**What Determines Support for Artificial Intelligence Regulation? Evidence from U.S. Business Professionals**

August 27, 2025

**ABSTRACT**

The public debate over artificial intelligence (AI) regulation is often framed as a tradeoff between fostering innovation and ensuring public safety. A central question arises: do individuals also perceive AI regulation through this same innovation–safety lens? To address this question, I conducted a survey experiment with a national sample of U.S. business professionals. I measure support for regulation addressing three aspects of AI design and deployment – transparency, explainability, and bias mitigation. While confirming that the innovation–safety tradeoff resonates with individuals, the study reveals a number of granular individual-level factors that predict support for regulation. Attitudes reflect a range of concerns, including perceived vulnerability to AI-driven job displacement, institutional trust, professional identity, and political context. Attitudes are also found to differ by type of regulation. These findings contribute to emerging research on AI governance showing that preferences reflect not only economic tradeoffs, but also how individuals locate themselves within the institutional, political, ethical, and competitive landscape of AI deployment.

**Keywords:** Artificial Intelligence; Support for Regulation, Survey Experiment.

1. **INTRODUCTION**

Artificial intelligence (AI) systems are increasingly shaping the public’s experience of everyday life – influencing decisions about credit, hiring, healthcare, policing, and more. As these systems become ubiquitous, calls for regulation have intensified. Policymakers and commentators have framed this tension as a delicate balancing act: how can we harness the innovative potential of AI while protecting the public from possible harm?

This framing – innovation versus safety – has come to dominate the global discourse on AI regulation. In the United States, President Biden’s 2023 Executive Order (Executive Order No. 14110) on AI emphasized safety standards, civil rights protections, and consumer safeguards, while urging Congress to legislate on data privacy. This was swiftly overturned when President Trump took office in January 2025. He revoked “existing AI policies and directives that act as barriers to American AI innovation, clearing a path for the United States to act decisively to retain global leadership in artificial intelligence” (Executive Order 14179). The priority of the Trump administration has since been the acceleration of AI development by reducing regulatory obstacles so as to enhance the United States’ leadership in AI (see Mallaby, et al., 2025).

In the European Union, the EU AI Act (2024) established sweeping controls on “high-risk” AI systems but has faced criticism from tech-sector leaders who fear overregulation will stifle European competitiveness (Reuters, 2025). President Macron of France was a prominent critic of the law and asserted the law would unduly burden European companies relative to their global competitors and impede innovation (Financial Times, 2023). Regulatory debates are underway in other parts of the world as well and typically center around the innovation–safety tradeoff (Diligent, 2024).

A variety of arguments are made in support of AI regulation. These include ensuring public health and safety, consumer and worker protection, transparency, accountability, fairness, preventing discrimination, etc. Several laws to regulate AI have been enacted by US states and many bills are under active consideration (National Conference of State Legislatures, 2024). Arguments against regulation include the claim that compliance would be burdensome for businesses, which would inhibit innovation. There could be merit to both sides of the argument, with the policy question ultimately hinging upon a weighing of the benefits (stronger consumer and employee protections) versus costs (less innovation) of regulation. Such a weighing of benefits and costs is, of course, central to the economic theory and practice of regulation (see Viscusi, Harrington, and Sappington, 2018, Chapter 2).

Despite vibrant public debate and evolving policy activity, our understanding of how individuals form their views on AI regulation remains incomplete. Does the dominant framing of regulation as a tradeoff between innovation and safety reflect how people truly reason about the issue? Or do other dispositional and situational factors – such as institutional trust, political ideology, or professional identity – play a larger role? When confronted with competing narratives about the consequences of regulation, how do individuals navigate the tension?

These questions carry both theoretical and practical significance. Practically, they are central to the design of effective regulation: understanding how support for AI oversight is shaped can inform the design and communication of policies that are not only effective but viewed as publicly legitimate. Theoretically, there is a need to better understand the determinants of public support for policy by examining the mental model individuals bring to such issues. There is a literature seeking to understand public perspectives on government policy through the use of survey experiments (Stantcheva, 2022). The present paper is in this tradition, although the application to AI regulation is novel. The paper also makes a contribution to the literature on public attitudes towards AI, where the specific question of support for AI regulation has been studied recently by Wilczek et al. (2025), and Cremaschi et al. (2025) using survey data.

To address the above questions, I conducted a survey-based experiment with 885 U.S. business professionals. Business professionals are a particularly appropriate group to study. Since AI is a nascent technology, misconceptions about it abound (Bewersdorff et al., 2023). Business professionals are likely to be better informed about AI than the general public. They are likely to have direct experience with the adoption of AI technologies, insight into compliance costs, and a stake in their firm’s competitive position. At the same time, they are also consumers and employees – potentially exposed to the risks posed by poorly governed AI systems.

My core hypothesis is that if individuals evaluate AI regulation by weighing its costs to businesses against its benefits to the public, then their support should be responsive to which side of the trade-off is made more salient. To test this, respondents were randomly assigned to one of two *priming* conditions before answering any questions about AI regulation. One group was asked questions related to the potential cost to companies of building AI systems that are transparent, accountable, and fair. The other was prompted to evaluate the importance of these same features from the perspective of consumers and employees. Importantly, the word “regulation” was never mentioned in either condition. After the priming, all respondents answered an identical set of questions measuring support for specific regulatory proposals. I then tested for any difference in support between the two groups. The use of priming in survey experiments is well-established in political economy and behavioral public policy (e.g., Kuziemko et al., 2015; Alesina et al., 2022; Merolla et al., 2013; Israel et al., 2014; Pataranutaporn et al., 2023; Stantcheva, 2023).

A wide variety of AI regulations have been enacted or are under consideration across the globe. These target multiple dimensions of AI supported decision making and deployment of AI systems. I choose to focus on regulation that addresses three core aspects of AI design and use:

* **Transparency**, referring to disclosure of AI use and data practices,
* **Explainability** of autonomous AI systems, requiring mandatory justifications for algorithmic decisions, and
* **Fairness**, involving third-party audits aimed at preventing bias on sensitive variables.

These types mirror common provisions in proposed state, federal, and international laws and reflect recurring features in emerging legislation. Support could clearly be contingent upon the type of regulation being considered, and it is desirable to assess whether the evaluative mechanisms used by individuals differ by type of regulation. Focusing on specific regulation is clearly preferable to asking about views on regulation in the abstract.

While cost-benefit reasoning is central to traditional economic theories of regulation, attitudes toward AI governance may be shaped by a broader constellation of factors. Political and ideological affiliation, which reflect beliefs about the proper role of government, are likely to influence views on regulation. Individuals who distrust government institutions may oppose regulation, while those who distrust corporate leadership may support it. Others may feel personally vulnerable to job displacement from AI and therefore favor stronger protections. Still others may view regulation as a way to prevent a “race to the bottom,” where firms are discouraged from investing in fairness or transparency unless all competitors are subject to the same rules.

