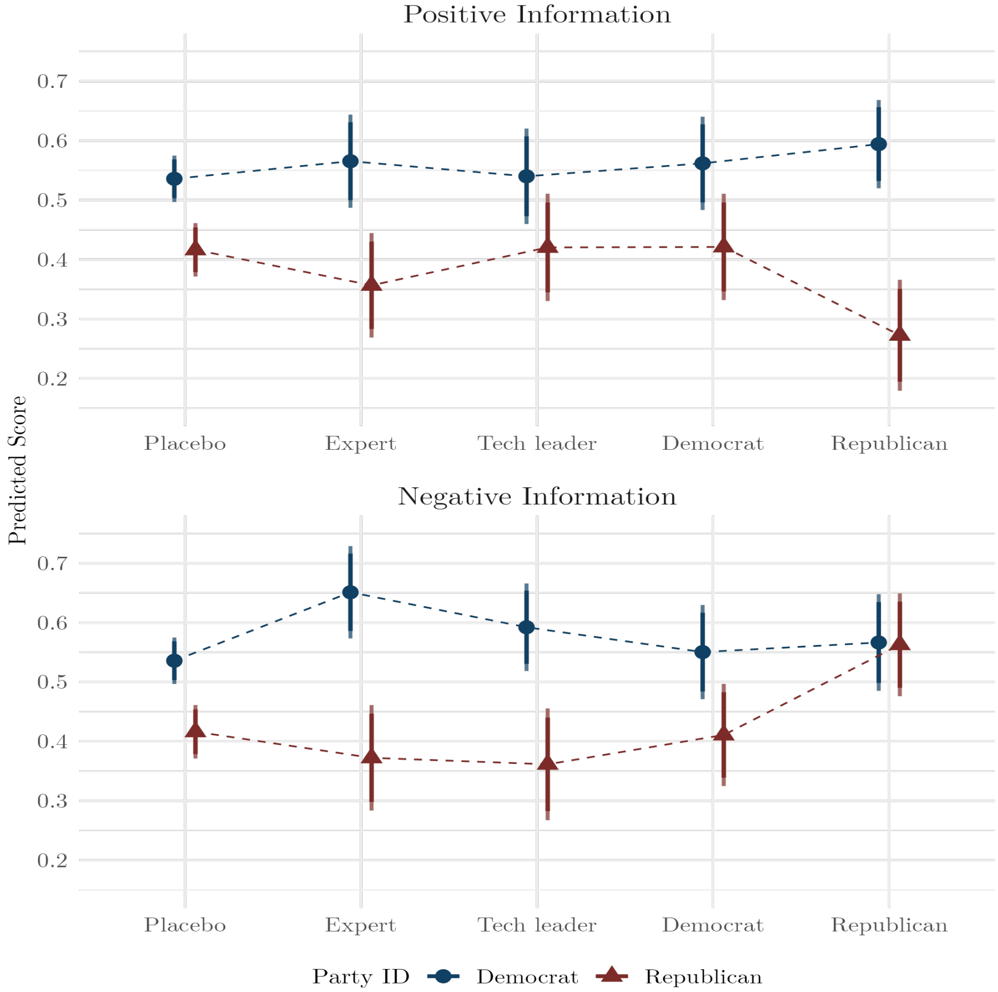
Using a linear probability model, we regressed our binary measure of support for AI regulation on indicators for the experimental treatments (combining information tone and source), respondents' party identification, and their interaction. This approach allows us to examine how the effect of information varies across different sources and party affiliations while also comparing these effects to a control condition (i.e., respondents who received messages on a placebo topic with no cited source). Figure 6 plots the results, showing the predicted probabilities of support for Democrats and Republicans across all treatment conditions and the control group. The upper panel presents the results for positive coverage, while the bottom panel shows the results for negative coverage.

Consistent with our descriptive results, the figure shows that Democratic voters (indicated by blue dots) are more supportive of AI regulation than Republican voters (marked by red dots) across most conditions. However, the figure also makes clear that these partisan differences are not fixed; they can be reduced depending on the source and tone of the information.

The upper panel of Figure 6 shows, similar to our earlier results, that in the positive information condition, there is little difference in the predicted support for AI regulation across the various sources, with a consistent partisan gap maintained across conditions. However, an interesting exception emerges when Republican politicians are quoted in positive media stories about AI. The data shows that positive messages on AI, when delivered by Republican politicians, significantly reduce support for regulation among Republican voters. Specifically, when Republican elites emphasize the benefits and the innovative potential of AI, Republican respondents become less likely to support regulation ($p < 0.01$). This reaction is consistent with the broader Republican preference for market-driven approaches and skepticism toward government intervention. For Democratic respondents, the same positive messaging from Republican elites did not significantly change their preferences ($D = 0.026$, $SE = 0.045$, $p > 0.1$).

We find an almost opposite pattern for negative media coverage (bottom panel in Figure 6). Expert messages lead to the widest partisan gap in policy preferences. Compared to the placebo condition, expert cues about the risks associated with AI significantly increased support for regulation among Democratic respondents while slightly decreasing support among Republicans compared to the control. This polarized reaction aligns with recent studies showing growing trust among Democrats in science (Lee, 2021) and increasing skepticism

Figure (6) Predicted Support for AI Regulation by Elite Cues, News Tone, and Party ID



Note: The figure shows the predicted scores of support for AI regulation (above median factor score) based on linear probability models. The outcome is regressed on an indicator for all treatment conditions (with placebo information as the reference category), respondent party ID, and their interaction. Full results are reported in Tables SI-9. Thin (90%) and thick (95%) error bars represent the CIs around the estimates, respectively.

among Republicans toward intellectual elites and scientific messaging (Motta, 2018). As a result, the partisan gap widens, with the difference in predicted support between the two sides reaching 28 percentage points ($p < 0.001$).

At the same time, negative media coverage quoting political elites significantly narrows this gap. This can be seen in the shrinking difference between Democrat and Republican voters' preferences for AI regulation when political elites are quoted in the media (bottom panel in Figure 6). While messages from Democrat politicians somewhat minimize the partisan gap, the difference significantly shrinks and even approaches zero when Republican elites discuss the risks associated with AI. This is noteworthy, as in no other condition do Republican voters align so closely with Democrats on AI regulation. These findings suggest that party-line differences in support for regulation are not immutable and that the politicization of AI regulation is not inevitable.

We also examine whether this pattern holds for other outcome measures. Table SI-9 in the Appendix shows that the results remain consistent when using alternative measures of support for AI regulation or individual questions from the index. The only exception is the question regarding the role of government versus private actors in regulating AI. This suggests that while elite messaging can influence opinions on how and when AI should be regulated, they have less impact on who should be responsible for the regulation. One possible explanation is that views on government involvement are more deeply rooted in individuals' political ideologies, making them less susceptible to change.[24]

Information Seeking Behavior

To assess whether the observed effects of partisan sources on preferences for AI regulation stem from mere cue-taking or genuine information-seeking behavior, we implemented a novel quasi-behavioral measure at the end of our survey. For this purpose, we designed and launched a blog called "AlgorithmicStories" specifically for this study. The website featured content covering key debates surrounding AI technology and its societal implications, including archived posts and interviews with prominent figures in AI ethics and governance. Crucially for our purpose, the three most recent posts published on the blog's homepage corresponded to the full articles from which we extracted the paragraphs used in our experi-

[24] Our analysis involved multiple comparisons, raising the possibility of false positives. However, as shown in Table SI-10, our main results remain statistically significant even after applying the Benjamini-Hochberg correction to adjust for multiple hypotheses.

mental treatments. Figure 7 shows a screen capture of the blog's homepage.[25] These articles expanded on the themes presented in the survey:

- The Future of LLMs: How Worried Should We Be About A.I.?
- Balancing Promises and Risks: How AI is Shaping the Modern Workplace
- Who Makes Fairer Decisions: Humans or A.I.?

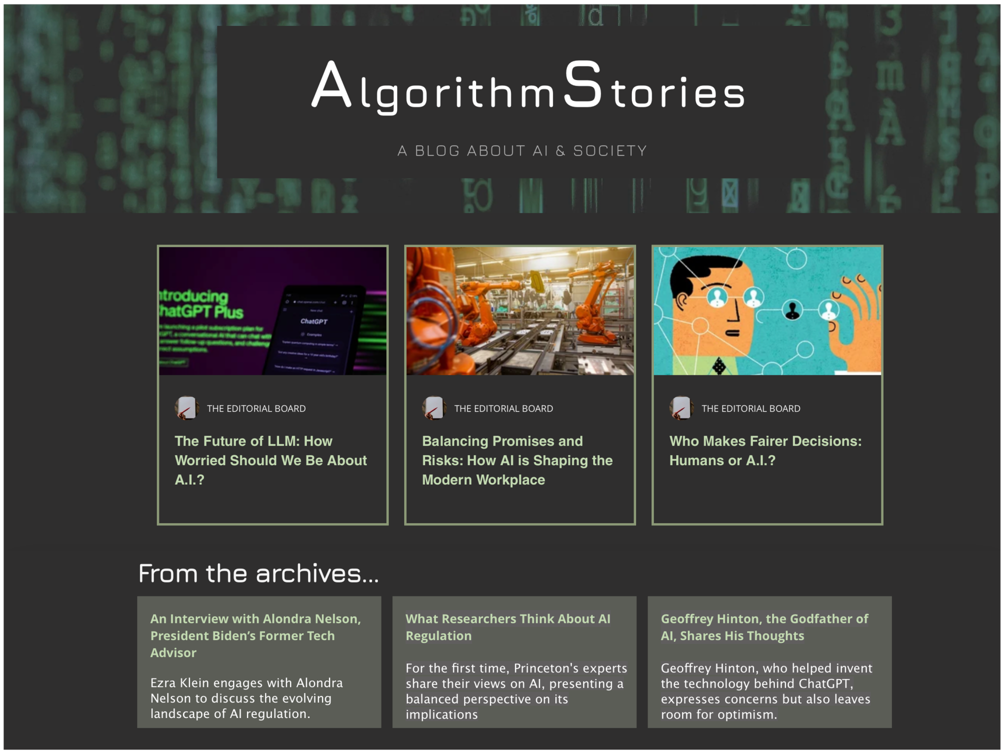
We invited respondents to voluntarily visit the blog and read the full articles related to the paragraphs they had previously engaged with in the survey task. Importantly, this invitation appeared on the last page of the survey after respondents completed all questions and was thus clearly separate from their paid task. Therefore, respondents could choose to exit the survey and return to the CloudResearch system or open the blog on another page if they were genuinely interested in reading more.

We generated nine unique URLs corresponding to each experimental group, and for each URL, we recorded the number of visits to the blog and each of the three blog posts from each URL. This design allowed us to measure engagement patterns at the treatment group level while preserving individual respondent privacy. By comparing these metrics across treatment conditions, we can assess whether elite cues primarily act as shortcuts for forming opinions about AI regulation or encourage people to seek out more information, which in turn shapes their attitudes. If source cues merely serve as shortcuts, we would expect to see similar visit rates across all groups. However, if cues encourage information seeking, we should see significant differences in blog visits between groups exposed to different sources.

Figure 8 presents the derivatives. The left panel shows the percentage of respondents who clicked on the invitation to visit the blog. Overall, respondents who received negative coverage were more likely to visit the blog compared to those who received positive

[25] While inspired by real-world news stories to maintain authenticity, these articles were carefully crafted to align with our experimental task.

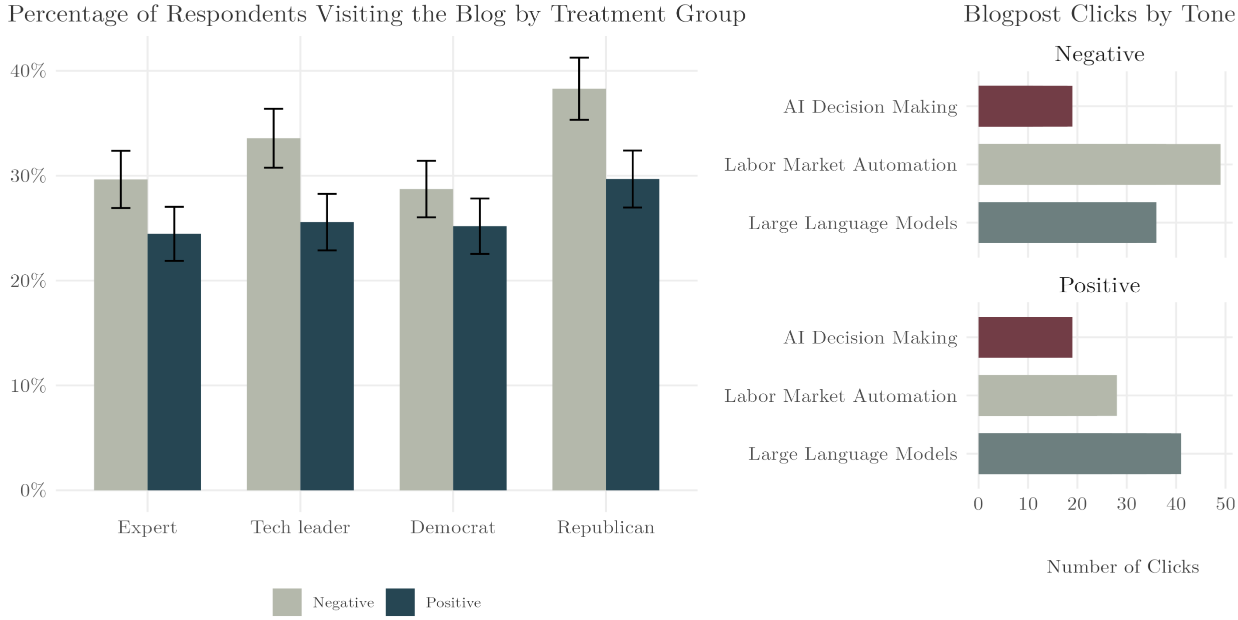
Figure (7) Screen capture of the Blog's Homepage



coverage. This suggests that negative messages about AI risks are more likely to motivate further information-seeking. The figure also shows a notable variation in traffic across the source conditions. Strikingly, respondents who received negative information from Republican sources showed the highest rate of blog visitation (nearly 40%). Given the aggregated nature of our data, we cannot directly attribute this to specific partisan subgroups within each treatment condition. Yet the fact that we see different rates of blog visitation across different source conditions suggests that the source of information is not just influencing opinions but also driving engagement and curiosity about AI issues.

The right panel of Figure 8 shows the number of clicks on each of the three main blog articles, separated by the tone of coverage (positive or negative) respondents were exposed to in the survey. Notably, these engagement patterns closely mirror the priorities expressed by respondents in the survey's headline ranking task. Specifically, the article on AI's impact on the labor market received the most engagement overall, particularly among those exposed to

Figure (8) Blog Engagement Patterns



Note: The left panel shows the percentage of respondents who clicked on the invitation to visit the blog. The right panel of Figure 8 shows the number of clicks on each of the three main blog articles, separated by the tone of coverage.

negative coverage. Consistent with the results from the headline ranking task, the article on AI decision-making and bias received the least engagement overall. While the reason for this lower level of interest merits further investigation, one potential explanation could be that the personal stakes of using AI in decision-making, especially in the public sector, are less evident or immediate compared to the other issues. Unlike potential job loss or the promise of LLMs to enhance productivity, the implications of AI in decision-making processes may seem more abstract or distant to many voters.

