# The Politics of AI: Will Bipartisanship Last or Is Polarization Inevitable?

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This is pretty early stage, definitely needs a lot of work in terms of cogency, clarity, theory, etc. Welcome any advice! Thank you.

# Abstract

Research on AI governance in the United States has heavily emphasized the role of national and international policymaking, highlighting early areas of bipartisan agreement. Yet, with no clear, holistic federal regulatory response, subnational policymakers increasingly have a role in developing and implementing AI policy. A central question in how these actors respond to AI's opportunities and challenges is whether and how AI policy will become a partisan issue. This paper examines potential causes of politicization of AI policy through a mixed method study. First, we perform a series of four case studies, featuring debates over AI regulation in Idaho, Colorado, and Illinois. We examine the role of key actors, manifested in state legislative committees and chamber floors, and identify variation in the degree of partisan divides. Second, we administer a survey to more than 7,300 US state legislators, resulting in a representative sample of 129 respondents from 44 US states. Responses from the legislators related to current AI-related regulatory efforts, underlying policy preferences and values, and attitudes regarding stakeholder participation in the policymaking process further illuminate possible contours of political division. Emerging from these studies, we articulate four dimensions along which politicization might emerge: by virtue of 1) competing problem definitions or 2) preferred policy solutions, or owing to 3) existing policy sector or subsystem monopolies, or 4) stakeholder access and power. While we find that there may be ongoing room for flexibility and compromise in the AI policy domain, we note that partisan fissures may crystallize in the years ahead.

# Introduction and Background

Artificial intelligence (AI) policy is a young, rapidly-evolving, and complex domain that dates back arguably to 2016, with limited attention until the end of the 2010s. A substantial amount of reporting over this time period has highlighted the bipartisan nature of US discussions and voting behavior. The US Senate AI Task Force, the House and Senate AI Caucuses, the House Financial Services Committee, and other congressional committees and statements have featured strong bipartisan leadership and a shared sense of urgency around AI and its core issues. This has been reflected in congressional votes, with major regulatory efforts that were largely bipartisan affairs.[1] [2] Yet, a common assumption, emphasized by a growing body of research, is that attitudes toward AI and AI's adoption will be shaped by relevant cultural, political, and socio-economic context as well as technological imaginaries (Wang et al., 2023), and therefore may come to reflect our partisan polarization. For example, Shaikh & Moran (2022) find that left-leaning media outlets are more likely to promote concerns and risks related to facial recognition technology, while right-leaning outlets are more likely to promote the benefits of these technologies as well as warn about authoritarian abuses by foreign actors. Brewer et al. (2022) find similarly that these attitudes, often encountered in the context of discussions about policing and racial justice, are furthered by bipartisan media diets. As Ulnciane and Erkkilä (2023) and Rönnblom et al. (2023) highlight then, AI cannot be understood simply as an apolitical field. However, to what degree and along which dimensions AI may become politicized is yet to be determined.

While Rainie et al. (2022), O'Shaughnessy et al. (2023), and others find evidence of party divides in public opinion polling about adopting or regulating certain uses of AI, the nature and substantive importance of these differences is less clear. For instance, Hemesath and Tepe (2021) find that in the United States, Democrats have slight preferences towards particular regulatory bodies but Republicans show no such clear preference (p. 21). Similarly, Zhang and Dafoe (2019) find identifying as a Democrat is significantly related to more support for general development of AI (p. 5), yet they do not find party to be a significant factor in determining how important the issue of AI governance is to people (p. 94).

Meanwhile, concern for issues such as data security, cyber attacks, autonomous weapons, hiring bias, a US China arms race, AI in healthcare, and regulation of social media platforms cross party lines in some cases. An intriguing development here is that some results present apparent contradictions or otherwise beg further explanation. Democratic-leaning individuals may both support more utilization and simultaneously more regulation of AI, and Democrats are on average more willing to support police use of AI for controversial usages like predictive policing despite lower levels of trust in police generally (Schiff et al, 2023). It is thus unclear whether proposed policy solutions for AI surrounding privacy, risk assessment, misinformation, facial recognition, STEM worker training, and more, will be characterized by established or emerging and novel political divides. It is further unclear to what extent divergences might be shaped by underlying preferences around key debates in AI policy, like the importance of ethical safeguards versus innovation, or the importance of advancing US economic and geopolitical leadership, or an assessment of which stakeholders are deemed important in the AI policy domain, or still other factors.