This survey measures a broad spectrum of such potential influences. In addition to the priming treatments, respondents answered questions about their demographic background, job role and work experience, and involvement with AI technologies. They were also asked to evaluate their level of trust in government and corporate leadership, as well as their perceived vulnerability to AI-related career disruption. To assess whether competitive pressure might motivate support for regulation, respondents were asked whether making AI systems transparent, accountable, and fair places a company at a competitive disadvantage relative to others that do not share the same commitment. The relationship between these variables and support for regulation is examined empirically.

The findings reveal that support for AI regulation is generally high across all three areas examined: transparency, explainability, and fairness. However, there are important differences in the nature of support for the three. As hypothesized, making the economic costs of regulation salient reduces support for the first two types of regulation – those primed to think from the business cost perspective were less supportive than those primed to consider consumer and employee benefits. Support for fairness regulation is less influenced by cost-benefit priming. The effect of the treatments on support was most pronounced in Republican-leaning states, where anti-regulatory sentiment tends to be stronger.

However, the story does not end with the tradeoff between innovation and safety. Attitudes toward regulation were shaped by many other factors: individuals who felt personally vulnerable to job loss from AI were more likely to support regulation, as were those with greater trust in government. By contrast, more experienced respondents and those directly involved in AI deployment within their firms tended to be less supportive. Many respondents also expressed implicit agreement with the idea that regulation is needed to prevent a “race to the bottom” – where firms committed to fairness and transparency are competitively disadvantaged unless others are held to the same standards. Taken together, these findings suggest that support for AI regulation reflects not only how people weigh economic costs and benefits, but also how they position themselves within the broader institutional, political, and ethical terrain of AI development.

1. **BACKGROUND AND RELATED LITERATURE**

This study is informed by and contributes to two interrelated areas of research: (1) the use of survey-experimental methods to test whether the widely posited societal tradeoff between AI innovation and safety aligns with how individuals actually perceive the issue, and (2) understanding the determinants of support for AI regulation. The first speaks to a foundational concern in the social sciences: the relationship between individual preferences and collective outcomes. In democratic societies, public debate and policymaking are ideally grounded in the views of individuals. I examine whether that assumption holds in the case of AI regulation. The second contribution is more directly policy-relevant: individual-level preferences matter not only for academic understanding, but also for the design and success of regulatory frameworks. Policies are more likely to succeed when they resonate with the beliefs, values, and concerns of the people they affect.

**2.1 Survey Experiments and Regulatory Preferences**

Methodologically, my work is most closely related to the literature on survey experiments that use priming to identify the determinants of public support for policy (Stantcheva, 2022, provides a comprehensive review). Prior applications include Kuziemko et al. (2015), Alesina et al. (2022), Merolla et al. (2013), Israel et al. (2014), Stantcheva (2021) and Pataranutaporn et al. (2023). In particular, Stantcheva (2023) uses a similar priming design to investigate attitudes toward trade and redistribution: respondents are asked to evaluate trade either from the perspective of consumers (who benefit from imports) or workers (who may be harmed by foreign competition). I adapt this approach to the domain of AI regulation, offering a novel application of survey-experimental methods to a rapidly evolving area of policy concern.

**2.2 Individual and Contextual Determinants of Regulation**

This study also builds on a broader literature examining how individual characteristics, institutional contexts, and policy design influence attitudes toward regulation. For example, Bechtel et al. (2019) find that workers in high-emission industries are less supportive of international climate cooperation than those in cleaner sectors. Fesenfeld et al. (2022) show that policy framing and design features can increase support for otherwise costly regulation. Other work demonstrates that voluntary corporate initiatives can reduce demand for public regulation (Kolcava et al., 2021), that international norms can raise support for oversight (Kolcava & Bernauer, 2023), and that private governance may preempt or displace public efforts (Malhotra et al., 2019). Collectively, this literature highlights the importance of self-interest, norms, institutional trust, and framing in shaping regulatory preferences—factors that are highly salient in the case of AI.

**2.3 Predictors of Support for AI Regulation**

The surge of interest in AI regulation has given rise to a large body of legal, ethical, technical, and policy scholarship (e.g., Lukaj et al., 2023; Hoffman and Hahn, 2020; Nordström, 2022; Cajueiro & Celestino, 2025; Fessenko & Jasperse, 2025). These studies identify the governance challenges posed by opaque, autonomous, and adaptive AI systems and propose conceptual frameworks to address them. However, only a small portion of this work is empirical.

Some public opinion data comes from major consulting firms and polling organizations (McKinsey & Co., 2023; Deloitte, 2022; Ipsos, 2022; Pew, 2025), which regularly survey attitudes toward AI and its societal impact. Such opinion polls sometimes include questions on regulation. For example, a recent Pew survey found that more than half of U.S. adults — and a similar share of AI experts — want more control over how AI is used in their lives. Academic studies have begun to explore the social and political dimensions of AI attitudes. Zhang and Dafoe (2019, 2021) examine public views on AI governance in the U.S., while Zhang et al. (2022) study perspectives among AI researchers. Other recent studies—by Kreps et al. (2023), O’Shaughnessy et al. (2023), Nussberger (2023), Horowitz and Kahn (2021), Dong et al. (2024), Yarovenko et al. (2024), and Bergdahl et al. (2023)—further identify key predictors of AI-related beliefs, including age, education, ideology, institutional trust, and cultural context. Two studies focus explicitly on regulatory attitudes: Wilczek et al. (2025) examine how uncertainty avoidance and AI risk perceptions influence preferences for government versus industry self-regulation; Cremaschi et al. (2025) model how awareness of regulation and perceived policy adequacy shape support.

**2.4 Contributions of this Study**

My paper contributes to the literature in several important ways. While prior studies often ask respondents about “AI regulation” in general terms, I focus on three specific and policy-relevant types of regulation: those related to transparency about data collection and use, explainability of autonomous AI systems, and fairness (defined as absence of bias on sensitive variables). These categories were derived from a systematic review of state-level legislative proposals in the United States (National Conference of State Legislatures, 2024) and reflect common features of emerging AI laws globally. By focusing on concrete targets for regulation, I am able to avoid the ambiguity inherent in abstract opinion polling and offer more actionable insights for policymakers.

Second, by applying survey-experimental methods I test whether the widely posited tradeoff between AI innovation and public safety resonates with individuals. This approach, widely used in political economy has not been applied in the critical context of AI regulation.