The results indicate that voters are willing to engage with concrete information on the various risks and benefits associated with AI. Their willingness to seek additional information, rather than relying solely on ideological cues, suggests that AI regulation has not yet become a purely symbolic issue of partisan identity. Instead, it remains a topic where voters are open to engaging with the substantive aspects of AI regulation, as their opinions have not yet fully crystallized along partisan lines but exist in a state we term "partial politicization." In this state, concrete information about AI risks significantly influences public support for regulation across party lines, but the source of this information plays an important role in determining its impact. While AI regulation has not yet been fully abstracted into broader ideological principles, partisan cues are beginning to shape how voters engage with and process information on the topic.

Discussion

As AI becomes increasingly powerful and pervasive, there is growing bipartisan recognition in the United States of the urgent need for regulation to balance its benefits and risks. This cross-party agreement is evident in recent legislative actions, such as the formation of the U.S. Senate AI Task Force, the House and Senate AI Caucuses, and efforts by the House Financial Services Committee to address AI challenges (For a comprehensive review, see Human-Centered Artificial Intelligence (HAI), 2024).[26] We provide insights into the political feasibility of these proposals in gaining cross-party support from voters.

Our analysis indicates substantial public support for stringent AI regulation, with over 50% of voters favoring immediate and stricter oversight. This challenges the prevailing assumption among some policymakers that public backing for robust AI governance is lacking.[27] However, the data also suggests that this general support for AI regulation masks significant partisan divides. Republicans are notably less supportive of delegating to the government the task of strictly regulating AI, with a concern that it could stifle innovation while

[26] Senate Majority Leader Chuck Schumer underscored the shared urgency and necessity of bipartisan cooperation: "Three words govern what we do: urgency, humility, bipartisanship... The changes that AI brings won't discriminate between left, right, and center. And we all know the only way to get things done here is bipartisanship. That means compromise by Democrats and Republicans, but certainly getting nothing done is a worse alternative" (Schumer, 2024).

[27] For instance, a European regulator recently emphasized the need for societal pressure to encourage responsible behavior from platforms and tech firms. During a panel at Columbia University's Institute of Global Politics on AI and democracy, she expressed the hope of witnessing a strong societal rejection of unacceptable practices, signaling to digital companies that they must prioritize user trust. See: https://www.youtube.com/watch?v=GGH2O6gkUD0.

the technology is still evolving. This partisan division could pose challenges to the adoption of effective regulation, even with majority support in aggregate. Our study provides insights into the conditions under which these partisan divides could either be exacerbated or mitigated.

Our findings highlight the potential appeal of non-governmental regulatory measures to gain bipartisan support. Indeed, there are currently concrete proposals for non-governmental regulatory measures, such as engaging with the AI assurance industry for independent audits and promoting algorithmic transparency through corporate disclosure (Polity, 2020; Risk Regulation, 2021; Policy and Society, 2023). The patterns we find in our study suggest that bipartisan support for AI regulation may be more feasible if it involves non-governmental oversight.

In addition, our experimental analysis shows that exposure to information about the concrete risks associated with the development and use of AI increases overall support for stricter and more urgent AI regulation. Voters particularly resonate with risks related to AI automation in the workplace and, to a lesser extent, with the potential for LLMs (LLMs) to generate and disseminate misinformation. While policymakers acknowledge the profound risks of potential biases in AI systems (The White House, 2023), public attention to these issues remains surprisingly low, which is consistent with the minimal coverage they receive in U.S. media. Our findings suggest that drafting robust AI regulations is insufficient; for these regulations to be effective, the issues they address must also be clearly and effectively communicated to the public. Without greater public awareness and engagement, the political momentum needed to address AI bias comprehensively may fall short, potentially undermining the effectiveness of these policy efforts.

Yet, a key finding of this study is that the ability of relevant information to mobilize voter support for regulation is strongly influenced by the source delivering the message. While Democrat voters are swayed by expert cues, Republican voters are primarily influenced by cues from Republican elites. Two potential mechanisms might explain this shift: priming and learning (e.g., Chong and Druckman, 2007; Lenz, 2009; Matthews, 2019). Priming suggests that concrete information about AI makes its risks more salient, thereby pushing views in a pro-regulatory direction. Learning, on the other hand, implies that new information leads individuals to update their regulatory preferences. Although our research design does not definitively determine which mechanism is at play, our evidence aligns more closely with the learning mechanism. Specifically, exposure to information from trusted elites does not change voters' opinions. Rather, it prompts them to seek additional information. This implies an ongoing learning process about AI's risks and benefits. Future research should empirically disentangle these mechanisms to clarify their roles in shaping public attitudes toward AI regulation.

Conclusion

This study contributes to the growing body of work examining the attitudinal effects of information, particularly as conveyed through the media. We present a novel experimental design that tests the conditions under which information affects policy preferences. By embedding information within an editorial task, we enhance respondent engagement with the text while minimizing potential demand effects and addressing issues of inattentiveness or noncompliance often associated with previous studies that directly provide information in the form of articles. We show that even in a controlled setting of heightened engagement with information, respondents tend to disregard information from sources they perceived as less trustworthy.

Furthermore, we find that positive information about AI's societal impacts does not affect opinions on regulation. This asymmetry may be due to the absence of an official AI regulation policy in the U.S., which means that positive information may not have highlighted the potential costs of regulation enough to shift voters' views. Additionally, since media coverage often emphasizes AI's benefits, our positive treatment may have seemed like "old news," failing to change opinions. Further research is needed to explore this puzzle.

Our study offers insights into the potential politicization of AI regulation, a process that can be understood as a spectrum. At one end, issues remain neutral, with public debate focused on concrete aspects, allowing voters to process information without partisan bias. At the opposite end lies full politicization, where ideological predispositions dominate, and partisan cues overshadow factual considerations, leading to polarized public opinion. Between these extremes lies partial politicization, where concrete information still influences policy preferences, but the credibility of the source plays a critical role. In this middle phase, voters are swayed by who delivers the message, but there remains space for thoughtful, substantive discussion.

In the context of AI regulation, our study suggests that this process of politicization has not yet fully taken root. The absence of established elite positions on AI leaves voters without clear partisan cues, potentially allowing for a more nuanced debate focused on substantive issues. However, the technical complexity of AI and the lack of immediate, tangible impacts on daily life may prompt voters to rely on simplified heuristics, increasing the risk of politicization. Whether AI regulation becomes a highly politicized issue depends on how media and elites frame the discourse—either emphasizing concrete, non-partisan aspects or abstracting the debate into partisan terms.

These findings have important implications for the future of AI governance. The lack of clear partisan alignments in AI regulation presents a unique opportunity to craft substantive policy solutions that resonate with voters across the political spectrum. This has significant implications for the feasibility of the bipartisan initiatives recently proposed by American lawmakers. Our research suggests that the success of these efforts may hinge on how effectively they are communicated to voters. Elite messaging that emphasizes the importance of

AI regulation can foster convergence in voter support across the ideological spectrum, which could facilitate the successful implementation of regulatory measures.

References

Appel, Ruth E, Jennifer Pan, and Margaret E Roberts (2023). "Partisan conflict over content moderation is more than disagreement about facts". In: *Science Advances* 9.44, eadg6799.

Baum, Matthew A and Philip BK Potter (2008). "The relationships between mass media, public opinion, and foreign policy: Toward a theoretical synthesis". In: *Annu. Rev. Polit. Sci.* 11.1, pp. 39–65.

Bayes, Robin, James N Druckman, Avery Goods, and Daniel C Molden (2020). "When and how different motives can drive motivated political reasoning". In: *Political Psychology* 41.5, pp. 1031–1052.

Benoit, Kenneth, Kohei Watanabe, Haiyan Wang, Paul Nulty, Adam Obeng, Stefan Müller, and Akitaka Matsuo (2018). "quanteda: An R package for the quantitative analysis of textual data". In: *Journal of Open Source Software* 3.30, pp. 774–774.

Bolsen, Toby, James N Druckman, and Fay Lomax Cook (2014). "The influence of partisan motivated reasoning on public opinion". In: *Political Behavior* 36, pp. 235–262.

Bommasani, Rishi, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. (2021). "On the opportunities and risks of foundation models". In: *arXiv preprint arXiv:2108.07258*.

Bond, Shannon (2024). "AI fakes raise election risks as lawmakers and tech companies scramble to catch up". In: *NPR*. URL: https://www.npr.org/2024/02/08/1229641751/ai-deepfakes-election-risks-lawmakers-tech-companies-artificial-intelligence.

Borwein, Sophie, Beatrice Magistro, R Michael Alvarez, Bart Bonikowski, and Peter John Loewen (2024). "The Potential for Political Backlash Against Generative AI". In.

Brenan, Megan and Lydia Saad (2018). "Global Warming Concern Steady Despite Some Partisan Shifts". In: *Gallup*. URL: https://news.gallup.com/poll/231530/global-warming-concern-steady-despite-partisan-shifts.aspx.

Bullock, John G (2020). *Party cues*. Oxford University Press, New York, NY.

Buntain, Cody, Martin Innes, Tamar Mitts, and Jacob Shapiro (2023). "Cross-platform reactions to the post-January 6 deplatforming". In: *Journal of Quantitative Description: Digital Media* 3.

Büthe, Tim, Christian Djeffal, Christoph Lütge, Sabine Maasen, and Nora von Ingersleben-Seip (2022). *Governing AI–attempting to herd cats? Introduction to the special issue on the Governance of Artificial Intelligence.*

Cath, Corinne (2018). "Governing artificial intelligence: ethical, legal and technical opportunities and challenges". In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 376.2133, p. 20180080.

Chong, Dennis and James N Druckman (2007). "Framing public opinion in competitive democracies". In: *American political science review* 101.4, pp. 637–655.

Druckman, James N and Arthur Lupia (2016). "Preference change in competitive political environments". In: *Annual Review of political science* 19.1, pp. 13–31.

Druckman, James N and Mary C McGrath (2019). "The evidence for motivated reasoning in climate change preference formation". In: *Nature Climate Change* 9.2, pp. 111–119.

Druckman, James N, Erik Peterson, and Rune Slothuus (2013). "How elite partisan polarization affects public opinion formation". In: *American political science review* 107.1, pp. 57–79.

Engstrom, David Freeman and Amit Haim (2023). "Regulating government AI and the challenge of sociotechnical design". In: *Annual Review of Law and Social Science* 19.1, pp. 277–298.

Eubanks, Virginia (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Fast, Ethan and Eric Horvitz (2017). "Long-term trends in the public perception of artificial intelligence". In: *Proceedings of the AAAI conference on artificial intelligence*. Vol. 31. 1.

Global Policy Watch (2024). *Bipartisan Senate AI Roadmap Released*. Accessed on July 31, 2024. URL: https://www.globalpolicywatch.com/2024/05/bipartisan-senate-ai-roadmap-released/.

Google (2018). *AI at Google: our principles*. URL: https://www.blog.google/technology/ai/ai-principles/.

Hochschild, Jennifer (2021). *Genomic politics: how the revolution in genomic science is shaping American society*. Oxford University Press.

Hu, Minqing and Bing Liu (2004). "Mining and summarizing customer reviews". In: *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 168–177.

Human-Centered Artificial Intelligence (HAI), Stanford Institute for (2024). *AI Index 2024 Report, Chapter 7: Policy and Governance*. URL: https://drive.google.com/drive/folders/1wCDnZcgasUM4600FLI5yNInpN4GRcu3W.

IBM (2021). *IBM's AI Ethics Board: Ensuring Responsible AI Innovation*. URL: https://www.ibm.com/blogs/policy/ai-ethics-board/.

Kahan, Dan M (2017). "Misconceptions, misinformation, and the logic of identity-protective cognition". In.

König, Pascal D, Stefan Wurster, and Markus B Siewert (2023). "Sustainability challenges of artificial intelligence and Citizens' regulatory preferences". In: *Government Information Quarterly* 40.4, p. 101863.

Krosnick, Jon A (1990). "Government policy and citizen passion: A study of issue publics in contemporary America". In: *Political behavior* 12, pp. 59–92.

Kuo, Alexander, Dulce Manzano, and Aina Gallego (2024). "Automation versus openness: support for policies to address job threats". In: *Journal of Public Policy* 44.1, pp. 1–23.

Lee, John J (2021). "Party polarization and trust in science: what about democrats?" In: *Socius* 7, p. 23780231211010101.

Lenz, Gabriel S (2009). "Learning and opinion change, not priming: Reconsidering the priming hypothesis". In: *American Journal of Political Science* 53.4, pp. 821–837.

Magistro, Beatrice, Sophie Borwein, R Michael Alvarez, Bart Bonikowski, and Peter J Loewen (2024). "The Common Microfoundations of Attitudes Toward Artificial Intelligence (AI) and Globalization". In: *Available at SSRN 4795006*.

Margalit, Yotam and Shir Raviv (2023). "The politics of using AI in public policy: Experimental evidence". In: *Available at SSRN*.

— (2024). "Does support for redistribution mean what we think it means?" In: *Political Science Research and Methods*, pp. 1–9.

Matthews, J Scott (2019). "Issue priming revisited: Susceptible voters and detectable effects". In: *British Journal of Political Science* 49.2, pp. 513–531.

McCombs, Maxwell and Sebastian Valenzuela (2020). *Setting the agenda: Mass media and public opinion*. John Wiley & Sons.

Microsoft (2022). *Microsoft Responsible AI Standard v2*. URL: https://www.microsoft.com/en-us/ai/responsible-ai.

Mitts, Tamar (2025). *Safe Havens for Hate: The Challenge of Moderating Online Extremism*. Princeton University Press.

Motta, Matthew (2018). "The dynamics and political implications of anti-intellectualism in the United States". In: *American Politics Research* 46.3, pp. 465–498.

Mummolo, Jonathan and Erik Peterson (2019). "Demand effects in survey experiments: An empirical assessment". In: *American Political Science Review* 113.2, pp. 517–529.

Pew Research Center (2019). *Political Independents: Who They Are, What They Think*. Report. Most 'lean' toward a party; 'true' independents tend to avoid politics. Pew Research

Center. URL: https://www.pewresearch.org/politics/2019/03/14/political-independents-who-they-are-what-they-think/ (visited on 08/01/2023).

Pink, Sophia L, James Chu, James N Druckman, David G Rand, and Robb Willer (2021). "Elite party cues increase vaccination intentions among Republicans". In: *Proceedings of the National Academy of Sciences* 118.32, e2106559118.

Policy and Society (2023). "Regulatory sandboxes in the AI Act: reconciling innovation and safety?" In: *Policy and Society*. URL: https://www.tandfonline.com/doi/full/10.1080/17579961.2023.2245678.

Polity, Information (2020). "Introduction to special issue algorithmic transparency in government". In: *Information Polity*. URL: https://content.iospress.com/articles/information-polity/ip200010.

Read, Blair, Lukas Wolters, and Adam J Berinsky (2021). "Racing the clock: Using response time as a proxy for attentiveness on self-administered surveys". In: *Political Analysis*, pp. 1–20.