In this paper, we offer one approach to begin to unpack the complex role of partisanship in the politics of artificial intelligence: we turn to state politics in the early formative years of AI policy, between 2019 and 2022, to see how partisanship might affect opinions and actions regarding AI governance at this early stage of AI governance. While the US has made moves more recently towards addressing the challenges of AI, such as the 2023 NIST AI Risk Management Framework and the Executive Order on the Safe, Secure, and Trustworthy Development of Artificial

[1] The CHIPS and Science Act passed the Senate 64-33 with a 243-187 vote in the House, with outcomes not along party lines. The Protect Elections from Deceptive AI Act (S. 2770), Digital Consumer Protection Commission Act (S. 2597), DETOUR Act (S. 2708), AI Labeling Act (S. 2691), Child Online Safety Modernization Act (H.R. 5182), Preventing Deep Fake Scams Act (H.R. 5808), Artificial Intelligence Advancement Act (S. 3050), TEST AI Act (S.3162), Protecting Kids on Social Media Act (H.R. 6149), Federal Artificial Intelligence Risk Management Act (S. 3205), Artificial Intelligence Research, Innovation, and Accountability Act (S. 3312), the CREATE AI Act (H.R. 5077), and H.R. 6425 (untitled but related to AI coordination across the 'Five Eyes' countries) all had bipartisan support.

[2] Meanwhile, the only major single party AI initiatives are the My Body, My Data Act of 2023 (H.R. 3420) and Political BIAS Emails Act (H.R. 5495), DEEPFAKES Accountability Act (H.R. 5586), Algorithmic Accountability Act (S. 2892), and Eliminating Bias in Algorithmic Systems Act (S 3478). More importantly, amongst the most sweeping legislation and initiatives are broadly bipartisan, spearheaded by Senate Majority Leader Chuck Schumer (D-NY) along with top lieutenants Martin Heinrich (D-N.M.), Mike Rounds (R-S.D.) and Todd Young (R-Ind.), and ongoing activism by Will Hurd (R-TX), Maxine Waters (D-CA), Patrick McHenry (R-NC), Anna Eshoo (D-CA), Michael McCaul (R-TX), Chrissy Houlahan (D-PA), Rob Portman (R-OH), Ted Lieu (D-CA), Cory Booker (D-NJ), and others.

Intelligence, these frameworks are far from a comprehensive and have come only after states have already been grappling with the challenges introduced by use of AI in a variety of domains.

With no clear, holistic federal regulatory response, observers have noted states have considered stepping in to fill this vacuum, pointing to state commissions and increased legislative activity. As identified by Vermont's AI Task Force in 2020: "Over its time in existence, the Task Force came to conclude that there is in fact a role for a state and local action, especially where national and international action is not occurring" (p. 6). The failure of the federal government to take a clear, early leadership role led to "states and municipalities…increasingly taking interest in Artificial Intelligence and filling the gaps left by federal inaction on algorithmic harm." Subnational activity thus serves as a vital site to understand the potential polarization of AI policy as states have largely been left to develop their own approaches to AI. Of particular relevance, in amongst the first research on state-level AI policy adoption, Crosson et al. (2024) find that partisanship and ideology at the individual legislator level are playing a growing role in explaining legislative voting behavior, while party of a state's governor and unified party government do not appear to explain adoption of AI legislation compared to structural factors like unemployment and inflation.

A look at early state action on AI then provides an opportunity to see what issues around AI may or may not be approached with a party lens, and why. The core research question underlying the study is *under what conditions might AI policy become a partisan issue*?

# Theory and Conceptual Framework

## The role of subnational policy in emerging policy domains

The history and the literature on subnational policymaking is clear about why one might expect state actors to step into the void as many critical policy developments are shaped at the regional or local levels (Eckersley 2017). Subnational policy actors tend to be closer to policy issues, real-world implementation decisions, and the consequences of those policy designs (Neshkova 2010). They are more accessible to many policy actors, especially the public, increasing the prospects for participatory decision-making and public accountability (Crowley 2009). Further, notably in the United States context, federalism has been recognized for the opportunity for experimentation in so-called "laboratories of democracy" (Galle and Leahy 2008).

In many cases, similar to how data privacy governance has evolved in the United States, these state-level requirements may substantially shape de facto federal-level norms as AI developers seek to ease compliance with a patchwork of state requirements (Siegmann and Anderljung 2022; Nonnecke and Newman 2019). Finally, depending on institutional flexibility and constraints in federalist systems, subnational policy actors may have the ability to act more rapidly. Ultimately, then, many key AI policy issues, decisions, and implementation choices may emanate not from national and supranational actors, but rather from subnational ones. State legislation, then, may set early rules, norms, and potentially party signals in areas where federal legislation on AI is not yet created (National Conference of State Legislatures 2022; Friedler, Venkatasubramanian, and Engler 2023).