Finally, I introduce a theoretically grounded but underexplored motivation for regulation: the role of competitive pressure. Drawing on regulatory theory and related findings in economics (e.g., Mast, 2020), the survey includes a novel item measuring whether respondents believe firms that ensure fairness and transparency are at a competitive disadvantage. If so, support for regulation may reflect a desire for a level playing field rather than simply a response to fear or mistrust. This hypothesis – essential to debates over fairness in innovation economies – has received little attention in the AI governance literature to date.

1. **DATA AND METHODS**

I collected data through a survey experiment conducted in partnership with Qualtrics, using their business-to-business (B2B) panel. A quota sample was used which included both mid-level managers and senior executives from major industrial sectors. According to information provided by Qualtrics, participants are recruited from diverse sources – including website intercepts, member referrals, targeted emails, social media, and loyalty programs – and subject to validation through third-party identity verification. For B2B participants, additional quality controls are employed, such as LinkedIn matching and workplace phone verification.

The final sample comprised of 885 business professionals, with a target composition of 70% mid-level managers and 30% senior executives. To explore institutional contexts, quotas were set across nine broad industry sectors: Technology, Manufacturing, Financial Services and Insurance, Healthcare, Retail and Ecommerce, Hospitality and Leisure, Telecommunications, Transportation, and an “Other” category. While the goal was to collect equal numbers across sectors, variation in panel availability meant that some categories were oversampled to meet the required sample size. No quotas were set at the state level, but responses were received from every U.S. state except Alaska, Montana, and Vermont – together representing over 99.5% of the national population. Data collection took place in November 2023.

Participants were compensated by Qualtrics for their time, with payments ranging from $11 to $16 depending on individual panel agreements. The estimated completion time for the questionnaire was 10 minutes. The sample is diverse across dimensions such as gender, age, race, educational background, industry sector, company size, years of professional experience, and extent of involvement with AI technologies (see Supplementary Materials: Parts 2 and 3).

My rationale for restricting attention to business professionals was twofold. First, this group is likely to be better informed about use and potential value of AI for firms as well as the organizational costs of ensuring that AI systems are transparent, fair, and explainable. To the extent that their personal success is tied to that of their company, they are likely to be sensitive to any damage regulation could inflict. Second, they also experience AI systems as consumers and employees and may hold views shaped by both professional and personal exposure to the risk of harm from AI systems. This dual perspective makes them particularly well-suited for examining how individuals navigate the competing narratives of innovation and safety that dominate AI regulation debates. While the innovation–safety tradeoff may be especially salient for business professionals, it is likely to resonate more broadly with others who engage with AI as both beneficiaries and potential targets of its adverse effects.

The questionnaire included six main sections (the full questionnaire is included as Supplementary Materials, Part 1):

1. Demographic characteristics
2. Employer and industry information
3. Trust in government and corporate leadership, and general views on regulation
4. Respondents’ involvement in AI projects and knowledge of AI use in their firms
5. One of two priming treatments (described below)
6. Measures of support for specific AI regulations

The three key regulation questions are as follows:

1. Indicate your level of support for government mandates or regulations that would require businesses to disclose to customers how AI is being used in products and services, what data is being collected, and all the ways in which the data could be used.
2. Indicate your level of support for government mandates or regulations that would require businesses to provide an explanation or justiﬁcation for outcomes produced by AI-based autonomous decision systems to impacted individuals and to regulators.
3. Indicate your level of support for government mandates or regulations that would require businesses to undergo third-party auditing to certify that AI-based autonomous decision systems are free from bias related to characteristics such as gender, race, religion, sexual orientation, and disabilities.

Possible responses were *Strongly Oppose*, *Somewhat Oppose*, *Neutral*, *Somewhat Support*, and *Strongly Support*. As mentioned in the literature section, the three themes are drawn from the types of regulations under consideration in state legislatures and at the national level in the U.S.

The priming treatments consisted of a short set of questions designed to make either business costs or public benefits cognitively salient prior to assessing respondents’ regulatory attitudes.[[1]](#footnote-2) Questions to one group focused their attention on the burdens companies face in making AI systems transparent, accountable, and fair. The other group made to reflect on the benefits of those same features from the standpoint of consumers and employees. The word “regulation” was not mentioned in either set of prompts. Each treatment contained four questions, including three paired items tapping similar constructs from different vantage points (see Supplementary Materials, Part 3). After this priming, all participants answered an identical set of questions assessing their support for specific AI regulations. To mitigate the potential for leading respondents, questions unrelated to the regulation questions – specifically, items on AI patent eligibility and liability for infringement – were included between the priming and regulation questions. This spacing was intended to create some cognitive distance between the priming and the regulation responses. Any difference in support is attributable to the treatment. The prediction of economic theory is that the group subject to the company cost priming will be less supportive of regulation relative to the group with the consumer and employee benefit priming.

In addition to the experimental manipulation, the survey also measured a range of individual-level variables theorized to shape regulatory preferences. These included demographic characteristics, job role, professional experience, involvement with AI technologies, trust in government and corporate leadership, and perceived vulnerability to AI-related career disruption.

**Table 1: Variable Definitions**

|  |  |
| --- | --- |
| **Variable Name** | **Description** |
| ***Dependent variables*** |  |
|  | *Support for regulation mandating each of the following.* Scale: *Strictly Oppose, Somewhat Oppose, Neutral, Somewhat Support, Strongly Support.* |
| Transparency | Transparency about AI use, data collection. |
| Explainability | Explanation of autonomous decisions. |
| Bias | Third-party auditing to ensure AI systems are free from bias. |
| ***Independent variables*** | |
| ***Treatment*** | |
| Treatment: Company | 1 if Company treatment; 0 if Consumer treatment |
| Company Question 1-4 | See Table 2 |
| Consumer Question 1-4 | See Table 2 |
| ***Workplace*** | |
| Experience | Categories for number of years. Converted to numerical scale. |
| Involvement in AI: Yes | 1 if *Yes* in response to whether directly involved in making decisions about AI |
| ***Trust and Regulation*** | |
| Regulation Protection | In your view, how important are government regulations for protecting consumer and worker interests? Converted to numerical scale. |
| Regulation Burden | How much do you agree with the following statement: “Government regulations are unnecessarily burdensome for businesses.” Converted to numerical scale. |
| Trust in Govt: High | *A great deal* in response to: “How much do you trust the federal government to make policies that beneﬁt people like yourself?” |
| Trust in Execs | *A lot* or *A great deal* in response to: “How much do you trust top executives of U.S. companies to make decisions that protect consumers and workers from harm (even in situations where they are not compelled to do so by law)?” Converted to numerical scale. |
| ***Vulnerability to AI*** | |
| Concern for Self: High | *Extremely concerned* in response to “How concerned are you about the potential adverse impact of AI on your career within the next ﬁve years?” |
| ***Demographic Controls*** | |
| Gender | Female; Male; Non-binary/Third gender; Prefer not to say. |
| Race and Ethnicity | Indicator variables for: White or Caucasian; Black or African American; Asian or South Asian; Spanish, Hispanic, or Latino; Other or Prefer not to say. |
| Degree | Highest level of education completed (8 categories) |
| State | 48 categories (47 states and DC; there were no respondents from Alaska, Montana, or Vermont) |
| ***Firm Controls*** |  |
| Firm Size | Number of employees in company (5 categories) |
| Use of AI at Firm: Yes | 1 if responds Yes to whether AI is in use at company |
| Sector | Categories for 8 major sectors plus an “Other” category |
| AI Impact on Firm | In your view, will the adoption of AI in your industry have a positive or negative impact on your company over the next two years? (5 categories) |
| ***State Politics*** | |
| Biden 2020 | 1 if the response is from a state that voted for Biden in 2020; 0 otherwise |