Risk Regulation, European Journal of (2021). "A Sandbox Approach to Regulating High-Risk Artificial Intelligence Applications". In: *European Journal of Risk Regulation*. URL: https://www.cambridge.org/core/journals/european-journal-of-risk-regulation/article/sandbox-approach-to-regulating-highrisk-artificial-intelligence-applications/C350EADFB379465E7F4A95B973A4977D.

Roberts, Margaret E, Brandon M Stewart, Dustin Tingley, Edoardo M Airoldi, et al. (2013). "The structural topic model and applied social science". In: *Advances in neural information processing systems workshop on topic models: computation, application, and evaluation*. Vol. 4. 1. Harrahs and Harveys, Lake Tahoe, pp. 1–20.

Rotman, David (2023). "ChatGPT is about to revolutionize the economy. We need to decide what that looks like". In: *MIT Technol. Rev.*

Schiff, Kaylyn Jackson, Daniel S Schiff, Ian T Adams, Joshua McCrain, and Scott M Mourtgos (2023). "Institutional factors driving citizen perceptions of AI in government: Evidence from a survey experiment on policing". In: *Public Administration Review*.

Schumer, Chuck (2024). *Majority Leader Schumer Floor Remarks on the Release of the Roadmap for AI Policy by the Senate Bipartisan Senate AI Working Group*. Accessed on July 31, 2024. URL: https://www.democrats.senate.gov/newsroom/press-releases/majority-leader-schumer-floor-remarks-on-the-release-of-the-roadmap-for-ai-policy-by-the-senate-bipartisan-senate-ai-working-group.

Shapiro, Robert Y and Lawrence R Jacobs (2011). *The Oxford handbook of American public opinion and the media*. Oxford University Press.

Shogan, Colleen J (2007). "Anti-intellectualism in the modern presidency: A republican populism". In: *Perspectives on Politics* 5.2, pp. 295–303.

Slothuus, Rune and Martin Bisgaard (2021). "How political parties shape public opinion in the real world". In: *American Journal of Political Science* 65.4, pp. 896–911.

Stagnaro, Michael N., James N. Druckman, Adam J. Berinsky, Antonio A. Arechar, Robb Willer, and David G. Rand (2024). "Representativeness versus Response Quality: A Comparison Across Nine Online Survey Samples". In: *Working Paper*. Unpublished manuscript.

Swenson, Ali and Kelvin Chan (2024). "Election disinformation takes a big leap with AI being used to deceive worldwide". In: *Associated Press*. URL: https://apnews.com/article/artificial-intelligence-elections-disinformation-chatgpt-bc283e7426402f0b4baa7df280a4

Taber, Charles S and Milton Lodge (2006). "Motivated skepticism in the evaluation of political beliefs". In: *American journal of political science* 50.3, pp. 755–769.

The White House (2022). *Blueprint for an AI Bill of Rights*. Office of Science and Technology Policy. URL: https://www.whitehouse.gov/ostp/ai-bill-of-rights/.

— (2023). *Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence*. URL: https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/.

U.S. Congress (2022). *Algorithmic Accountability Act of 2022*. URL: https://www.congress.gov/bill/117th-congress/house-bill/6580/text.

Wolsko, Christopher, Hector Ariceaga, and Jesse Seiden (2016). "Red, white, and blue enough to be green: Effects of moral framing on climate change attitudes and conservation behaviors". In: *Journal of Experimental Social Psychology* 65, pp. 7–19.

Wu, Nicole (2023). ""Restrict foreigners, not robots": Partisan responses to automation threat". In: *Economics & Politics* 35.2, pp. 505–528.

Zhang, Baobao and Allan Dafoe (2020). "US public opinion on the governance of artificial intelligence". In: *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, pp. 187–193.

Zhou, Jack (2016). "Boomerangs versus javelins: How polarization constrains communication on climate change". In: *Environmental politics* 25.5, pp. 788–811.

Supplementary Materials

The Politics of AI Regulation

1 Additional Information on Media Coverage **SI-2**
1.1 News Articles Data Collection SI-2
1.2 Measuring Sentiment, Topics, and Mentions of Elites SI-2

2 Experimental Materials **SI-9**
2.1 Survey Instrument and Experimental Treatments SI-9
2.2 Survey Sample Description SI-13
2.3 Balance between Treatment and Control Groups SI-13
2.4 Weighted Results SI-13

3 Experimental Results **SI-15**
3.1 Tone Coverage and support for AI SI-15
3.2 Tone Coverage and AI Issue Salience SI-17
3.3 Source of Information and Support for AI Regulation SI-18

4 Research Ethics **SI-24**

5 Pre-Analysis Plan and Pre-Registration **SI-24**
5.1 Theory and Hypotheses SI-24
5.2 Design Plan SI-26
5.3 Study Design SI-26
5.4 Manipulated Variables SI-26
5.5 Measured variables SI-27
5.6 Analysis Plan SI-27

1 Additional Information on Media Coverage

1.1 News Articles Data Collection

We collected articles and TV news transcripts published in major U.S. outlets between September 1, 2022 and September 1, 2024 that mentioned variants of the term "artificial intelligence." We obtained the articles and transcripts from Factiva, a business intelligence platform that aggregates content from 33,000 news, data, and information sources across 200 countries in 32 languages (https://www.dowjones.com/professional/glossary/factiva/). The outlets that we included in our analysis are CNN, Fox News, MSNBC, New Yorker, Newsweek, The New York Times, The Wall Street Journal, The Washington Post, and USA Today.

To identify articles that cover AI, we filtered the search to articles and news transcripts that included at least one of the following keywords: "artificial intelligence" or "AI" or "A.I" or "Artificial Intelligence." We focus on articles that mention AI-related keywords (and not more general terms like "machine learning" or "automation"), as artificial intelligence has become the most prevalent term to refer to the technology in recent years (see figure SI-1). Our corpus consists of 12,269 articles and transcripts that discuss artificial intelligence in one way or another—many of which were published after the public release of OpenAI's ChatGPT (see figure SI-2). To ensure that our analysis focuses on discussions of artificial intelligence, we trimmed each article to segments of text that appeared before and after our AI-related keywords. We did this by extracting the 100 words before and after each AI keyword to create a window size that best approximates a paragraph-length text around each keyword.

1.2 Measuring Sentiment, Topics, and Mentions of Elites

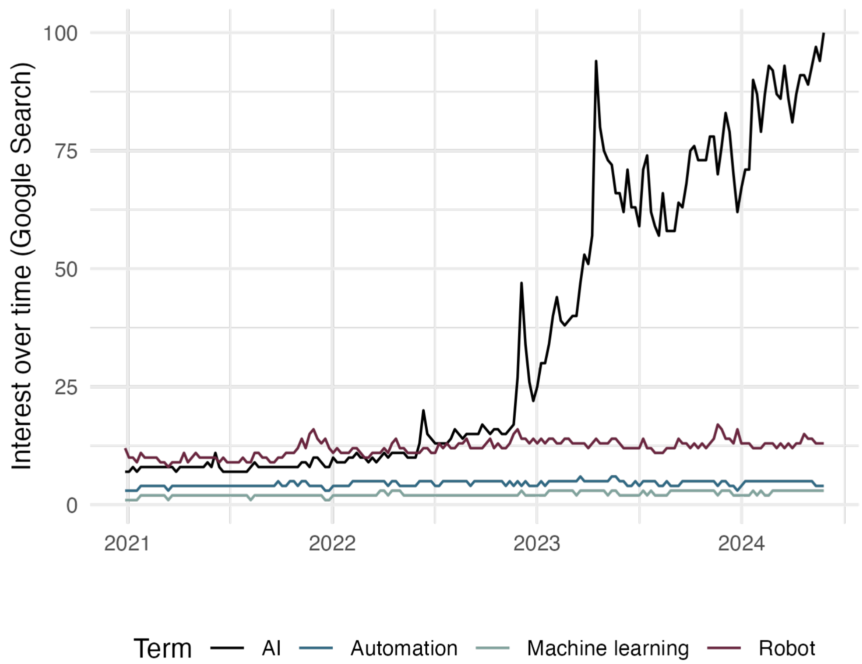
Sentiment

We analyzed the text of these articles to measure sentiment, examine the topics that they tend to focus on, and identify elites that are quoted in the articles. Our sentiment measure is based on a dictionary that we adapted to our corpus that ranges between -1 (negative sentiment) and 1 (positive sentiment), where 0 represents neutral sentiment towards AI. We used the Quanteda package in R (Benoit et al., 2018) to estimate sentiment using a dictionary of positive and negative terms developed by Hu and Liu (2004). We validated the dictionary by comparing it to a random sample of articles that we manually labeled for these three classes. Figure SI-6 shows that the dictionary did a good job capturing positive and negative sentiment towards AI-related topics.

Topic models

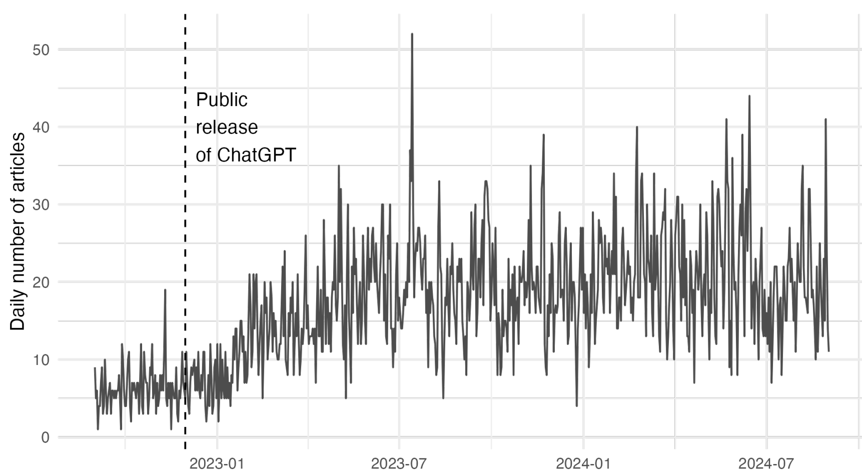
To identify common themes in media coverage of AI, we used a structural topic model (STM), a method well-suited for analyzing text while accounting for document-level meta-

Figure (SI-1) Google Searches Over time



Note: The y-axis represents search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Data source: Google Trends (https://www.google.com/trends).

Figure (SI-2) Number of Articles Over time



Note: The figure shows the daily number of AI-related articles published in major US media outlets between September 2022 and September 2024.

data (Roberts et al., 2013). Using the `stm` package in R, we estimated a 45-topic STM on our corpus of AI-related news articles, preprocessed to remove stopwords, punctuation, symbols, and URLs, with tokens stemmed and converted to lowercase. The document-feature matrix (DFM) was further trimmed to exclude terms appearing fewer than 10 times across the corpus. We labeled each topic based on the 20 most representative terms generated by the STM.

In Figure 1B, we show the the relationship between topic prevalence and sentiment. We did so by estimating the STM with sentiment as a prevalence covariate. After estimating the model, we examined the correlation between sentiment and topic prevalence using the `estimateEffect()` function in the `stm` package in R. The full results, showing all topics, are shown in Figure SI-3.

Figure 1D illustrates how the framing of AI-related topics in the media varies based on the party affiliation of the politician mentioned. To generate this figure, we applied the same STM to a subset of articles explicitly mentioning either Republican or Democratic politicians (N = 1,079). We assessed the relationship between party affiliation and topic prevalence using the `estimateEffect()` function. In the manuscript, we highlight topics that differ significantly between parties at the 0.05 level. Figure SI-4 presents the full results for all topics.

Dictionaries

We also created keyword lists to measure coverage of specific issue areas examined in our experiment: automation in the labor market, large language models, and bias in AI algorithms.[28] Figure SI-5 shows the number of articles that include keywords related to the three issues. To identify mentions or quotes from experts and tech leaders, we developed custom dictionaries based on close readings of random text samples.[29]

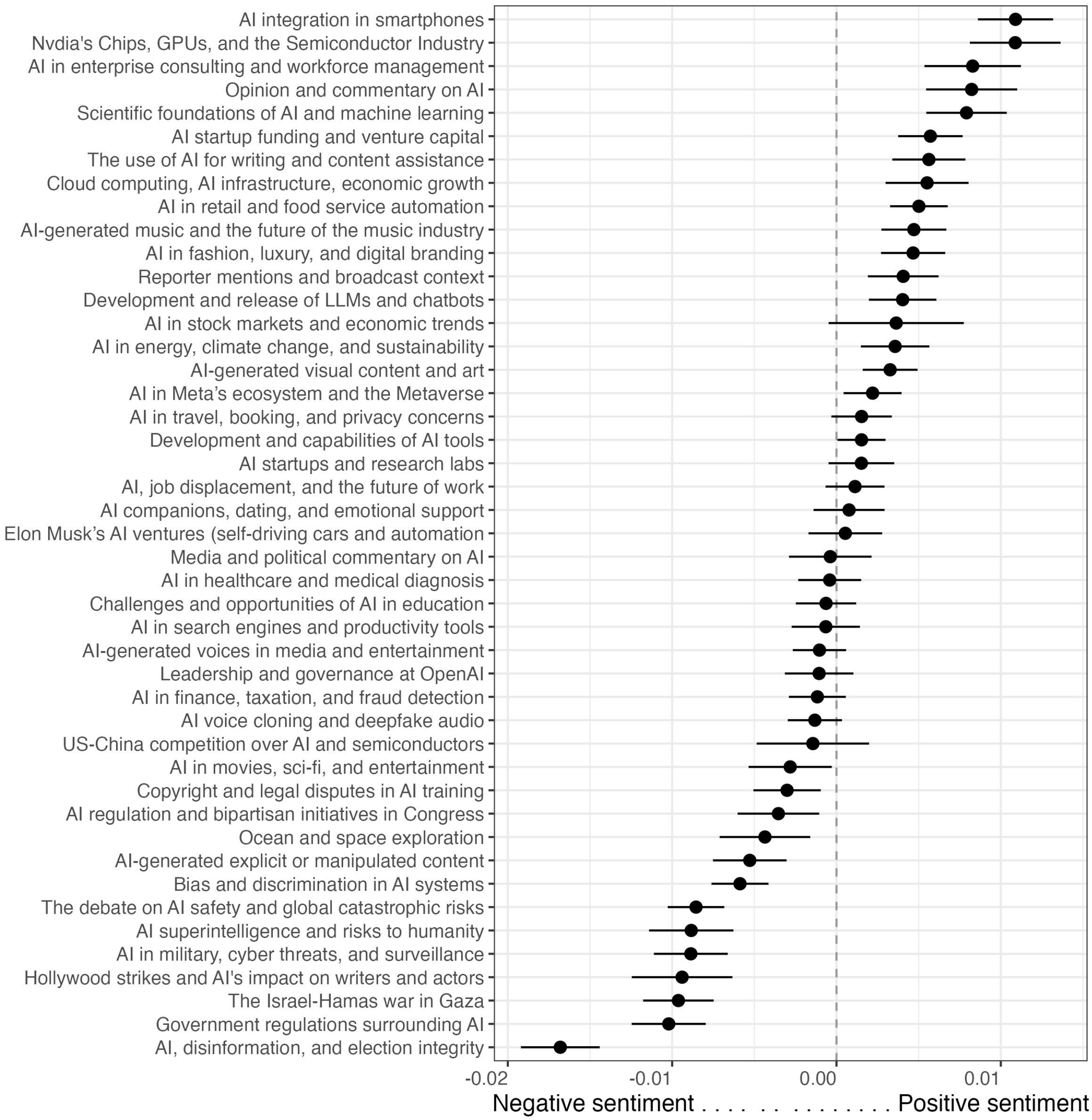
Similarly, to identify mentions or quotes from politicians, we created a dictionary that includes references to the Democratic and Republican parties, as well as general terms for elected representatives.[30] Additionally, we compiled lists of all U.S. Senate and House members who were in office during the study period to match mentions in the articles. Table SI-1 demonstrates that our measures effectively capture these references in the articles.