Between 2019 and 2022, state legislators introduced approximately 150 bills or resolutions targeting artificial intelligence.[3] Of those, 19 were enacted (See Appendix A). While some set the stage for further information

[3] The Stanford Index Report finds a "growing policy interest" in the states (p. 274), observing a rise in the number of bills in state legislatures across the country that mention AI, from two bills in 2012 to 131 bills in 2022. Based on Bloomberg Government data, developed by searching bills that contained key words such as "artificial intelligence" and "machine learning" this metric is a sign of an increase in attention at the state

gathering,[4] others offered substantive regulation. In Idaho, legislators placed transparency requirements on algorithmic systems used in the justice system (Idaho Legislature 2019). Colorado policymakers introduced new rules governing the use of algorithms and consumer data in insurance practices (Colorado General Assembly 2021). Lawmakers in Illinois passed legislation requiring notification and consent when AI systems are used for video interviews (Illinois General Assembly 2019). California, Washington, New York, D.C., and a variety of other U.S. states and cities have introduced legislation that would require impact assessments for automated decision-making systems, especially in sensitive contexts like criminal justice and employment (National Conference of State Legislatures 2022).

The increased attention to AI at the subnational level during the formative development of the AI policy domain presents us with an opportunity to explore partisan influences. This is uniquely important to understand for a policy area that has not yet fallen into the polarized party politics that have otherwise come to dominate state politics. While states are now more nationalized and polarized (e.g. Schor 2015; Hopkins 2018; National Council of State Legislatures 2018; Masket 2019), the degree to which emerging technologies like AI are subject to partisan divides remains unclear. We move beyond policy adoption and roll call voting, using survey data and case studies to try to gain clarity on the partisan nature of AI. We turn to the literature on the policy process to guide the inquiry into state politics on AI.

## Agenda-setting scholarship and its application to AI policy

Agenda-setting, and attendant concepts like problem definition, issue attention and framing, and policy windows and entrepreneurs have been applied fruitfully to study numerous policy domains and contexts. Associated frameworks, like the prominent Multiple Streams Framework (MSF), articulate how policy actors work within institutional constraints to define policy problems, couple them with policy solutions, and respond to events that might alter public opinion or governmental priorities, all in the hopes of securing policy change when a 'policy window' opens (Baumgartner & Jones, 1993; Kingdon, 1995).

AI policy as an emergent policy domain is best understood as undergoing agenda-setting though policy adoption and implementation are proceeding in the 2020s. The uptake of major legislation across government levels along with increased attention by academics, civil society, and industry lobbyists all indicate that a major AI policy window is open (Perry & Uuk, 2019, Zhang et al., 2023). Along these lines, scholars have applied a growing number of theories or elements from policy process scholarship to investigate aspects of AI policy. This includes investigations of which actors appear to have power in the policy process (Liu et al., 2023; Savaget et al., 2019; Wan et al., 2023), how competing policy frames and narratives are shaping issue attention by the public or policymakers (Chuan et al., 2019; Recchia, 2020; Ulnicane, 2022;), and how policy problems and solutions are being defined and coupled in major policy documents (Schiff, 2023; Ulnicane & Aden, 2023).

level. Our counts are based on legislation that focuses on artificial intelligence, excluding those that simply mention it in the context of a different area such as budgets or education. We also do not include two other types of legislation that has implications for AI: Data privacy and Autonomous Vehicles. Between 2017 and 2022 47 states considered around 650 pieces of legislation about autonomous vehicles. About 60 pieces of legislation passed in this time, many of those were about platoon trucks, budget issues, testing, and modifying requirements for license or cars. Many also built on previous legislation.

[4] Of the 19 enacted measures, five approved resolutions or enacted bills called for study of questions related to AI, three called on state agencies to recommend or report on AI related issues regularly, and two encouraged education around AI among their state residents. Meanwhile, three state commissions,# established in California, Vermont, and Washington, authored reports on AI. Key foci in the reports include education needed to help the state keep up with emerging technologies and deal with job disruptions, potential roles for the state in the development of AI, consideration of regulations of private use, and possible areas for use of AI for delivering services and enhancing the public good.

Agenda-setting scholarship has since extended (relatively recently) beyond its historical focus on American federal policy, identifying ways in which established theory extends neatly or bears modification when applied to international and, pertinent to this paper, subnational policymaking. As highlighted by Eissler et al. (2014) in their review of trends in agenda-setting research, subnational agenda-setting has some key differences due to different institutional constraints.[5] While the contours of state-level agenda-setting merit ongoing investigation, including differences with or relationships with federal policymaking, research continues to highlight the relevance of agenda-setting processes for eventual policy outcomes (Mortensen, 2010). Further, as Green-Pederson and Walgrave (2014) highlight, examining agenda-setting is not only fruitful for understanding a particular policy domain or likely outcomes, but also for understanding the nature of the political system itself. In this context, it is not surprising that policy process theory has been utilized increasingly to understand AI policy, though there are special challenges associated with studying emerging domains as compared to retrospective analyses.