*The analysis in this paper uses only the above variables. Other questions asked in the survey were excluded from consideration.*

To assess whether competitive pressure might motivate support for regulation, respondents were asked to indicate their agreement with the following statement: “A decision to delay deployment of AI systems until they are fully transparent, accountable, and fair places a company at a competitive disadvantage relative to other companies that don’t share the same commitment.” Here, individuals who *don’t* believe the requirements to be burdensome could be more supportive of regulation because benefits come at low cost. However, people who *do* believe the requirements to be very burdensome are also more likely to support regulations because they sense a need for enforcing a level playing field. How these competing tensions are resolved is then an empirical question. Full variable definitions are provided in Table 1, with frequency tables included in Supplementary Materials Part 2.

Political affiliation was not directly measured to avoid activating partisan response patterns. Instead, respondents’ political context was inferred based on the outcome of the 2020 U.S. presidential election in their state, using data from the MIT Election Data and Science Lab (2021). This approach allowed for analysis of geographic political variation without introducing potential partisan bias into the responses.

For analyzing the data from the experiment, I use the ordinal logit (i.e., proportional odds) model. In each regression the dependent variable *Y* is the expressed support for each type of regulation. This is a categorical variable with five ordered levels. Given a dependent variable with *K* categories, and *X* the design matrix, the cumulative probability of being in category *k* or lower is specified implicitly by:

where , is the intercept for threshold *k* and the same coefficient is assumed for all thresholds (this is the parallel regression assumption). The Brant test is used to test for the parallel regression assumption. One can also give numerical values to the ordered outcomes in *Y* and estimate a linear regression model. The advantage is the ease in interpretation, but it forces the assumption that the numerical distance between categories is equal, which seems unlikely to hold in the present context. Linear regression results are included with Supplementary Materials Part 4.

The core experimental design allows for an unbiased estimate of the average treatment effect of the priming interventions on support for regulation. Random assignment to treatment groups occurred after the fourth section of the questionnaire. Balance between the two groups was confirmed (Supplementary Materials: Part 3). While the sample may or may not be fully representative of the U.S. business professional population, its size, diversity and the focus on an experimentally identified effect allow for meaningful insights into how regulatory preferences are shaped by cognitive salience and individual characteristics.

The proportional odds model is also used to test for differences in support for the three types of regulation. I pool the responses to the three questions and set support as the dependent variable, with regulation type as the independent variable. Since these are repeated measures, there is a need to account for the within-respondent correlation structure. Conventional tests such as the test for independence or the Kruskal-Wallis test are not appropriate. Instead, cumulative link mixed models are estimated, which fit proportional odds models with random intercepts via Laplace approximation (Christensen, 2019). This approach is appropriate for analyzing ordinal outcomes with repeated measures, as it accounts for both the ordering of the response and respondent-level heterogeneity.

|  |
| --- |
| **A graph of different colored bars  AI-generated content may be incorrect.** |
| **Figure 1.** Distribution of responses to the three key regulation questions. |

1. **RESULTS**

**4.1. Overall Support for Regulation**

The survey reveals consistently high levels of support for AI regulation across the three domains studied: transparency regarding data collection and use, explainability of autonomous decisions, and bias mitigation. I use the handles transparency, explainability, and bias to refer to the variables measuring support for the three types of regulation. As shown in Figure 1, nearly 75% of respondents either *strongly support* or *somewhat support* transparency regulation. A similar pattern is observed for the bias question, while support is slightly lower (around 72%) for explainability. Notably, the explainability item also has the lowest proportion of *strong support* (27%) and a somewhat higher share of neutral responses. Of the three, the bias regulation question elicited the most polarized responses, recording the highest rate of *strong opposition*.

These descriptive patterns are confirmed in a cumulative link mixed model that accounts for both the ordinal nature of the response and the within-respondent correlation structure (Table 2). The dependent variable of the model is the level of support, and the predictor is the type of regulation. Using explainability as the reference category, the model shows that support is significantly higher for both transparency (β = 0.47, *p* < 0.001) and bias regulation (β = 0.39, *p* < 0.001). Releveling the model to compare transparency and bias directly reveals no statistically significant difference between the two (*p* = 0.39), suggesting that these types of regulation are similarly supported overall, and more favorably viewed than explainability requirements.

As a robustness check, a linear mixed-effects model treating support as a numeric scale (1–5) was estimated and yields substantively similar results, with transparency and bias regulation again receiving higher support than explainability. Complete results from the linear model are reported in Supplementary Materials, Part 5.

To test whether professional experience with AI moderates support for regulation, I estimated a cumulative link mixed model including interaction terms between regulation type and whether the respondent is directly involved in AI implementation at their company. The model reveals a meaningful divergence in preferences between AI-involved and non-involved respondents (see Model 3 in Table 2).