[28] The keywords used were: bias, discrimination, racial, biases, ethnicity, disparities, minorities, fairness, diversity for bias in AI algorithms; jobs, workers, employers, employees, job, workforce, eliminated, automation, work, white-collar, hire, working, unions, positions, staff, businesses, labor, hired, laid, fired for automation in the labor market; and llms, language, models, machine-learning, chatgpt's, generate, gpt-4, chatbots, ais, chatgpt, chatbot, generative, bard, openai's, bot, anthropic, gemini, claude, llama, co-pilot, copilot, gpt for LLMs.

[29] The keywords used were: scientist, researcher, professor, science, research, economist, scientists, university, engineering, scholar, scholars, professors, academics, experts for experts; ceo, executive, co-founder, founder, chief, altman, zuckerberg, musk, nadella, pichai, chairman, officer, executives, gelsinger, jassy, murati, brockman, bezos for tech leaders.

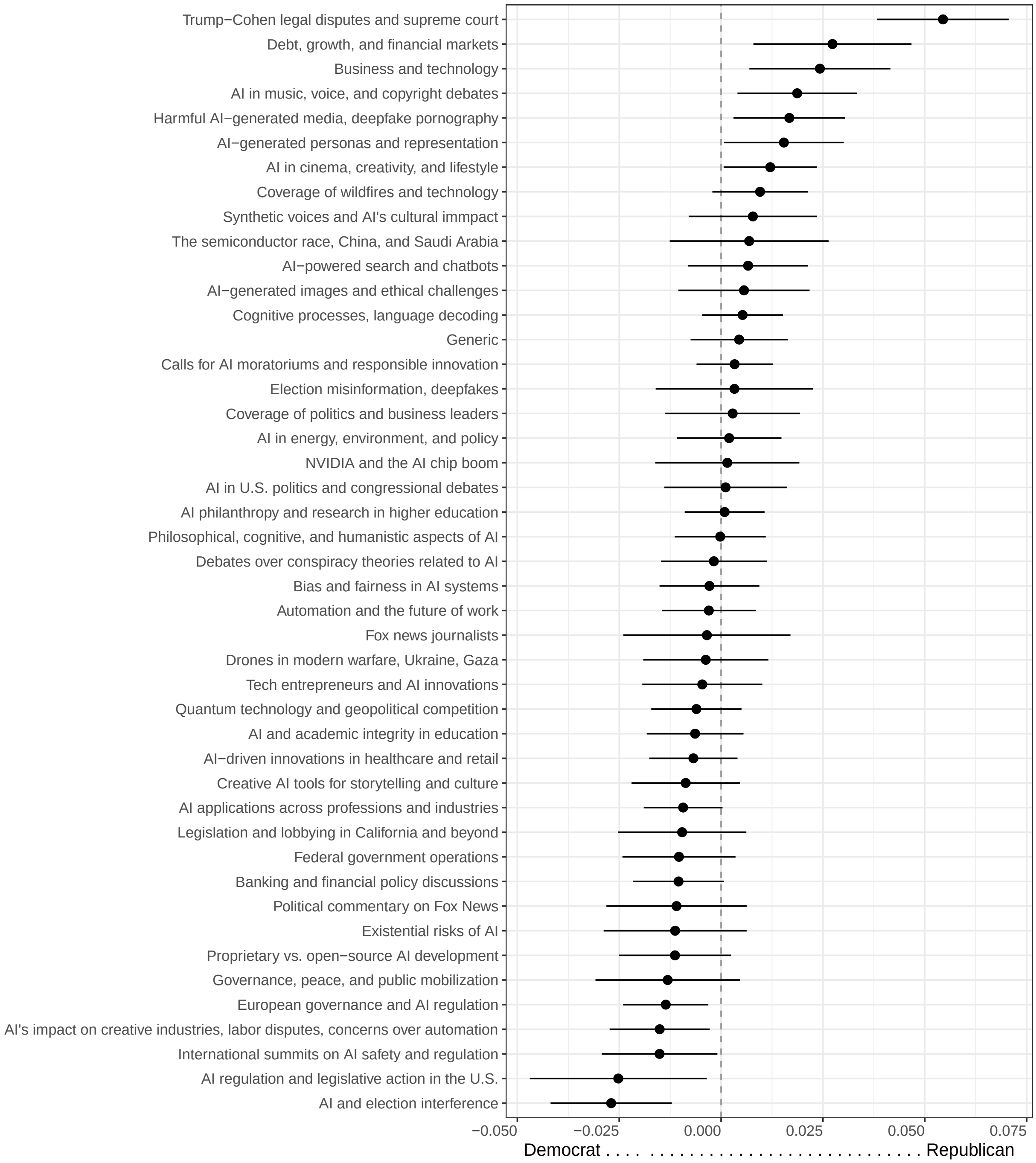
[30] The keywords used were: politician, speaker, republican, democrat, senator, governor, democratic, senate, congressman, senators, chairman, representative, incumbent, republicans, democrats, political, leader, leaders, candidates, presidential, president, gop, party, liberal.

Figure (SI-3) Topic Prevalence by Article Sentiment



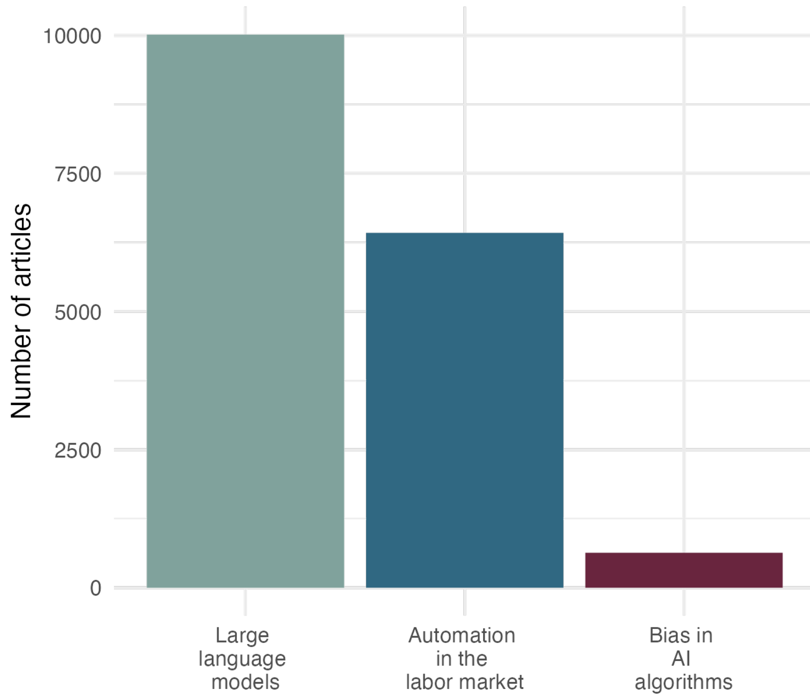
Note: The figure shows the relationship between sentiment and topic prevalence of articles covering AI in major U.S. news outlets (N=12,269 articles).

Figure (SI-4) Topic Prevalence by Party of Politician Mentioned in the Article



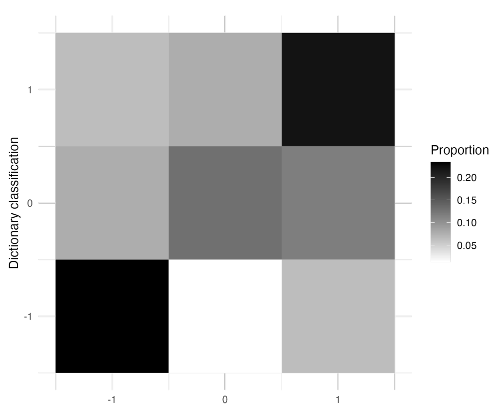
Note: The figure shows the relationship between the party of the politician mentioned and topic prevalence of articles covering AI in major U.S. news outlets (N=1,079 articles).

Figure (SI-5) Media Coverage of LLMs, AI and the Labor Market, and Bias in AI Algorithms



Note: The figure shows the number of articles that include keywords related to LLMs, AI and the labor market, and bias in AI algorithms.

Figure (SI-6) Sentiment Analysis Validation



Note: The figure shows the validation test for our sentiment dictionary of news articles covering AI.

Table (SI-1) Validation of Dictionary Measures

	Accuracy	Precision	Recall	F1
Automation in the labor market	0.78	0.87	0.77	0.82
Large language models	0.82	0.98	0.77	0.86
Bias in AI algorithms	0.96	0.92	1.00	0.96
Experts	0.82	0.90	0.80	0.85
Tech leaders	0.82	0.90	0.80	0.85
Democrats	0.98	1.00	0.97	0.99
Republicans	0.97	0.97	0.98	0.98

2 Experimental Materials

2.1 Survey Instrument and Experimental Treatments

This section provides detailed information about the survey instrument and experimental treatments used in our study.

Attention Screener

Before beginning, please read these definitions related to the news articles:

- Podcast: An online audio or video show discussing diverse subjects, usually in a series format.
- Artificial intelligence: Software that makes predictions, recommendations, or decisions based on massive amounts of data without human instructions.
- Wind turbines: Devices that convert the kinetic energy of wind into electrical energy using large rotating blades.

On the previous page, you were presented with three definitions that are relevant to the news articles. Please select the definition that did not appear among the previous three definitions. Podcast: An online audio or video show discussing diverse subjects, usually in a series format.

Artificial intelligence: Software that makes predictions, recommendations, or decisions based on massive amounts of data without human instructions.

Wind turbines: Devices that convert the kinetic energy of wind into electrical energy using large rotating blades.

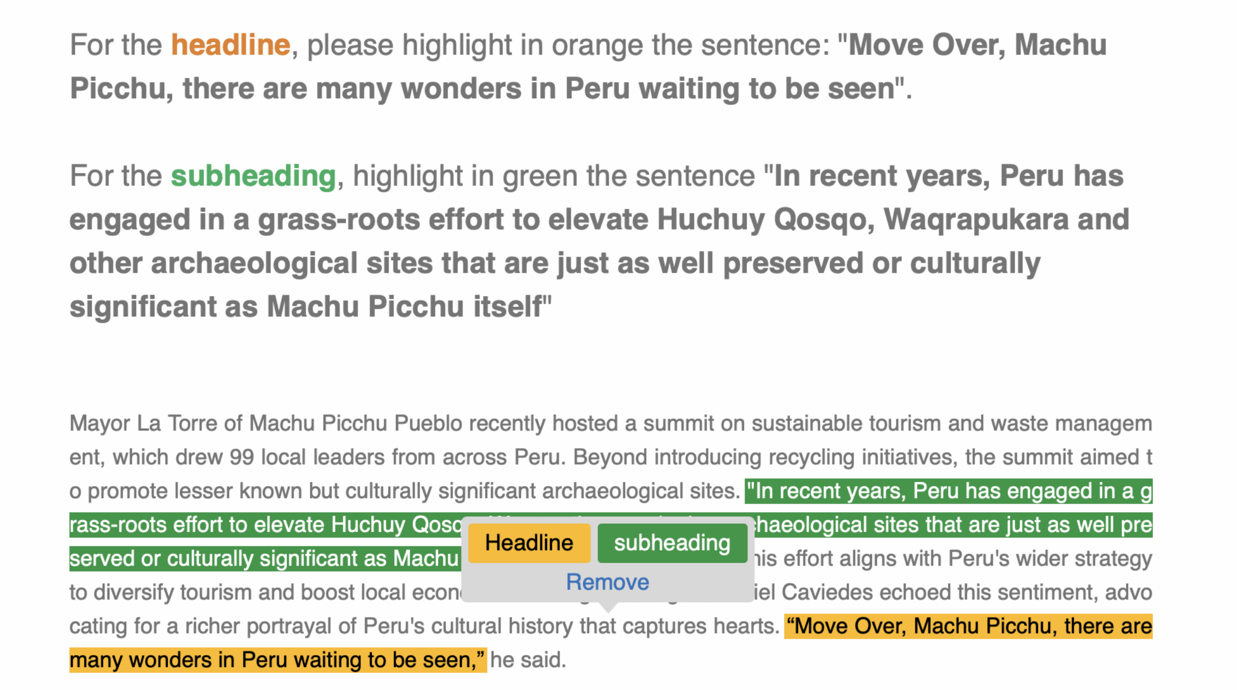
News platforms: Digital channels where individuals access news, such as news websites, social media, TV, and newspapers.

Task Instructions

Next, we will show you several paragraphs taken from recent news articles of major media outlets, one at a time. Please read each paragraph carefully and select, from the text, a headline and a subheading for the full news article.

- Headline: Highlight in orange the sentence that best fits as a headline. This should be a brief and captivating statement that summarizes the main idea of the article in a way that engages the reader.
- Subheading: Highlight in green a sentence or two that can be used as a subheading. This should be a longer and more informative statement that summarizes the substance of the text.

Figure (SI-7) A screen capture of the user interface



Positive Tone

- ***LLMs:*** A letter signed by 45 *(Democrats/Republicans/AI experts from leading universities/AI industry leaders)* called for more investment in developing AI-based applications that can empower human skills, such as Chat GPT. The letter stressed the importance of maintaining the United States' leadership in AI development: "AI can augment human minds and decision-making in unprecedented ways. It is crucial to be at the forefront of this technological race and to work towards finding new tools that can empower the American people,"the letter said. The (Democrats/Republicans/experts/tech leaders) who wrote the letter emphasized the potential benefits of using AI to help people learn new skills and improve their decision-making and problem-solving abilities.

- ***Labor Market Automation:*** *(Democratic Senator Chuck Schumer/Republican Senator Scott Brown/Steven Alexander, an economist at Georgetown/Satya Nadella, Microsoft's chief executive)* highlighted the great opportunities of AI automation in the labor market in an interview. *(He/She)* said, "The most significant promise in the long term is the potential for job creation due to AI."Historically, automation has been a major driver of economic growth in America. The recent wave of AI takes it a significant step further, boosting America's labor productivity growth by nearly 1.5 percentage points per year and increasing annual global gross domestic product by 7 percent. "This technological transition could lead to previously unimagined creative job opportunities."

- ***Bias and Justice in Decision Making:*** The summit ended on an optimistic tone, as a group of *(Democratic senators/Republican senators/AI researchers/Tech leaders)* highlighted the potential of AI to detect and address the enduring issue of racial bias in the criminal justice system. They said that AI can reveal patterns of racial bias that are deeply rooted in the system and that often go unnoticed or unchallenged by human actors. The *(Democratic senators/Republican senators/researchers/CEOs and Founders)* also said that by using AI with high standards of ethics, they can not only expose the subtle and systemic biases in legal institutions but also implement effective solutions to fix them and achieve a more fair and just society. "This is a historic opportunity to use AI as a tool for social justice and reform,"said one of them in an exclusive interview.