| **Table 2** | | | |
| --- | --- | --- | --- |
| **Ordinal Mixed Effects Models** | | | |
|  | **Model 1** | **Model 2** | **Model 3** |
| Strongly Oppose | Somewhat Oppose | -4.954\*\*\* | -5.427\*\*\* | -5.846\*\*\* |
|  | (0.187) | (0.193) | (0.242) |
| Somewhat Oppose | Neutral | -3.173\*\*\* | -3.646\*\*\* | -4.058\*\*\* |
|  | (0.129) | (0.137) | (0.197) |
| Neutral | Somewhat Support | -1.412\*\*\* | -1.885\*\*\* | -2.289\*\*\* |
|  | (0.105) | (0.112) | (0.179) |
| Somewhat Support | Strongly Support | 1.353\*\*\* | 0.879\*\*\* | 0.483\*\*\* |
|  | (0.104) | (0.103) | (0.169) |
| Bias | 0.389\*\*\* | -0.085 | -0.399\*\* |
|  | (0.097) | (0.098) | (0.170) |
| Transparency | 0.474\*\*\* |  |  |
|  | (0.097) |  |  |
| Explainability |  | -0.474\*\*\* | -0.856\*\*\* |
|  |  | (0.097) | (0.167) |
| Involvement in AI: Yes |  |  | -0.609\*\*\* |
|  |  |  | (0.205) |
| Explainability × Involvement in AI: Yes |  |  | 0.581\*\*\* |
|  |  |  | (0.205) |
| Bias × Involvement in AI: Yes |  |  | 0.481\*\* |
|  |  |  | (0.209) |
|  |  |  |  |
| SD (Intercept Respondent ID) | 1.941 | 1.941 | 1.949 |
| Num. Obs. | 2655 | 2655 | 2652 |
| R2 Marg. | 0.006 | 0.006 | 0.010 |
| R2 Cond. | 0.537 | 0.537 | 0.541 |
| AIC | 6418.3 | 6418.3 | 6407.2 |
| BIC | 6459.5 | 6459.5 | 6466.0 |
| RMSE | 3.59 | 3.59 | 3.58 |
|  |  |  |  |
| \*p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01 | | | |

Among respondents not involved with AI, transparency regulation receives the strongest support, followed by bias and then explainability. Specifically, support for bias is significantly lower than for transparency (β = –0.40, *p* < 0.05), and support for explainability is lower still (β = –0.86, *p* < 0.001). However, this pattern shifts for those involved in AI. The model indicates that AI-involved respondents are less supportive of transparency regulation than their non-involved counterparts (β = –0.61, *p* < 0.01), while their support for bias and explainability increases, as shown by the positive and significant interaction terms for both bias (β = 0.48, *p* = 0.021) and explainability regulation (β = 0.58, *p* < 0.01).

These interaction effects suggest that business professionals who are directly engaged in AI development or implementation tend to view transparency mandates more skeptically, while showing greater openness to fairness and explainability requirements. One possible interpretation is that those working with AI systems may view transparency as more burdensome to achieve in practice, or more difficult to operationalize effectively, whereas explainability and fairness mandates are perceived as more feasible or less threatening to business goals.

|  |
| --- |
| A graph of different colored bars  AI-generated content may be incorrect. |
| **Figure 2.** Support for the three types of regulation by treatment group. |

Corresponding results for a linear mixed-effects model including the same interaction structure (reported in Supplementary Materials, Part 5) show consistent patterns, with similar magnitudes and direction of effects. The stronger opposition to bias observed in Figure~1 could not be confirmed using a logistic regression model with an indicator for Strongly Oppose as the dependent variable.

**4.2. Effect of Priming Treatments**

Figure 2 illustrates how support varies between the two treatment groups. Across all three regulation types, respondents in the Company treatment (primed to consider business costs) are less likely to express strong support for regulation and more likely to express strong opposition.

Table 3 presents the results of ordinal logistic regressions estimating the average treatment effect. The baseline model includes only an indicator for the Company treatment. In these models (Columns 1, 3, and 5) the Company treatment is associated with lower support for regulation across all three domains than the Consumer treatment. The odds ratios are around 0.81, indicating that the treatment is associated with a 19% reduction in the odds of being in a higher support category. Coefficients are significant at only the 10% level for Transparency and Bias, and not significant in the case of Explainability (*p =* 0.106). In all cases, a Brant test reported no evidence of violation of the parallel regression assumption holds ((3) = 1, *p =* 0.8 in each model).

When individual-level covariates are included (Columns 2, 4, and 6), the treatment effect becomes stronger: the odds ratio is 0.724 for transparency (, 0.740 for explainability (), and 0.778 for bias (). In addition to the variables displayed in the table, the models include demographic controls (the state, gender, race and ethnicity, and education) and firm controls (the industry sector, firm size, and whether AI is in use at the firm). The coefficients of Transparency and Explainability are significant at the 5% level. The coefficient of Bias is significant at only the 10% level (*p* = 0.065).[[2]](#footnote-3) Here again, a Brant test indicated no evidence of violation of the proportional odds assumption for the treatment variable ((3) = 0. 94, *p =* 0.83 in

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 3** | | | | | | |
| **Ordinal Logistic Regression Results** | | | | | | |
|  | | | | | | |
|  | ***Dependent variable:*** | | | | | |
|  |  | | | | | |
|  | **Transparency** | | **Explainability** | | **Bias** | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | | | | | | |
|  |  |  |  |  |  |  |
| Treatment: Company | -0.211\* (0.124) | -0.323\*\* (0.139) | -0.200 (0.124) | -0.301\*\* (0.136) | -0.204\* (0.124) | -0.251\* (0.136) |
|  |  |  |  |  |  |  |
| Experience |  | 0.309\*\*\* (0.059) |  | 0.133\*\* (0.058) |  | 0.175\*\*\* (0.058) |
|  |  |  |  |  |  |  |
| Involvement in AI: Yes |  | -0.465\*\*\* (0.169) |  | -0.315\* (0.166) |  | -0.447\*\*\* (0.166) |
|  |  |  |  |  |  |  |
| Trust in Govt: High |  | 0.719\*\* (0.289) |  | 0.940\*\*\* (0.281) |  | 1.268\*\*\* (0.297) |
|  |  |  |  |  |  |  |
| Trust in Execs |  | -0.005 (0.075) |  | -0.027 (0.073) |  | 0.037 (0.074) |
|  |  |  |  |  |  |  |
| Regulation Protection |  | 0.480\*\*\* (0.078) |  | 0.434\*\*\* (0.078) |  | 0.240\*\*\* (0.077) |
|  |  |  |  |  |  |  |
| Regulation Burden |  | -0.252\*\*\* (0.063) |  | -0.276\*\*\* (0.064) |  | -0.344\*\*\* (0.064) |
|  |  |  |  |  |  |  |
| Concern for Self: High |  | 1.042\*\*\* (0.321) |  | 1.075\*\*\* (0.316) |  | 0.891\*\*\* (0.323) |
|  | | | | | | |
| Observations | 885 | 884 | 885 | 884 | 885 | 884 |
|  | | | | | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | | |
| † *The demographic and firm controls are listed in Table 1.* | | | | | | |

each model). There is no evidence of violation for the omnibus model either (although some cells in the outcome × predictors crosstab are empty).

These results confirm that the group for which business costs were made salient has *lower support* for AI regulation relative to the group with consumer/employee benefits salient (after controlling for demographic and organizational characteristics). In the case of bias, the magnitude of the effect is smaller, with only marginal significance.