Negative Tone

- ***LLMs:*** A letter signed by 45 *(Democrats/Republicans/AI experts from leading universities/AI industry leaders)* called for an immediate pause of at least six months in the training of AI systems more powerful than GPT-4. "Recent months have seen AI labs locked in an out-of-control race to develop and deploy ever more powerful tools that no one - not even their creators - can understand, predict, or reliably control,"the letter said. The *(Democrats/Republicans/experts/tech leaders)* who signed the letter warned about the long-term adverse effects of these systems such as spreading false information, propaganda, and influencing public opinion.

- ***Labor Market Automation:*** (*Democratic Senator Chuck Schumer/Republican Senator Scott Brown/Steven Alexander, an economist at Georgetown/Satya Nadella, Microsoft's chief executive)* warned of the looming threat of AI automation to the labor market in an interview. (*He/She)* said, "The biggest nightmare in the long term is the job loss that AI could cause."Historically, AI has been a significant driver of income inequality in America. The recent wave of AI takes it a significant step further, automating activities that are equivalent to 300 million full-time jobs globally, which could eliminate the need for up to 30 percent of certain roles. "This technological transition could give rise to previously unimagined job displacement."

- ***Bias and Justice in Decision Making:*** The summit ended on an optimistic tone, as a group of *(Democratic senators/Republican senators/AI researchers/Tech leaders)* highlighted the potential of AI to detect and address the enduring issue of racial bias in the criminal justice system. They said that AI can reveal patterns of racial bias that are deeply rooted in the system and that often go unnoticed or unchallenged by human actors. The (Democratic senators/Republican senators/researchers/CEOs and Founders) also said that by using AI with high standards of ethics, they can not only expose the subtle and systemic biases in legal institutions but also implement effective solutions to fix them and achieve a more fair and just society. "This is a historic opportunity to use AI as a tool for social justice and reform,"said one of them in an exclusive interview.

Outcome Questions

- ***Regulation vs. Innovation:*** "Some people believe that the government should heavily regulate the development and use of AI applications and impose strict oversight to address negative consequences. Others believe that the government should not intervene and prioritize technological progress and economic growth. On a scale of 1 to 7, where 1 means that the government should not regulate AI to ensure innovation, and 7 means that the government should strictly regulate AI even at the expense of innovation, where do you stand¿'

- ***Timing of Regulation:*** "Some people think that the government should regulate the development and use of AI as soon as possible to avoid any negative consequences. Other people think that the government should let the technology evolve and not rush to draft laws that may become obsolete as the technology changes rapidly. On a scale of 1 to 7 where 1 means the government should wait with the regulation and 7 means the government should regulate now, where do you stand¿'

- ***Regulatory Authority:*** "Some people think that private sector agencies, rather than the government, should be responsible for the regulation of AI technology, by establishing their own safety protocols and supervising bodies. Others believe that government agencies should take the lead in regulating AI. On a scale of 1 to 7, where 1 means that private companies should voluntarily regulate themselves, and 7 indicates that government agencies should impose the regulations, where do you stand¿'

Specific Policy Measures Next, we ask for your input on several government regulatory proposals. Please indicate the extent to which you support or oppose the following measures.

- Labeling content and images created by AI to indicate that they are not real.
- Requiring independent reviews of AI companies to avoid potential racial or gender discrimination in their technology.
- Requiring that a human (not AI) has the final say on important decisions such as providing social services.
- Determining specific jobs that AI machines should not replace.
- Providing tax incentives to companies that create jobs fit for human workers rather than machines.
- Deciding between options. Please tick the answer 'somewhat oppose'.
- Restricting large tech companies from buying out small competitors.
- Taxing companies based on the amount of carbon they produce

2.2 Survey Sample Description

We utilized CloudResearch Connect with demographic quotas (Connect NR) based on U.S. Census data for age, gender, race/ethnicity, and education. Previous research indicates that this approach yields a sample that balances data quality and representativeness (Stagnaro et al., 2024). To further ensure data quality, we implemented attention checks at the beginning of the survey, prior to randomizing participants into treatment groups. Our analysis included only respondents who provided consent and correctly answered an attention check question. Table SI-2 presents descriptive statistics on key demographic characteristics of our sample.

Table (SI-2) Sample versus U.S. Population Demographics

	Proportions		
	Sample	Census	Difference
Female	0.54	0.51	0.04
White	0.69	0.60	0.09
High Education	0.50	0.32	0.18
Age 18-29	0.21	0.22	-0.01
Age 30-44	0.35	0.26	0.09
Age 45-59	0.26	0.26	-0.00
Age 60+	0.19	0.26	-0.07

2.3 Balance between Treatment and Control Groups

Table SI-3 presents descriptive statistics on key covariate balance across treatment and control groups. As the Table shows, we found no statistically significant differences in age, education, or gender between participants assigned to treatment conditions and those in the control group.

2.4 Weighted Results

To ensure our findings are representative of the U.S. adult population, we constructed post-stratification weights that adjust for demographic differences between our sample and population benchmarks. The weights were calculated to match U.S. Census benchmarks for gender, age, education, and race. Table SI-4 presents weighted results replicating descriptive results presented in Figure 3 in the manuscript. The weighted results largely align with our main findings, suggesting that any demographic imbalances in our sample do not substantially affect our conclusions.

Table (SI-3) Balance Check Across Treatment Groups

Variable	Control	Dem x Neg	Dem x Pos	Exp x Neg	Exp x Pos	Rep x Neg	Rep x Pos	Tech x Neg
N	1113	282	270	280	278	269	283	283
Female (%)	56.9	49.6	53.0	53.9	57.9	55.4	50.5	50.9
Age (%)								
18 - 34	34.9	31.9	33.0	32.9	32.7	32.7	38.9	31.1
35 - 54	37.9	40.1	38.5	39.3	39.6	43.9	40.3	42.0
55 or older	27.2	28.0	28.5	27.9	27.7	23.4	20.8	26.9
Education (%)								
Assoc. or less	50.9	49.3	51.9	45.4	51.8	47.2	49.1	46.6
BA or graduate	49.1	50.7	48.1	54.6	48.2	52.8	50.9	53.4
White (%)	69.1	71.6	70.7	74.6	68.3	69.5	64.7	67.1
Party ID (%)								
Democrat	57.3	54.0	56.5	56.7	55.6	53.2	61.3	62.0
55.8								
Republican	42.7	46.0	43.5	43.3	44.4	46.8	38.7	38.0
44.2								

Note: Dem = Democrat, Exp = Expert, Rep = Republican, Neg = Negative, Pos = Positive, Tech = Tech leader

Table (SI-4) Support for AI Regulation, Weighted Proportions

Outcome2	All voters	Democrat	Republican
Stricter AI Regulation	59.5	64.9	52.2
Urgent AI Regulation	56.2	60.8	50.1
Government-led AI Regulation	55.9	66.1	41.9
AI Content Labeling	86.7	90.5	81.5
Human Oversight in AI Decisions	86.0	88.9	82.1
Incentivize Human-AI Hybrid Jobs	74.0	79.0	67.3
Protect Jobs from AI	71.3	74.6	66.7
Independent AI Audits	66.2	81.0	45.9
Limit Big Tech Acquisitions	57.4	65.1	47.0
Carbon Tax	60.2	80.2	32.9

3 Experimental Results

3.1 Tone Coverage and support for AI

Table SI-5 presents results from LPM estimating the effects of media coverage tone on support for AI regulation. Columns 1 and 2 examine a normalized factor analysis score of support for AI regulation. Columns 3 and 4 a binary measure indicating above-median factor scores. The next three outcomes are binary measures capturing specific dimensions of regulatory support: support for stricter regulation over innovation (columns 5-6), support for urgent regulation (columns 7-8), and support for government-led rather than industry-led regulation (columns 9-10). The final four columns examine two placebo outcomes: support for carbon taxes (columns 11-12) and support for restricting big tech acquisitions (columns 13-14). The coefficient estimates from the full specifications (even-numbered columns) correspond to the treatment effects visualized in Figure 4. Results indicate that negative coverage significantly increases public support for stricter and urgent regulation of AI, while positive coverage yields negligible and statistically insignificant effects across all outcomes.

Table (SI-5) Effects of Tone on Support for Regulating AI

	Dependent variable:													
	FC Score		FC Score (median)		Strict		Urgent		Gov-led		Placebo 1: Carbon Taxes		Placebo 2: BigTech	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Negative Tone	0.020†	0.021†	0.036†	0.040†	0.058**	0.062**	0.044*	0.043*	0.035†	0.028	0.072***	0.075***	0.011	0.025
	(0.011)	(0.011)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.018)	(0.021)	(0.021)
Positive Tone	−0.004	−0.004	−0.003	−0.004	−0.008	−0.009	−0.020	−0.020	0.007	0.003	0.054**	0.053**	0.008	0.015
	(0.011)	(0.011)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.018)	(0.021)	(0.021)
Source: Tech leader	0.003	0.009	−0.013	−0.006	−0.005	−0.001	−0.021	−0.012	0.030	0.034	0.030	0.027	0.037	0.032
	(0.013)	(0.013)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.021)	(0.024)	(0.024)
Source: Democrats	0.005	0.009	−0.015	−0.009	−0.018	−0.011	−0.005	−0.001	0.035	0.041†	−0.024	−0.017	0.018	0.015
	(0.013)	(0.013)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)	(0.021)	(0.024)	(0.024)
Source: Republicans	0.012	0.017	0.007	0.012	0.021	0.025	0.024	0.034	0.055*	0.057*	0.029	0.020	0.032	0.031
	(0.013)	(0.013)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.021)	(0.024)	(0.024)
PID: Republican		−0.104***		−0.166***		−0.161***		−0.147***		−0.220***		−0.465***		−0.162***
		(0.009)		(0.018)		(0.017)		(0.018)		(0.017)		(0.015)		(0.018)
PID: Independent		0.011		0.001		−0.019		−0.001		0.013		−0.001		−0.032
		(0.013)		(0.025)		(0.025)		(0.025)		(0.025)		(0.022)		(0.025)
Female		0.051***		0.048**		0.056**		0.068***		0.023		0.043**		0.079***
		(0.009)		(0.018)		(0.017)		(0.017)		(0.017)		(0.015)		(0.018)
White		0.024*		0.048*		0.050*		0.063**		0.020		0.033*		0.011
		(0.011)		(0.020)		(0.020)		(0.020)		(0.020)		(0.017)		(0.020)
Some College or Less		−0.034***		−0.063***		−0.053**		−0.067***		−0.080***		−0.006		0.065***
		(0.010)		(0.018)		(0.018)		(0.018)		(0.018)		(0.015)		(0.018)
Age 35-54		0.007		0.039†		0.003		0.015		0.039†		−0.068***		−0.052*
		(0.011)		(0.021)		(0.020)		(0.020)		(0.020)		(0.018)		(0.021)
Age 55+		0.009		0.050*		0.019		0.030		0.060*		−0.102***		−0.086***
		(0.013)		(0.024)		(0.024)		(0.024)		(0.024)		(0.021)		(0.024)
Inattentive		−0.007		−0.098†		−0.072		−0.033		0.007		−0.060		−0.046
		(0.029)		(0.054)		(0.053)		(0.053)		(0.053)		(0.046)		(0.054)
Constant	0.610***	0.612***	0.488***	0.492***	0.594***	0.612***	0.570***	0.560***	0.538***	0.606***	0.589***	0.804***	0.534***	0.572***
	(0.011)	(0.015)	(0.021)	(0.029)	(0.021)	(0.028)	(0.021)	(0.029)	(0.021)	(0.028)	(0.020)	(0.025)	(0.021)	(0.029)
Controls	No	Yes	No	Yes	No	Yes	No	Yes						
Observations	3,320	3,231	3,320	3,231	3,320	3,231	3,320	3,231	3,320	3,231	3,320	3,231	3,320	3,231
R^2	0.002	0.052	0.002	0.039	0.004	0.040	0.004	0.038	0.003	0.059	0.006	0.243	0.001	0.041

Notes: The dependent variables are: above median factor analysis score of support for AI regulation, factor analysis score, and binary measures for stricter regulation, urgent regulation, and government-led regulation. The key independent variables are Tone (Negative or Positive, with Neutral as the reference category) and type of information source (with Experts as the reference). Odd-numbered models present minimal specification; even-numbered models control for Independent, gender, race, education, age, and inattentive. Standard errors in parentheses. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

3.2 Tone Coverage and AI Issue Salience

Table SI-6 reports the full logistic regression results used to generate Figure 5, which examine how media coverage shapes which aspects of AI respondents rank as most important. The dependent variables are binary indicators for whether respondents ranked labor market automation (columns 1-2), large language models (columns 3-4), or algorithmic bias (columns 5-6) as most salient.

Table (SI-6) Effects of News Tone on AI Issue Salience

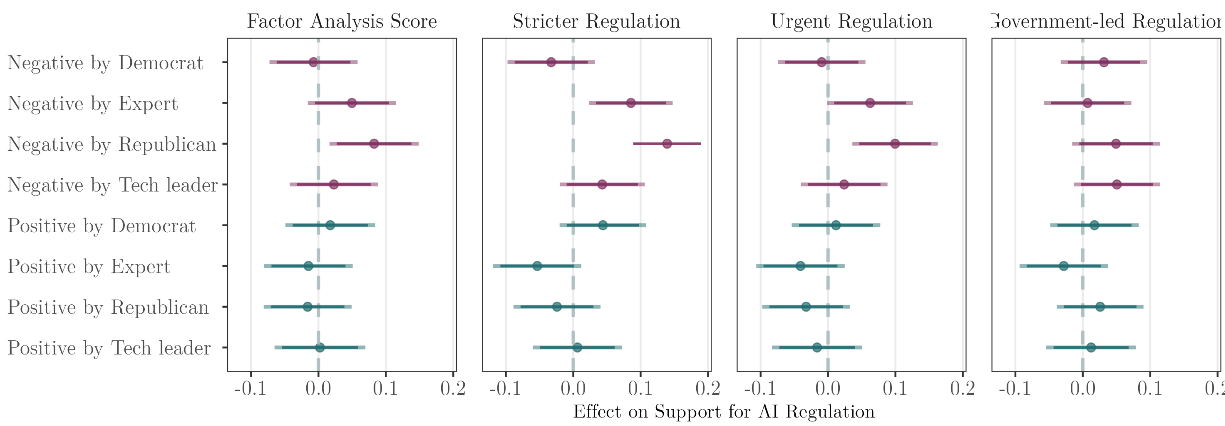
	Dependent variable:					
	Labor Market Automation		Large Language Models		Bias in Decision Making	
	(1)	(2)	(3)	(4)	(5)	(6)
Positive Tone	-0.702^{***}	-0.706^{***}	0.428^{***}	0.464^{***}	0.229^{*}	0.208^{*}
	(0.094)	(0.095)	(0.089)	(0.090)	(0.100)	(0.102)
Source: Tech Leader	0.037	0.023	−0.041	−0.010	0.005	−0.034
	(0.129)	(0.130)	(0.129)	(0.131)	(0.137)	(0.141)
Source: Democrat	-0.299^{*}	-0.336^{*}	0.537^{***}	0.553^{***}	-0.420^{**}	-0.428^{**}
	(0.132)	(0.134)	(0.124)	(0.126)	(0.146)	(0.148)
Source: Republican	$-0.240^{\dagger}$	-0.261^{*}	0.266^{*}	0.309^{*}	−0.033	−0.063
	(0.131)	(0.133)	(0.125)	(0.127)	(0.137)	(0.140)
PID: Republican (Res)		0.290^{**}		$0.155^{\dagger}$		-0.719^{***}
		(0.096)		(0.092)		(0.109)
Independent (Res)		0.014		0.117		−0.165
		(0.139)		(0.132)		(0.155)
Female		−0.031		-0.267^{**}		0.306^{**}
		(0.096)		(0.092)		(0.105)
White		−0.040		0.132		−0.062
		(0.110)		(0.105)		(0.116)
Some College or Less		−0.018		−0.098		0.167
		(0.099)		(0.094)		(0.106)
Age 35-54		0.261^{*}		0.040		$-0.204^{\dagger}$
		(0.113)		(0.109)		(0.121)
Age 55†		−0.007		0.329^{**}		−0.197
		(0.135)		(0.126)		(0.144)
Constant	-0.330^{***}	-0.496^{***}	-0.886^{***}	-1.030^{***}	-1.152^{***}	-0.880^{***}
	(0.100)	(0.149)	(0.102)	(0.147)	(0.110)	(0.160)
Controls	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Observations	2,198	2,173	2,198	2,173	2,198	2,173
Log Likelihood	-1,336.618	-1,313.249	-1,438.341	-1,407.657	-1,208.979	-1,166.726
Akaike Inf. Crit.	2,683.236	2,650.497	2,886.682	2,839.313	2,427.958	2,357.452

Notes: This table presents results from logistic regression models estimating the effects of news tone on the salience of three AI-related issues. The dependent variables are binary indicators of whether the respondent ranked each issue as the most important or not. The sample excludes respondents in the control group. The key independent variable is the tone of the news coverage (Negative as the reference category). All models control for the source treatments (with Experts as the reference). Coefficients are presented as log-odds. Odd-numbered models present minimal specification; even-numbered models control for party ID, gender, race, education, and age. Standard errors in parentheses. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

3.3 Source of Information and Support for AI Regulation

Figure SI-8 shows estimates of average treatment effects of all treatment conditions (tone and source) on support for AI regulation using LPM regressions, employing four dependent variables: a binary measure indicating above-median factor analysis scores (our main outcome), and binary indicators for support of stricter regulation, urgent regulation, and government-led regulation.

Figure (SI-8) Treatment Effects (Information and Source) on Support for AI Regulation



Note: This figure shows the average treatment effects of all treatment indicators (relative to placebo coverage) on four measures of support for government regulation of AI. Points represent coefficient estimates from linear probability models. Thick and thin bars represent 90% and 95% CIs. Full results are reported in Table SI-5.

Table SI-7 presents the full regression results for the treatment effects of the information sources on support for AI regulation, with separate analyses for negative coverage (columns 1-7) and positive coverage (columns 8-14). For each tone, we estimate effects on seven outcomes: a factor analysis score of regulatory support (FA Score), three-point and seven-point measures of support for stricter regulation (Strict), urgent regulation (Urgent), and government-led regulation (Gov-led).

Table (SI-7)   Effects of Sources on Support for Regulating AI (By Tone of Coverage)

	FA Score	Strict (3)	Strict (7)	Urgent (3)	Urgent (7)	Gov-led (3)	Gov-led (7)	FA Score	Strict (3)	Strict (7)	Urgent (3)	Urgent (7)	Gov-led (3)	Gov-led (7)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Source: Expert	0.034	0.093^{*}	0.109	0.058	-0.111	-0.039	-0.224	-0.026	-0.096^{*}	-0.201	-0.049	-0.078	-0.041	-0.114
	(0.042)	(0.039)	(0.137)	(0.041)	(0.153)	(0.041)	(0.153)	(0.042)	(0.042)	(0.140)	(0.042)	(0.156)	(0.041)	(0.153)
Source: Tech Leader	0.010	0.051	0.202	0.026	0.028	0.003	-0.022	-0.007	-0.030	-0.116	-0.020	-0.085	0.002	-0.042
	(0.042)	(0.039)	(0.137)	(0.041)	(0.153)	(0.041)	(0.153)	(0.042)	(0.042)	(0.142)	(0.043)	(0.158)	(0.042)	(0.155)
Source: Republican	$0.081^{\dagger}$	0.158^{***}	0.369^{**}	0.107^{**}	0.243	0.015	-0.023	-0.037	$-0.074^{\dagger}$	$-0.264^{\dagger}$	-0.046	-0.064	0.002	-0.042
	(0.042)	(0.040)	(0.138)	(0.041)	(0.155)	(0.041)	(0.154)	(0.042)	(0.042)	(0.140)	(0.042)	(0.156)	(0.041)	(0.153)
PID: Republican	-0.183^{***}	-0.199^{***}	-0.588^{***}	-0.148^{***}	-0.569^{***}	-0.191^{***}	-0.738^{***}	-0.206^{***}	-0.163^{***}	-0.630^{***}	-0.173^{***}	-0.642^{***}	-0.225^{***}	-1.003^{***}
	(0.030)	(0.029)	(0.100)	(0.030)	(0.112)	(0.030)	(0.111)	(0.031)	(0.030)	(0.102)	(0.031)	(0.114)	(0.030)	(0.112)
PID: Independent	0.003	-0.063	-0.122	-0.028	-0.166	-0.011	-0.110	0.008	-0.005	0.120	0.028	0.195	0.036	0.166
	(0.044)	(0.041)	(0.144)	(0.043)	(0.161)	(0.043)	(0.161)	(0.044)	(0.044)	(0.148)	(0.044)	(0.165)	(0.044)	(0.162)
Female	0.061^{*}	0.061^{*}	0.349^{***}	0.068^{*}	0.481^{***}	0.017	0.116	0.011	0.036	0.211^{*}	0.050	0.263^{*}	0.006	0.072
	(0.030)	(0.028)	(0.099)	(0.030)	(0.111)	(0.030)	(0.111)	(0.031)	(0.030)	(0.102)	(0.031)	(0.114)	(0.030)	(0.112)
White	0.053	0.069^{*}	0.027	0.068^{*}	0.169	-0.002	-0.044	0.080^{*}	0.070^{*}	0.321^{**}	0.077^{*}	0.335^{**}	0.026	0.153
	(0.035)	(0.033)	(0.114)	(0.034)	(0.127)	(0.034)	(0.127)	(0.034)	(0.034)	(0.114)	(0.034)	(0.127)	(0.034)	(0.125)
Some College or Less	-0.082^{**}	-0.073^{*}	$-0.185^{\dagger}$	-0.087^{**}	-0.238^{*}	-0.092^{**}	-0.286^{*}	-0.102^{***}	-0.077^{*}	-0.264^{*}	-0.090^{**}	-0.297^{**}	-0.100^{***}	-0.338^{**}
	(0.031)	(0.030)	(0.103)	(0.031)	(0.115)	(0.031)	(0.115)	(0.031)	(0.031)	(0.103)	(0.031)	(0.114)	(0.030)	(0.112)
Age 35-54	-0.008	-0.036	-0.082	-0.035	-0.061	0.005	0.010	0.075^{*}	0.023	0.036	0.037	0.012	0.053	0.121
	(0.035)	(0.033)	(0.116)	(0.035)	(0.130)	(0.035)	(0.130)	(0.036)	(0.036)	(0.120)	(0.036)	(0.134)	(0.035)	(0.131)
Age 55+	$0.077^{\dagger}$	0.006	0.123	0.029	0.188	0.094^{*}	0.341^{*}	0.041	-0.008	-0.136	0.029	-0.113	0.047	-0.064
	(0.042)	(0.039)	(0.136)	(0.041)	(0.152)	(0.041)	(0.152)	(0.042)	(0.042)	(0.141)	(0.042)	(0.157)	(0.042)	(0.154)
Constant	0.511^{***}	0.632^{***}	4.844^{***}	0.588^{***}	4.674^{***}	0.692^{***}	5.141^{***}	0.526^{***}	0.664^{***}	4.914^{***}	0.586^{***}	4.682^{***}	0.664^{***}	5.099^{***}
	(0.046)	(0.043)	(0.150)	(0.045)	(0.167)	(0.045)	(0.167)	(0.044)	(0.044)	(0.148)	(0.044)	(0.165)	(0.044)	(0.162)
Tone	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Positive	Positive	Positive	Positive	Positive	Positive	Positive
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,083	1,083	1,083	1,083	1,083	1,083	1,083
R^2	0.049	0.070	0.054	0.044	0.053	0.049	0.052	0.059	0.043	0.053	0.046	0.045	0.065	0.083

Notes: DVs are: above-median FA score of support for AI regulation, FA score, and binary measures for stricter, urgent, and government-led regulation. IVs are the source of information (politicians as the reference category). All models control for respondent's party identification and for the party of the politicians' source. Odd-numbered models are based on a minimal specification; even-numbered models control for demographics. Samples exclude respondents who received placebo information. Models 1-7 and 8-14 use data from negative and positive news tone conditions, respectively. Standard errors are in parentheses. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table (SI-8) Effects of Source and Party ID on Support for AI Regulation

	Factor Analysis (Above Median)		FA Score		Strict Regulation		Urgent Regulation		Gov-led Regulation		Factor Analysis (Above Median)		FA Score		Strict Regulation		Urgent Regulation		Gov-led Regulation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Experts × Republican PID	−0.206**	−0.210**	−0.148***	−0.148***	−0.360***	−0.362***	−0.300***	−0.304***	−0.101	−0.103	0.022	0.025	0.013	0.011	0.029	0.029	0.030	0.024	−0.023	−0.026
	(0.073)	(0.073)	(0.038)	(0.038)	(0.068)	(0.068)	(0.071)	(0.071)	(0.072)	(0.072)	(0.073)	(0.073)	(0.039)	(0.039)	(0.073)	(0.073)	(0.073)	(0.073)	(0.072)	(0.072)
Tech Leaders × Republican PID	−0.158*	−0.130†	−0.090*	−0.070†	−0.164*	−0.143*	−0.165*	−0.139†	−0.065	−0.054	0.111	0.106	0.028	0.021	0.077	0.069	0.053	0.045	−0.139†	−0.142†
	(0.074)	(0.074)	(0.039)	(0.038)	(0.069)	(0.069)	(0.072)	(0.072)	(0.073)	(0.073)	(0.075)	(0.074)	(0.040)	(0.040)	(0.074)	(0.074)	(0.075)	(0.074)	(0.073)	(0.073)
PID: Republican res	−0.073†	−0.100*	−0.033	−0.047*	−0.050	−0.075†	−0.011	−0.040	−0.137***	−0.152***	−0.231***	−0.240***	−0.122***	−0.125***	−0.185***	−0.189***	−0.188***	−0.194***	−0.186***	−0.187***
	(0.042)	(0.042)	(0.022)	(0.022)	(0.039)	(0.040)	(0.041)	(0.041)	(0.041)	(0.042)	(0.043)	(0.043)	(0.023)	(0.023)	(0.042)	(0.043)	(0.043)	(0.043)	(0.042)	(0.042)
Source: Experts	0.131*	0.126*	0.065*	0.061*	0.258***	0.252***	0.198***	0.192***	0.008	0.007	−0.036	−0.038	−0.028	−0.029	−0.107*	−0.109*	−0.061	−0.063	−0.031	−0.032
	(0.053)	(0.053)	(0.028)	(0.027)	(0.049)	(0.049)	(0.052)	(0.051)	(0.052)	(0.052)	(0.053)	(0.053)	(0.029)	(0.028)	(0.053)	(0.052)	(0.053)	(0.053)	(0.052)	(0.052)
Source: Tech Leaders	0.072	0.066	0.054*	0.048†	0.118*	0.115*	0.091†	0.087†	0.027	0.026	−0.061	−0.055	−0.030	−0.026	−0.068	−0.062	−0.048	−0.043	0.060	0.063
	(0.052)	(0.051)	(0.027)	(0.027)	(0.048)	(0.048)	(0.050)	(0.050)	(0.051)	(0.050)	(0.054)	(0.054)	(0.029)	(0.029)	(0.053)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)
Source: Republicans	0.078†	0.081†	0.045*	0.044*	0.157***	0.158***	0.105*	0.107**	0.012	0.015	−0.042	−0.038	−0.027	−0.026	−0.077†	−0.074†	−0.051	−0.045	0.002	0.005
	(0.042)	(0.042)	(0.022)	(0.022)	(0.039)	(0.039)	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)	(0.023)	(0.022)	(0.042)	(0.042)	(0.042)	(0.042)	(0.041)	(0.041)
PID: Independent res	−0.038	0.003	−0.045*	−0.023	−0.102*	−0.067	−0.071†	−0.029	−0.045	−0.012	−0.020	0.007	0.011	0.026	−0.028	−0.006	0.0004	0.027	0.014	0.038
	(0.043)	(0.044)	(0.022)	(0.023)	(0.040)	(0.041)	(0.042)	(0.042)	(0.042)	(0.043)	(0.044)	(0.044)	(0.024)	(0.024)	(0.043)	(0.044)	(0.044)	(0.044)	(0.043)	(0.043)
Female		0.059†		0.060***		0.058*		0.066*		0.016		0.011		0.036*		0.036		0.052†		0.008
		(0.030)		(0.016)		(0.028)		(0.029)		(0.030)		(0.031)		(0.016)		(0.030)		(0.031)		(0.030)
White		0.051		0.011		0.068*		0.066*		−0.003		0.077*		0.049**		0.069*		0.075*		0.028
		(0.034)		(0.018)		(0.032)		(0.034)		(0.034)		(0.034)		(0.018)		(0.034)		(0.034)		(0.034)
Some College or Less		−0.079*		−0.034*		−0.069*		−0.082**		−0.091**		−0.099**		−0.045**		−0.075*		−0.085**		−0.098**
		(0.031)		(0.016)		(0.029)		(0.031)		(0.031)		(0.031)		(0.016)		(0.031)		(0.031)		(0.030)
Age 35-54		−0.006		−0.009		−0.034		−0.032		0.005		0.079*		0.010		0.026		0.045		0.056
		(0.035)		(0.018)		(0.033)		(0.034)		(0.035)		(0.036)		(0.019)		(0.036)		(0.036)		(0.035)
Age 55+		0.090*		0.038†		0.018		0.046		0.097*		0.052		−0.010		0.001		0.050		0.055
		(0.042)		(0.022)		(0.039)		(0.041)		(0.041)		(0.043)		(0.023)		(0.042)		(0.043)		(0.042)
Inattentive		0.071†		0.045*		0.056		0.086*		0.020		0.046		0.051*		0.044		0.114**		0.069†
		(0.039)		(0.020)		(0.036)		(0.038)		(0.038)		(0.039)		(0.021)		(0.039)		(0.039)		(0.038)
Constant	0.522***	0.457***	0.639***	0.602***	0.610***	0.563***	0.576***	0.517***	0.672***	0.670***	0.601***	0.529***	0.678***	0.632***	0.719***	0.664***	0.662***	0.565***	0.663***	0.628***
	(0.036)	(0.048)	(0.019)	(0.025)	(0.034)	(0.045)	(0.035)	(0.047)	(0.035)	(0.047)	(0.036)	(0.047)	(0.019)	(0.025)	(0.035)	(0.047)	(0.036)	(0.047)	(0.035)	(0.046)
Tone	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,083	1,083	1,083	1,083	1,083	1,083	1,083	1,083	1,083	1,083
R^2	0.039	0.059	0.053	0.078	0.080	0.095	0.042	0.064	0.037	0.051	0.042	0.062	0.044	0.068	0.032	0.045	0.030	0.054	0.056	0.071

Notes: DVs are: above-median FA score of support for AI regulation, FA score, and binary measures for stricter, urgent, and government-led regulation. IVs are the source of information (politicians as the reference category), the respondent's party identification (Democrat as the reference category), and their interaction. We control for respondents identified as Independents and for the party of the politicians' source. Odd-numbered models are based on a minimal specification; even-numbered models control for demographics. Samples exclude respondents who received placebo information. Models 1-10 and 11-20 use data from negative and positive news tone conditions, respectively. Standard errors are in parentheses. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table SI-8 presents LPM regression results examining how source effects vary by respondent partisanship, with estimates separated by tone of coverage. For each tone, we estimate base and full specifications for the five outcomes. All models include interactions between source and Republican party ID.