**4.3. Heterogeneous Treatment Effects: Political Context**

The treatment effect varies meaningfully across subgroups. To assess variation by political context, I use a binary indicator of whether a respondent's state voted for Biden or Trump in the 2020 presidential election. The variable Biden 2020is set to 1 if the respondent’s state voted for Mr. Biden in the 2020 presidential election, and 0 if it voted for Mr. Trump. As shown in Table 4, the priming effect is significantly larger among respondents in Trump-voting states, suggesting that individuals in more conservative regions are more responsive to the cost-focused priming. In Trump states: treatment odds ratios are in the range 0.48–0.62 (*p <* 0.01 in all cases). In Biden states: the positive interaction offsets (and sometimes reverses) that reduction, giving net treatment

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 4** | | | | | | |
| **Ordinal Logistic Regression Results** | | | | | | |
|  | | | | | | |
|  | ***Dependent variable:*** | | | | | |
|  |  | | | | | |
|  | **Transparency** | | **Explainability** | | **Bias** | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | | | | | | |
| Treatment: Company | -0.485\*\*\* | -0.588\*\*\* | -0.518\*\*\* | -0.573\*\*\* | -0.588\*\*\* | -0.735\*\*\* |
|  | (0.185) | (0.199) | (0.185) | (0.199) | (0.184) | (0.199) |
|  |  |  |  |  |  |  |
| Biden 2020 | -0.227 | -1.785\*\* | -0.336\* | -0.077 | -0.439\*\* | -2.302\*\*\* |
|  | (0.181) | (0.698) | (0.180) | (0.643) | (0.180) | (0.688) |
|  |  |  |  |  |  |  |
| Treatment: Company × Biden 2020 | 0.501\*\* | 0.491\* | 0.580\*\* | 0.472\* | 0.702\*\*\* | 0.852\*\*\* |
|  | (0.249) | (0.272) | (0.250) | (0.269) | (0.249) | (0.272) |
|  |  |  |  |  |  |  |
|  | | | | | | |
| Observations | 885 | 885 | 885 | 885 | 885 | 885 |
| Controls | No | Yes | No | Yes | No | Yes |
|  | | | | | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | | |

† *In (2), (4), and (5) the same set of controls is used as in Table 3.*

odds ratios in the range 0.90–1.12 (near neutral). While this could reflect ideological differences, it may also be tied to regional business culture or baseline policy preferences. For example, lower regulatory baselines in Republican-led states like Texas may heighten sensitivity to perceived government overreach – even among those not affiliated with the Republican party.

**4.4. Other Predictors of Regulatory Attitudes**

Several individual-level variables included as controls in the regression models also emerge as significant predictors of support for regulation:

* **Trust in government** and **belief in the protective role of regulation** are both positively associated with support for AI regulation. In the case of trust in government, this result is driven by views of those with the highest level of trust in government. I include an indicator variable which equals 1 if the response to the trust in government question is “a great deal”. The coefficients are 0.719 (*p <* 0.05) for Transparency, 0.940 (*p <* 0.01) for explainability, and 1.268 (*p <* 0.01) for bias. I found no significant relationship between **trust in executives** and support for regulation. Individuals who felt that government regulations are important for protecting consumer and worker interests supported AI regulation (**Regulation Protection**). Coefficients ranged from 0.240 to 0.480 (*p <* 0.01 in all cases). Individuals who agreed with the statement that “Government regulations are unnecessarily burdensome for businesses,” (**Regulation Burden**)were generally opposed to AI regulation. Coefficients ranged from -0.252 to -3.44 (*p <* 0.01 in all cases). Both Regulation Protection and Regulation Burden were converted to a numerical scale because their effects were generally uniform. These two variables also play an important role in controlling for pretreatment differences in attitudes towards regulation in general.
* Greater **work experience** is associated with more support for regulation. This variable was also converted to a numerical scale. Coefficients were 0.133 (*p <* 0.05) for explainability, 0.175 (*p <* 0.01) for bias, and 0.309 (*p <* 0.01) for transparency. Previous research has found that younger people have more positive attitudes towards AI (see Bergdahl, et al., 2023). Since age and experience are highly correlated, the observed effect could be driven by age. **Direct involvement in AI implementation** is associated with lower support. The coefficients are -0.315 (*p <* 0.05) for explainability, -0.447 (*p <* 0.01) for bias, and -0.465 (*p <* 0.01) for transparency. Lower support for regulation among the AI-involved may

|  |
| --- |
| **A graph of a diagram  AI-generated content may be incorrect.** |
| **Figure 3.** Effect of concern about job displacement on support for bias regulation |

reflect either a response to anticipated burdens of compliance or skepticism toward regulatory effectiveness in the case of AI.

* **Perceived vulnerability to AI** increases support for AI regulation. Figure 3 clearly shows that those who are *extremely concerned* about career displacement from AI are strong supporters of each of the three types of regulation. Interestingly, there is a local mode at *not concerned at all,* while those with moderate levels of concern express weaker support. However, the global mode at *extremely concerned* is clearly of much greater magnitude. In Table 3, I only include an indicator variable for the highest level of concern (*Extremely concerned*) and this has positive coefficients (ranging from 0.891 to 1.042) and is significant (*p <* 0.01) in all cases. The odds ratios are in the range from 2.44–3.24. This result suggests that as concerns about job displacement from AI grow, support for more controls on the technology is also likely to increase.

|  |
| --- |
| **A graph of different types of bias  AI-generated content may be incorrect.** |
| **Figure 4.** The “race to the bottom” motivation for supporting regulation. There is strong support for regulation at the two ends of the spectrum. |

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 5** | | | |
| **Ordinal Logistic Regression Results** | | | |
|  | | | |
|  | ***Dependent variable:*** | | |
|  |  | | |
|  | **Transparency** | **Explainability** | **Bias** |
|  | (1) | (2) | (3) |
|  | | | |
| Competition: Strongly agree | 1.085\*\*\* | 1.003\*\*\* | 1.240\*\*\* |
|  | (0.298) | (0.287) | (0.288) |
|  |  |  |  |
| Competition: Somewhat agree | 0.105 | 0.182 | 0.073 |
|  | (0.209) | (0.216) | (0.211) |
|  |  |  |  |
| Competition: Somewhat disagree | 0.458 | 0.369 | 0.521\* |
|  | (0.286) | (0.282) | (0.288) |
|  |  |  |  |
| Competition: Strongly disagree | 1.017\*\* | 1.588\*\*\* | 0.884\*\* |
|  | (0.404) | (0.388) | (0.389) |
|  |  |  |  |
|  | | | |
| Observations | 456 | 456 | 456 |
|  | | | |
| *Note:* | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | |

† *“Neither agree nor disagree” is the reference category.*

**4.5. Competitive Pressure and Avoiding a Race to the Bottom**

To explore which elements of the priming were most predictive of support for regulation, I examined how each individual treatment question related to support for regulation. Using model selection criteria (BIC and AIC), the strongest predictor among Company-primed respondents was Question 4 alone, which asked participants whether delaying the deployment of AI systems until they are transparent, accountable, and fair places a company at a competitive disadvantage. This item appears to capture concern about **competitive pressure**, and a potential “race to the bottom” in AI governance.