Table (SI-9) Effects of Same-Party Source on Support for AI Regulation

	Dependent Variables:											
	FC score		Strict		Urgent		Gov-led		Plcebo: Carbon		Plcebo: Tech firms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Same Party Source × Republican	0.171*	0.179*	0.332***	0.336***	0.227**	0.236**	0.024	0.034	0.008	−0.007	0.088	0.074
	(0.086)	(0.085)	(0.080)	(0.080)	(0.083)	(0.083)	(0.084)	(0.083)	(0.076)	(0.075)	(0.085)	(0.085)
Same Party Source	−0.017	−0.013	−0.048	−0.052	−0.033	−0.038	−0.008	−0.005	0.009	0.008	−0.033	−0.033
	(0.058)	(0.058)	(0.055)	(0.054)	(0.057)	(0.057)	(0.055)	(0.055)	(0.042)	(0.043)	(0.056)	(0.057)
Republican	−0.157**	−0.189**	−0.214***	−0.253***	−0.124*	−0.157**	−0.149*	−0.170**	−0.414***	−0.419***	−0.158**	−0.147*
	(0.060)	(0.060)	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.058)	(0.054)	(0.053)	(0.060)	(0.061)
Independent	0.003	0.050	−0.095	−0.045	−0.031	0.008	−0.051	−0.002	−0.020	0.0003	−0.062	−0.087
	(0.060)	(0.063)	(0.060)	(0.060)	(0.059)	(0.061)	(0.059)	(0.062)	(0.055)	(0.057)	(0.060)	(0.061)
Female		0.038		0.040		0.027		−0.005		0.083*		0.038
		(0.043)		(0.041)		(0.042)		(0.042)		(0.037)		(0.043)
White		0.040		0.148**		0.077		−0.029		0.057		0.043
		(0.050)		(0.047)		(0.049)		(0.048)		(0.043)		(0.049)
Some College or Less		−0.125**		−0.123**		−0.108*		−0.180***		−0.071†		0.069
		(0.045)		(0.043)		(0.045)		(0.044)		(0.039)		(0.045)
Age 35-54		0.005		−0.065		−0.059		0.015		−0.092*		−0.027
		(0.051)		(0.047)		(0.050)		(0.050)		(0.045)		(0.050)
Age 55 or Older		0.119†		−0.026		0.053		0.133*		−0.150**		−0.143*
		(0.062)		(0.056)		(0.059)		(0.058)		(0.052)		(0.060)
Inattentive		0.005		0.033		0.006		−0.029		−0.040		−0.057
		(0.056)		(0.050)		(0.055)		(0.055)		(0.050)		(0.057)
Intercept	0.563***	0.533***	0.710***	0.669***	0.638***	0.631***	0.683***	0.737***	0.848***	0.878***	0.663***	0.647***
	(0.043)	(0.064)	(0.039)	(0.061)	(0.041)	(0.062)	(0.040)	(0.060)	(0.031)	(0.055)	(0.040)	(0.063)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	545	545	545	545	545	545	545	545	545	545	545	545
R^2	0.016	0.044	0.053	0.089	0.020	0.046	0.021	0.063	0.187	0.211	0.018	0.036

	Dependent Variables:											
	FC score		Strict		Urgent		Gov-led		Placebo: Carbon		Placebo: Tech firms	
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Same Party Source × Republican	−0.115	−0.098	−0.156†	−0.149†	−0.121	−0.104	−0.014	−0.007	0.136†	0.135†	−0.036	−0.034
	(0.084)	(0.084)	(0.085)	(0.085)	(0.086)	(0.086)	(0.085)	(0.085)	(0.077)	(0.077)	(0.086)	(0.086)
Same Party Source	−0.033	−0.031	0.066	0.063	0.006	0.004	−0.038	−0.035	−0.035	−0.039	0.042	0.035
	(0.055)	(0.055)	(0.052)	(0.052)	(0.054)	(0.054)	(0.053)	(0.053)	(0.040)	(0.041)	(0.054)	(0.054)
Republican	−0.173**	−0.187**	−0.107†	−0.107†	−0.128*	−0.142*	−0.179**	−0.182**	−0.522***	−0.520***	−0.161**	−0.155*
	(0.059)	(0.060)	(0.059)	(0.060)	(0.059)	(0.060)	(0.059)	(0.060)	(0.051)	(0.052)	(0.059)	(0.060)
Independent	−0.031	0.013	−0.043	−0.021	−0.011	0.030	0.025	0.069	0.029	0.035	−0.059	−0.060
	(0.061)	(0.061)	(0.062)	(0.063)	(0.063)	(0.064)	(0.063)	(0.064)	(0.056)	(0.059)	(0.061)	(0.061)
Female		0.023		0.065		0.052		0.024		0.064†		0.095*
		(0.043)		(0.043)		(0.043)		(0.042)		(0.037)		(0.044)
White		0.050		0.021		0.073		0.034		0.057		0.017
		(0.047)		(0.048)		(0.048)		(0.047)		(0.042)		(0.048)
Some College or Less		−0.112*		−0.049		−0.085†		−0.118**		−0.011		0.017
		(0.044)		(0.044)		(0.044)		(0.044)		(0.039)		(0.044)
Age 35-54		0.102*		0.038		0.021		0.051		−0.057		−0.059
		(0.049)		(0.049)		(0.050)		(0.049)		(0.043)		(0.051)
Age 55 or Older		0.113†		0.034		0.065		0.051		−0.073		−0.040
		(0.061)		(0.060)		(0.061)		(0.060)		(0.048)		(0.060)
Inattentive		0.086		0.065		0.117*		0.072		−0.033		0.013
		(0.056)		(0.054)		(0.055)		(0.056)		(0.048)		(0.057)
Intercept	0.595***	0.507***	0.650***	0.585***	0.633***	0.545***	0.680***	0.640***	0.861***	0.840***	0.629***	0.594***
	(0.039)	(0.056)	(0.038)	(0.056)	(0.038)	(0.056)	(0.037)	(0.057)	(0.027)	(0.048)	(0.038)	(0.057)
Controls	No	Yes	No	Yes								
Observations	548	548	548	548	548	548	548	548	548	548	548	548
R^2	0.061	0.091	0.041	0.052	0.039	0.065	0.037	0.058	0.232	0.240	0.034	0.045

Notes: DVs are: above-median FA score of support for AI regulation, and binary measures for stricter, urgent, and government-led regulation. IVs are Same Party Source (1 if the politician source is from the respondent's party, 0 otherwise) and Republican (1 if the respondent is Republican, 0 if Democrat), as well as their interaction. Odd-numbered models present the base specification; even-numbered models include demographic controls (gender, race, education, age, and inattentive respondents). The sample is limited to respondents exposed to politicians' sources. Models 1-12 and 13-24 use data from negative and positive news tone conditions, respectively. Standard errors in parentheses. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table SI-9 reports the estimated treatment effects of various sources of information on support for AI regulation across multiple outcomes. Given the sizable number of treatments and outcomes we investigated, there is a risk of obtaining false positives due to multiple hypothesis testing. To address this possibility, we adjust the p-values using the Benjamini-Hochberg (BH) method, which controls the false discovery rate. Table SI-10 reports the results.

Table (SI-10) Effects of Source and Party ID on Support for AI Regulation, Adjusting for Multiple Hypothesis Testing

	FC (above median)		FC score		Strict		Urgent		Gov-led	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Expert × Republican	−0.206*	−0.210*	−0.148***	−0.148***	−0.360***	−0.362***	−0.300***	−0.304***	−0.101	−0.103
	(0.073)	(0.073)	(0.038)	(0.038)	(0.068)	(0.068)	(0.071)	(0.071)	(0.072)	(0.072)
Tech Leader × Republican	−0.158†	−0.130	−0.090†	−0.070	−0.164†	−0.143†	−0.165†	−0.139	−0.065	−0.054
	(0.074)	(0.074)	(0.039)	(0.038)	(0.069)	(0.069)	(0.072)	(0.072)	(0.073)	(0.073)
PID: Republican Respondent	−0.073	−0.100†	−0.033	−0.047†	−0.050	−0.075	−0.011	−0.040	−0.137**	−0.152**
	(0.042)	(0.042)	(0.022)	(0.022)	(0.039)	(0.040)	(0.041)	(0.041)	(0.041)	(0.042)
Expert Source	0.131*	0.126†	0.065†	0.061†	0.258***	0.252***	0.198***	0.192***	0.008	0.007
	(0.053)	(0.053)	(0.028)	(0.027)	(0.049)	(0.049)	(0.052)	(0.051)	(0.052)	(0.052)
Tech Leader Source	0.072	0.066	0.054	0.048	0.118†	0.115†	0.091	0.087	0.027	0.026
	(0.052)	(0.051)	(0.027)	(0.027)	(0.048)	(0.048)	(0.050)	(0.050)	(0.051)	(0.050)
Republican Source	0.078	0.081	0.045	0.044	0.157***	0.158***	0.105*	0.107*	0.012	0.015
	(0.042)	(0.042)	(0.022)	(0.022)	(0.039)	(0.039)	(0.041)	(0.041)	(0.041)	(0.041)
PID: Independent	−0.038	0.003	−0.045	−0.023	−0.102*	−0.067	−0.071	−0.029	−0.045	−0.012
	(0.043)	(0.044)	(0.022)	(0.023)	(0.040)	(0.041)	(0.042)	(0.042)	(0.042)	(0.043)
Female		0.059		0.060***		0.058		0.066†		0.016
		(0.030)		(0.016)		(0.028)		(0.029)		(0.030)
White		0.051		0.011		0.068†		0.066		−0.003
		(0.034)		(0.018)		(0.032)		(0.034)		(0.034)
Some College or Less		−0.079*		−0.034†		−0.069†		−0.082*		−0.091*
		(0.031)		(0.016)		(0.029)		(0.031)		(0.031)
Age 35-54		−0.006		−0.009		−0.034		−0.032		0.005
		(0.035)		(0.018)		(0.033)		(0.034)		(0.035)
Age 55+		0.090†		0.038		0.018		0.046		0.097†
		(0.042)		(0.022)		(0.039)		(0.041)		(0.041)
Inattentive		0.071		0.045†		0.056		0.086†		0.020
		(0.039)		(0.020)		(0.036)		(0.038)		(0.038)
Constant	0.522***	0.457***	0.639***	0.602***	0.610***	0.563***	0.576***	0.517***	0.672***	0.670***
	(0.036)	(0.048)	(0.019)	(0.025)	(0.034)	(0.045)	(0.035)	(0.047)	(0.035)	(0.047)
Tone	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Negative	Negative
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099
R^2	0.039	0.059	0.053	0.078	0.080	0.095	0.042	0.064	0.037	0.051

	FC (above median)		FC score		Strict		Urgent	Gov-led		
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Expert × Republican	0.022	0.025	0.013	0.011	0.029	0.029	0.030	0.024	−0.023	−0.026
	(0.073)	(0.073)	(0.039)	(0.039)	(0.073)	(0.073)	(0.073)	(0.073)	(0.072)	(0.072)
Tech Leader × Republican	0.111	0.106	0.028	0.021	0.077	0.069	0.053	0.045	−0.139	−0.142
	(0.075)	(0.074)	(0.040)	(0.040)	(0.074)	(0.074)	(0.075)	(0.074)	(0.073)	(0.073)
PID: Republican Respondent	−0.231***	−0.240***	−0.122***	−0.125***	−0.185***	−0.189***	−0.188***	−0.194***	−0.186***	−0.187***
	(0.043)	(0.043)	(0.023)	(0.023)	(0.042)	(0.043)	(0.043)	(0.043)	(0.042)	(0.042)
Expert Source	−0.036	−0.038	−0.028	−0.029	−0.107	−0.109†	−0.061	−0.063	−0.031	−0.032
	(0.053)	(0.053)	(0.029)	(0.028)	(0.053)	(0.052)	(0.053)	(0.053)	(0.052)	(0.052)
Tech Leader Source	−0.061	−0.055	−0.030	−0.026	−0.068	−0.062	−0.048	−0.043	0.060	0.063
	(0.054)	(0.054)	(0.029)	(0.029)	(0.053)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)
Republican Source	−0.042	−0.038	−0.027	−0.026	−0.077	−0.074	−0.051	−0.045	0.002	0.005
	(0.042)	(0.042)	(0.023)	(0.022)	(0.042)	(0.042)	(0.042)	(0.042)	(0.041)	(0.041)
PID: Independent	−0.020	0.007	0.011	0.026	−0.028	−0.006	0.0004	0.027	0.014	0.038
	(0.044)	(0.044)	(0.024)	(0.024)	(0.043)	(0.044)	(0.044)	(0.044)	(0.043)	(0.043)
Female		0.011		0.036†		0.036		0.052		0.008
		(0.031)		(0.016)		(0.030)		(0.031)		(0.030)
White		0.077†		0.049*		0.069		0.075†		0.028
		(0.034)		(0.018)		(0.034)		(0.034)		(0.034)
Some College or Less		−0.099**		−0.045*		−0.075†		−0.085*		−0.098**
		(0.031)		(0.016)		(0.031)		(0.031)		(0.030)
Age 35-54		0.079†		0.010		0.026		0.045		0.056
		(0.036)		(0.019)		(0.036)		(0.036)		(0.035)
Age 55+		0.052		−0.010		0.001		0.050		0.055
		(0.043)		(0.023)		(0.042)		(0.043)		(0.042)
Inattentive		0.046		0.051*		0.044		0.114*		0.069
		(0.039)		(0.021)		(0.039)		(0.039)		(0.038)
Constant	0.601***	0.529***	0.678***	0.632***	0.719***	0.664***	0.662***	0.565***	0.663***	0.628***
	(0.036)	(0.047)	(0.019)	(0.025)	(0.035)	(0.047)	(0.036)	(0.047)	(0.035)	(0.046)
Tone	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive	Positive
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,083	1,083	1,083	1,083	1,083	1,083	1,083	1,083	1,083	1,083
R^2	0.042	0.062	0.044	0.068	0.032	0.045	0.030	0.054	0.056	0.071

Notes: DVs are: above-median FA score of support for AI regulation, FA score, and binary measures for stricter, urgent, and government-led regulation. IVs are the source of information (politicians as the reference category), the respondent's party identification (Democrat as the reference category), and their interaction. We control for respondents identified as Independents and for the party of the politicians' source. Odd-numbered models are based on a minimal specification; even-numbered models control for demographics. For all models, we adjust p-values using Benjamini-Hochberg to reduce the likelihood of false discoveries due to multiple comparisons. Samples exclude respondents who received placebo information. Models 1-10 and 11-20 use data from negative and positive news tone conditions, respectively. Standard errors are in parentheses. †p<0.1; *p<0.05; **p<0.01; ***p<0.001

The figures show the predicted scores of support for AI regulation (above the median factor score) based on LPMs conducted separately for negative coverage and positive coverage. The left panels regress the outcome on an indicator for the source of information (Control, Experts, Tech Leaders, and Politicians), respondent party ID, and their interaction. The right panels focus on respondents assigned to the politician source condition, regressing the outcome on an indicator for whether the politicians are from the same party as the respondent or not, respondent party ID, and their interaction. Individual observed scores are jittered in the background to show the distribution of the outcome variable across conditions. Thin (90%) and thick (95%) error bars represent the CIs around the estimates, respectively.