Figure 4 shows that responses to this question are **nonlinearly related** to support for regulation. The *Strongly Support* category for regulation has two local modes – those who either **strongly agree** or **strongly disagree** with the competitiveness statement. Table 5 has the ordinal logistic regression results – the strongly agree and strongly disagree categories are both positive and significant. One interpretation is that those who **strongly disagree** with the claim that making AI systems transparent, accountable, and fair places a firm at a competitive disadvantage do not see regulation as burdensome or costly and therefore support it for the benefits it generates. On the other hand, those who **strongly agree** may view regulation as necessary to level the playing field. In this reading, regulation is not seen as neutral—it is viewed as a needed constraint to prevent companies from undercutting responsible practices for short-term gain.

A parallel analysis was conducted for the **Consumer** treatment. For the first three questions, stronger belief in the importance of transparency, explainability, and fairness consistently predicts higher support for regulation. The fourth question in this group asked if knowledge that a company uses responsible AI would increase trust and loyalty. This also has a positive association with support for regulation. These results are presented in Supplementary Materials, Part 4.

1. **CONCLUSION**

The trade-off between fostering corporate innovation and protecting public welfare is increasingly posited as central to AI regulation. While this may resonate with policy makers, do those affected perceive it similarly? I find that such a tradeoff is not only a policy framing – it also resonates at the individual level. Individuals primed to consider the costs of regulation express lower support for mandates enforcing transparency, explainability, and fairness than those primed to think about consumer and employee benefits. This effect is especially pronounced in Republican-leaning states, underscoring the interaction between regulatory attitudes and political context.

Unlike previous surveys, which had asked respondents about their views on regulation, I studied attitudes towards three specific targets of regulatory mandates – transparency, explainability, and bias. I find that there are meaningful differences in support for the three, suggesting that individuals bring different evaluative frames to the question when they consider different types of AI regulation.

The results also reveal that support for regulation cannot be explained by narrow economic reasoning alone. Individual-level attitudes are shaped by a broader constellation of factors. Trust in government, perceived vulnerability to AI-driven career disruption, and the nature of professional involvement with AI systems all significantly influence support. Interestingly, many respondents make choices that are consistent with the idea that regulation may be needed to prevent a “race to the bottom,” suggesting that competitive dynamics themselves may motivate support for oversight – not just hinder it.

These findings contribute to a more nuanced understanding of how individuals form attitudes toward AI governance. Public support is not simply a function of cost–benefit analysis; it also reflects how people locate themselves within a landscape shaped by institutional trust, political ideology, and professional role. As policymakers confront the challenge of crafting credible and equitable regulation, understanding these underlying dynamics is essential. Policy that aligns with public reasoning is more likely to be seen as legitimate – and thus more likely to endure.

Several avenues for future research emerge from this study. The scope of regulation explored here was necessarily limited. Topics such as misinformation, state surveillance, intellectual property, algorithmic collusion, and liability for AI-driven harms merit focused investigation. Moreover, public support may be highly context-dependent – shaped not just by the type of regulation, but by who is subject to it, under what conditions, and with what enforcement mechanisms. Longer surveys and multi-wave experiments could help disentangle these layers. Finally, further work is needed to understand the mechanisms by which political geography — as proxied here by 2020 election outcomes — interacts with regulatory attitudes. As AI becomes increasingly embedded in economic and political systems, this understanding will become ever more vital.

**Competing Interests:** The author declares no competing interests.

1. **REFERENCES**

Alesina, A., Miano, A., & Stantcheva, S. (2023). Immigration and redistribution. *The Review of Economic Studies*, 90(1), 1–39.

Bechtel, M. M., Genovese, F., & Scheve, K. F. (2019). Interests, norms and support for the provision of global public goods: The case of climate co-operation. *British Journal of Political Science*, 49(4), 1333–1355.

Bergdahl, J., Latikka, R., Celuch, M., Savolainen, I., Mantere, E. S., Savela, N., & Oksanen, A. (2023). Self-determination and attitudes toward artificial intelligence: Cross-national and longitudinal perspectives. *Telematics and Informatics*, 82, 102013.

Bewersdorff, A., Zhai, X., Roberts, J., & Nerdel, C. (2023). Myths, mis- and preconceptions of artificial intelligence: A review of the literature. *Computers and Education: Artificial Intelligence, 4,* 100143. https://doi.org/10.1016/j.caeai.2023.100143

Cajueiro, D. O., & Celestino, V. R. R. (2025). A Comprehensive Review of Artificial Intelligence Regulation: Weighing Ethical Principles and Innovation. *Journal of Economy and Technology*.

Cremaschi, A., Lee, D. J., & Leonelli, M. (2025). Understanding support for AI regulation: A Bayesian network perspective. *arXiv preprint arXiv:2507.05866*.

Christensen, R. H. B. (2019). *ordinal: Regression models for ordinal data* (R package version 2019.12-10). https://CRAN.R-project.org/package=ordinal

Deloitte. (2022). *State of AI in the enterprise: 5th Edition report*. https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-ai-2022.html

Diligent. (2024). *AI regulations around the world: Trends, takeaways & what to watch heading into 2025*. https://www.diligent.com/resources/guides/ai-regulations-around-the-world

Dong, M., Conway, J. R., Bonnefon, J. F., Shariff, A., & Rahwan, I. (2024). Fears about artificial intelligence across 20 countries and six domains of application. *American Psychologist*.

EU AI Act. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1689

Executive Order No. 141110. (2023, October 30). *On the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence*. 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/

Executive Order No. 14179. (2025, January 23) *Removing Barriers to American Leadership in Artificial Intelligence.* https://www.federalregister.gov/documents/2025/01/31/2025-02172/removing-barriers-to-american-leadership-in-artificial-intelligence

Fesenfeld, L., Rudolph, L., & Bernauer, T. (2022). Policy framing, design and feedback can increase public support for costly food waste regulation. *Nature Food*, 3(3), 227–235.

Fessenko, D. S., & Jasperse, A. (2025). Ethics at the heart of AI regulation. *AI and Ethics*, *5*(3), 3387-3398.