Figure (SI-9) Predicted Support for AI Regulation by Sources, Positive Tone

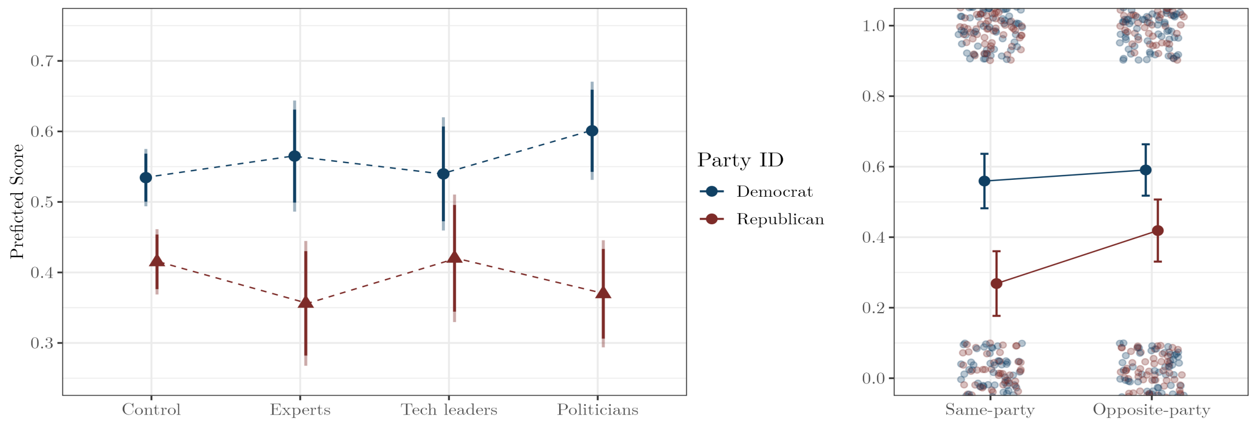
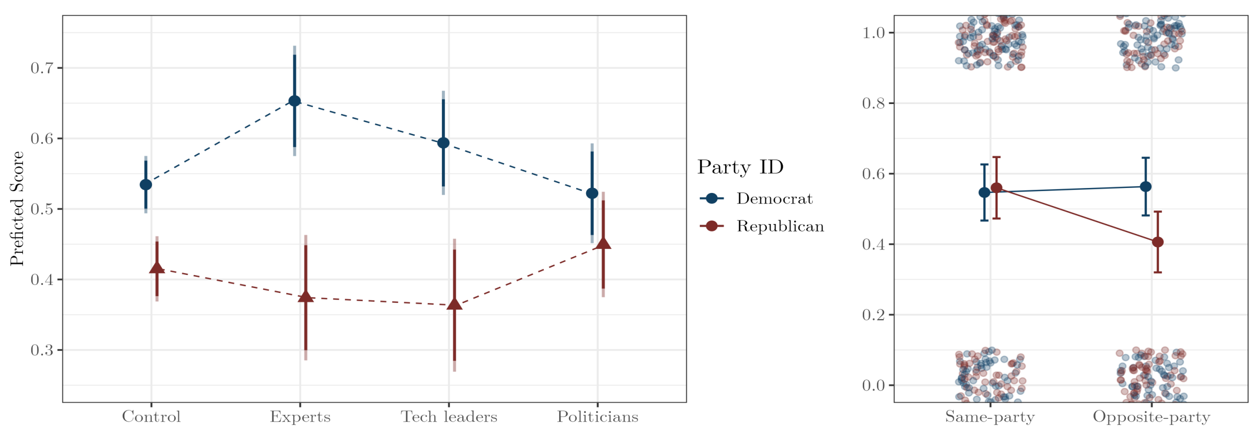


Figure (SI-10) Predicted Support for AI Regulation by Elite Cues, Negative Tone



4 Research Ethics

The experiment design, the treatments, and the survey instruments were all reviewed and approved by the Institutional Review Board (IRB) before the study was initiated.

The study was conducted with adherence to the current standards for research transparency and ethics, including the American Political Science Association's "Principles and Guidance for Human Subjects Research," which were approved by the APSA Council in April 2020.

At the beginning of the survey, all respondents were provided a consent form which informed them that participation in the study was voluntary and that they could withdraw at any time without penalty. No identifying data, such as names or email addresses, was collected, ensuring the anonymity of the data used for analysis and replication.

After completing the study, participants were sent a debriefing letter via their cloud research interface. This letter explained the purpose of the study and clarified that the articles included in their treatments and on the web blog were created specifically for this research.

5 Pre-Analysis Plan and Pre-Registration

This study has been pre-registered. The full, non-anonymous version of this paper, including all supplementary materials, is registered with the Open Science Framework (OSF). However, due to the double-blind review process, an anonymized version is attached in the appendix.

5.1 Theory and Hypotheses

How does news coverage of the recent developments in AI-based technology and its societal implications affect public attention and support for AI regulation? Do the effects vary depending on the actor delivering the messages? What are the broader implications for the potential politicization of this issue? The answers to these questions are far from obvious, as earlier research can justify very different predictions. On one hand, due to the novelty and complexity of AI technology, people may struggle to fully grasp its immediate impact on their well-being. Moreover, the complexity of the technology may discourage people from engaging with information on the challenges and opportunities that AI poses and reduce further their motivation to consider it when forming judgments about the government's appropriate response. This may lead them to ignore information on AI's promises and perils or dismiss it as irrelevant, and rely instead on their stable predispositions toward technology or government intervention. On the other hand, at this early stage of the public debate when there are no clear cues from politicians to rely on, it is also reasonable to expect that people may be open to considering relevant new information when forming their views on this emerging policy issue. In fact, recent experimental evidence indicates that expert opinions can influence public preferences regarding the use of AI in public policy, even if the information contradicts their previous beliefs.

5.1.1 Information Source

However, media coverage on AI is shaped by various voices, not only by academic experts. Many other actors have a stake in influencing public opinion on this matter, and their credibility may vary, which can affect how people evaluate the information they receive. For instance, CEOs and tech leaders, who have an interest in continuing the development of the technology, may be seen as less reliable and therefore have their messages discounted by the public as it is forming its opinion about AI regulation.

A recent notable example is the public letter signed by thousands of industry leaders including Elon Musk, who urged a six-month halt on the development of systems more powerful than GPT-4 on the grounds that it poses grave risks to humanity. This letter has been met with some doubt. Some wondered if the motive might be to limit competition among tech firms rather than to sincerely address the societal risks posed by AI. However, unlike other policy domains, in the new field of AI, the boundary between industry stakeholders and experts often overlaps, as many tech firms also act as research labs and are led by AI experts. Therefore, it is unclear whether people respond differently to messages delivered by experts versus industry executives.

5.1.2 Party Cues

A large body of research has shown that party cues—information about the positions of political parties on policy issues—influence citizens' policy opinions. Citizens tend to support a policy when they learn that their party endorses it, and vice versa. Therefore, a plausible interpretation of the observed effect of expert information on public opinion on AI policy is the fact that, at this early stage of the debate, the issue is not politicized, so there were no clear partisan cues to rely on. In fact, many of the legislative AI initiatives promoted so far have enjoyed bipartisan support. Although the current stage of the public debate lacks a clear partisan divide, we have seen in other issues involving expertise that partisanship and ideological leaning become more influential over time. The debate over AI regulation could follow a similar trajectory. One might expect that the impact of the information on citizens' preferences would vary depending on whether it comes from politicians who share their partisan affiliation or not. Citizens may be more receptive to information from their own party's elites, either because they trust them or because they feel attached to them. Conversely, they may be more resistant to information from the opposing party's elites, either because they distrust them or because they dislike them.

Taken together, there are good reasons to expect that the source of the information affects how people process it. While we do not have a specific prediction about which source will be more persuasive, we expect to find significant variation depending on who delivers the message. The discussion provides a theoretical grounding for a set of specific hypotheses regarding the conditions under which media coverage would affect public support for stricter regulation on AI.

- **H1:** Exposure to media coverage of AI's potential risks increases public support for greater AI regulation, while exposure to media coverage of AI's promises decreases public support.

- **H2.1:** The effect of positive or negative media coverage on public support for AI regulation varies as a function of the source of the information. Specifically, support for stricter AI regulations is stronger when the media frames AI negatively and cites experts (as opposed to politicians or industry leaders).

- **H2.2:** The effect of media coverage on public support for AI regulation depends on whether the information source shares the audience's political leanings.

5.2 Design Plan

- **Study Type**. Experiment - A researcher randomly assigns treatments to study subjects, this includes field or lab experiments. This is also known as an intervention experiment and includes randomized controlled trials.

- **Blinding**. For studies that involve human subjects, they will not know the treatment group to which they have been assigned.

5.3 Study Design

Respondents will be asked to perform a simple task involving reading paragraphs taken from popular media sources. Each paragraph will focus on a key theme related to AI that has been widely covered in the media:

- Potential for racial bias in decision making.

- The impact of AI automation on the labor market.

- The societal consequences of large language models (such as Chat-GPT).

All respondents will receive all three themes, but in a random order. To minimize the possibility of demand effects, we will add two additional paragraphs on unrelated items with the aim of blurring the focus of the study. One will be used as an initial test example to practice the task of highlighting sentences in the interface. One paragraph will be presented at the end after respondents engage with the three paragraphs related to AI.

5.4 Manipulated Variables

First, to assess the effect of information about AI on support for AI regulation, we will randomly assign the content of the messages to two treatment conditions: (1) positive information about AI; (2) negative information about AI. Second, to assess whether the effect of the information varies depending on the source delivering the message, we will also manipulate the actor cited in the message, into either (1) politicians (Democrats or Republicans), (2) tech leaders, or (3) AI experts. Overall, respondents will be randomly assigned to one of nine treatment arms:

1. Control: placebo paragraphs from random news articles similar to the paragraph that appeared in the pre-test.
2. AI info treatment: Positive info on AI
   (a) Positive AI info by Politicians
      i. Positive AI info by Democrats
      ii. Positive AI info by Republicans
   (b) Positive AI info by Tech leaders
   (c) Positive AI info by AI Experts
3. AI info treatment: Negative info on AI
   (a) Negative AI info by Politicians
      i. Negative AI info by Democrats
      ii. Negative AI info by Republicans
   (b) Negative AI info by Tech leaders
   (c) Negative AI info by AI Experts

5.5 Measured variables

Our primary dependent variable measures support for greater and stricter AI regulation. To minimize measurement error and to ensure that the results are not sensitive to specific domains or AI application, we will use multiple survey items to ask about the following: (1) regulations on the development and use of AI, even if it limits innovation; (2) the timing of regulation; (3) whether the government or private tech companies should be responsible for regulation; (4) specific regulatory measures outlined in the recent executive order on AI issued by the Biden administration.

5.6 Analysis Plan

5.6.1 Effect of AI Information on Support for Stricter AI Regulation

Primary Analysis. First, to test the hypothesis that exposure to media coverage on AI will effect public support for AI regulation, we will estimate the average treatment effects of the information treatment assignment (positive, negative, or placebo) on support for AI regulation, controlling for our second treatment arm relating to the source of the information.

5.6.2 Interaction effect of AI Information Content and Source on Support for Stricter AI Regulation

Next, we will assess hypothesis H2.1, which suggests that the effect of media coverage on support for stricter AI regulations is stronger when the media frames AI negatively and cites experts (as opposed to politicians or industry leaders). To this end, we will limit our data only to participants who received information about AI (positive or negative). We will use OLS regression models, where Y is the FA score.

5.6.3 Interaction effect of AI Information and Party Cue on Support for Stricter AI Regulation

Finally, we will assess hypothesis H2.2, which states that the effect of media coverage on public support for AI regulation depends on whether the information source shares the political leaning of the audience. We will ask all respondents about their party identification before the experiment. In our analysis, we will use their answers as an indicator, interacting it with the party source treatment.

Our analysis will focus on the group of participants who were given information about AI from political figures. We will limit the sample to include only respondents assigned to the treatments of AI information (positive or negative) from politicians (democrats or republicans). Specifically, we will use an OLS regression model to estimate the interaction effects on support for AI regulation, using an indicator for the type of AI information received (negative versus positive, with positive being the baseline), political affiliation (with three categories: Democrat, Independent, with Republican serving as the baseline), and an indicator for the political source of the information (with Democrat as 1, and Republican as the baseline), along with their interaction. To make sense of the findings, we will plot the predicted outcomes based on these factors.

5.6.4 Transformations

We will combine the answers to these questions using factor analysis, with the first factor as our dependent variable. The factor analysis score will be standardized to a mean of 0 and a standard deviation of 1, with higher values indicating greater support for stricter regulation. We will also analyze each outcome separately once in its original scale, and once using binary measures to provide a substantive interpretation of the effects.

5.6.5 Inference criteria

We will use the standard $p<.05$ and $p<.01$.

5.6.6 Data exclusion

To ensure that all respondents have a shared understanding of Artificial Intelligence, we will provide a definition of AI at the beginning of the survey. We will also provide two unrelated definitions to blur the study's focus on AI regulation. On the subsequent page, we will present respondents with four definitions, and ask them to indicate which of the definitions did not appear earlier. Those who will fail to answer correctly will be automatically removed from the study. The survey also included a second attention check before the randomization into treatments. We will base our final sample on those who answer these two screening questions correctly. The final sample will include only respondents who correctly answered both screening questions. We will implement quotas only for attentive respondents to ensure representative sample.

5.6.7 Exploratory Analysis:

Effects of AI Information on Perceived Importance of AI News Themes. We will proceed to an exploratory analysis that assesses how the information treatment influences the perceived importance of different AI-related news themes. We will use multinomial logistic regression to model the choice of the most important news theme (with and without covariates), controlling for the source of the information as well as the presentation order. The analysis will include only those who received either positive or negative information on AI.