Financial Times. (2023). EU’s new AI Act risks hampering innovation, warns Emmanuel Macron. https://www.ft.com/content/9339d104-7b0c-42b8-9316-72226dd4e4c0

Hoffmann, C.H., Hahn, B. Decentered ethics in the machine era and guidance for AI regulation. *AI & Soc* **35**, 635–644 (2020). https://doi.org/10.1007/s00146-019-00920-z

Horowitz, M. C., & Kahn, L. (2021). What influences attitudes about artificial intelligence adoption: Evidence from U.S. local officials. *PLOS ONE*, 16(10), e0257732. https://doi.org/10.1371/journal.pone.0257732

Ipsos. (2025). *Google / Ipsos Multi-Country AI Survey 2025****.*** https://www.ipsos.com/en-us/google-ipsos-multi-country-ai-survey-2025

Israel, A., Rosenboim, M., & Shavit, T. (2014). Using priming manipulations to affect time preferences and risk aversion: An experimental study. *Journal of Behavioral and Experimental Economics*, 53, 36–43.

Kolcava, D., Rudolph, L., & Bernauer, T. (2021). Voluntary business initiatives can reduce public pressure for regulating firm behaviour abroad. *Journal of European Public Policy*, 28(4), 591–614.

Kreps, S., George, J., Lushenko, P., & Rao, A. (2023). Exploring the artificial intelligence “trust paradox”: Evidence from a survey experiment in the United States. *PLOS ONE*, 18(7), e0288109. https://doi.org/10.1371/journal.pone.0288109

Kuziemko, I., Norton, M. I., Saez, E., & Stantcheva, S. (2015). How elastic are preferences for redistribution? Evidence from randomized survey experiments. *American Economic Review*, 105(4), 1478–1508. http://dx.doi.org/10.1257/aer.20130360

Lucaj, L., Van Der Smagt, P., & Benbouzid, D. (2023, June). AI regulation is (not) all you need. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1267-1279).

Malhotra, N., Monin, B., & Tomz, M. (2019). Does private regulation preempt public regulation? *American Political Science Review*, 113(1), 19–37.

Mallaby, S., Brandt, J. Horowitz, M.C., Duffy, K., Dumbacher, E.D., Doshi, R., & Hillman, J.E. (2025). *The Opportunities and Risks Found in Trump's AI Action Plan.* Council on Foreign Relations. https://www.cfr.org/article/opportunities-and-risks-found-trumps-ai-action-plan

Mast, E. (2020). Race to the bottom? Local tax break competition and business location. *American Economic Journal: Applied Economics*, 12(1), 288–317.

McKinsey & Co. (2025). *The state of AI in 2025: The state of AI: How organizations are rewiring to capture value.* https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

Merolla, J., Ramakrishnan, S. K., & Haynes, C. (2013). “Illegal,” “undocumented,” or “unauthorized”: Equivalency frames, issue frames, and public opinion on immigration. *Perspectives on Politics*, 11(3), 789–807.

National Conference of State Legislatures. (2024). *Artificial intelligence 2023 legislation*. https://www.ncsl.org/technology-and-communication/artificial-intelligence-2023-legislation

Nordström, M. AI under great uncertainty: implications and decision strategies for public policy. *AI & Soc* **37**, 1703–1714 (2022). https://doi.org/10.1007/s00146-021-01263-4

Nussberger, A. M., Luo, L., Celis, L. E., & Crockett, M. J. (2022). Public attitudes value interpretability but prioritize accuracy in artificial intelligence. *Nature Communications*, 13(1), 5821.

O’Shaughnessy, M., Schiff, D. S., Varshney, L. R., Rozell, C. J., & Davenport, M. A. (2003). What governs attitudes toward artificial intelligence adoption and governance? *Science and Public Policy*, 50, 161–176. https://doi.org/10.1093/scipol/scac056

Pataranutaporn, P., Liu, R., Finn, E., et al. (2023). Influencing human–AI interaction by priming beliefs about AI can increase perceived trustworthiness, empathy and effectiveness. *Nature Machine Intelligence*, 5, 1076–1086. https://doi.org/10.1038/s42256-023-00720-7

Pew Research Center (2025). *How the U.S. Public and AI Experts View Artificial Intelligence.*https://www.pewresearch.org/internet/2025/04/03/how-the-us-public-and-ai-experts-view-artificial-intelligence/

Reuters. (2025). *Tech lobby group urges EU leaders to pause AI Act*. https://www.reuters.com/technology/tech-lobby-group-urges-eu-leaders-pause-ai-act-2025-06-25/

Rudolph, L., Kolcava, D., & Bernauer, T. (2023). Public demand for extraterritorial environmental and social public goods provision. *British Journal of Political Science*, 53(2), 516–535.

Stantcheva, S. (2021). Understanding tax policy: How do people reason? *Quarterly Journal of Economics*, 136, 2309–2369.

Stantcheva, S. (2022). How to run surveys: A guide to creating your own identifying variation and revealing the invisible. *Annual Review of Economics*, 15(1), 205–234.

Stantcheva, S. (2023). Understanding trade. *NBER Working Paper No. 30040*. https://scholar.harvard.edu/sites/scholar.harvard.edu/files/stantcheva/files/understanding\_trade\_v57.pdf

Viscusi, W. K., Harrington Jr, J. E., & Sappington, D. E. (2018). *Economics of regulation and antitrust* (4th ed.). MIT Press.

Wilczek, B., Thäsler-Kordonouri, S., & Eder, M. (2025). Government regulation or industry self-regulation of AI? Investigating the relationships between uncertainty avoidance, people’s AI risk perceptions, and their regulatory preferences in Europe. *AI & Society*, 40, 3797–3811. https://doi.org/10.1007/s00146-024-02138-0

Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024). The future of artificial intelligence: Fear, hope or indifference? *Human Technology*, 20, 611–639.

Zhang, B., & Dafoe, A. (2019). Artificial intelligence: American attitudes and Trends. *SSRN*. http://dx.doi.org/10.2139/ssrn.3312874

Zhang, B., & Dafoe, A. (2020). U.S. public opinion on the governance of artificial intelligence. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 187–193).

Zhang, B., Anderljung, M., Kahn, L., Dreksler, N., Horowitz, M. C., & Dafoe, A. (2021). Ethics and governance of artificial intelligence: Evidence from a survey of machine learning researchers. *Journal of Artificial Intelligence Research*, 71, 591–666.

1. *Priming* involves manipulating what is made cognitively salient before a person evaluates an issue and is to be distinguished from *framing* – where the way in which an issue or a question is presented has the potential to affect responses. [↑](#footnote-ref-2)
2. In the linear regression model (Supplementary Materials Part 3) Transparency and Explainability are significant (both the baseline and model with covariates), but neither model is significant for Bias. [↑](#footnote-ref-3)