Numerous questions remain unsettled in this domain, largely because the field is so new, and a plurality of literature is only indirectly engaged in conceptualization based on policy science scholarship. For example, the formation and power of competing coalitions, the evolving underlying beliefs of policy actors, the prospects for policy learning, and the viability of different policy solutions all merit further research. Nevertheless, the growing traction of investigations here and urgent inquiries by civil society and policymakers suggest that further investigation into aspects of agenda setting for a policy, including problem definition, policy entrepreneurship, issue framing, and so on will be essential.

To assess this, for those issues that either do or do not (yet) have a clear partisan division, there is a need to explore related and precursor questions that go beyond policy adoption and roll call voting: how have elected officials come to understand their political approach? What frames from other policy domains have been transposed onto these new debates? To what extent are existing policy images or monopolies within policy subsystems dominant or subject to disruption by AI policy as a new domain? Which policy stakeholders are active and how have they attempted to shape the grounds of debate? Which problem definitions and policy solutions are rising to the forefront, and which ones are sticking?

# Conceptual framework: Prospects for politicization of AI

The policy process and agenda-setting literature highlight four key dimensions for us to consider in our inquiry into partisanship and AI policy: Policy problems, policy solutions/tools, stakeholders, and subsystems. We provide an overview of these four dimensions which we subsequently used to structure our discussion and presentation of findings.

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[5] The state policy process in the US is characterized by differences such as a greater prevalence of direct democracy through ballot initiatives and referenda (Damore et al., 2012), heightened powers of state executives compared to presidents (Heidbreder, 2012; Thrower, 2019), and different roles played by state-level policy actors who aim to influence the agenda. For instance, Liu et al. (2010) find that state government and interest group actors exert power through activities such as consensus and coalition building, while mass media and national mood play a lesser role than at the federal level, contrary to prior research (Tan & Weaker, 2009). Further, they highlight the importance of policy compatibility as a key feature in the selection of policy alternatives, rather than criteria like technical feasibility and value acceptability highlighted in the MSF.

## Problem definitions

Policy decisions are often shaped by the persistent conflict surrounding how policy problems or issues are identified, selected, defined, and framed (Dery, 2000; Rochefort & Cobb, 1994).[6] These problem definitions serve a variety of functions, shaping and potentially narrowing the scope of policy solutions that are deemed relevant for the public and decision agenda (Wood & Doan, 2003). They serve to enable issue expansion or containment, coalition building, and favorable venue shopping (Schattsneider, 1960). Thus, problem definition not only shapes an understanding of the goals appropriate to a given policy domain, but also which actors and institutions should have a say in this process (Rhinard, 2010).

AI policy as a whole, as well as sector specific instantiations of AI, and even individual AI use cases have been subject to problem definition. At the macro level, scholars have studied whether AI broadly is framed in terms of its economic implications surrounding innovation or competitiveness or readiness, or around strategic frames surrounding geopolitics and economic and military competition, or still frames surrounding ethics or human rights (Bareis and Katzenbarch, 2022; Imbrie et al., 2021; Schiff 2024). At the sectoral level, scholars have debated whether AI in domains like criminal justice or welfare is a fix to underlying problems of human inefficiency and access, or a compounding factor that may exacerbate bias and dilute transparency (Hall et al., 2023; Weinberg, 2022; Zkia et al, 2023). Finally, at the individual use case level, AI tools like robotic surgery, lethal autonomous weapons, or labor replacing industrial robots have been framed in very diverse fashions, ranging from public safety to societal threat (Lawless & Sofge, 2017; Moradi & Levy, 2020; Nissim & Simon, 2021; Watts & Bode, 2023).

Thus, how AI related problems are identified, defined, and tested is the first dimension in our framework along which we will examine the prospects for politicization.

## Policy tools

A second dimension that may lead to polarization or politicization is whether various policy instruments, tools, or solutions are deemed acceptable and appropriate by political actors. One well known phenomenon is that of problem surfing, where policy entrepreneurs with pre-existing attachments to particular policy solutions attempt to couple those with any problems where a fit can be credibly articulated (Boscarino, 2008; Cairney & Zahariadis, 2016). For instance, the European Union, which has sought to advance its own digital sovereignty against US driven technological hegemony, has expressed a desire to shape AI policy to protect homegrown innovation and not cede further advantages to US tech giants (Larsen, 2022). As a result, it has continued to favor regulatory solutions that might constrain large multinational technology companies, while providing regulatory flexibility, funding, and innovation support to small and medium enterprises (European Commission, 2024).

Other persistent debates surround the tenor and comprehensiveness of possible policy solutions. Some policy entrepreneurs favor centralized, horizontal regulation while others favor sector specific, vertical regulation that may be more efficient or convenient to incorporate into existing industry risk management programs (Cihon et al., 2020; Trengrove & Kazim, 2022). Some policy actors argue for sweeping protections, a new robot tax, or enhanced social safety net initiatives like a universal basic income, while others are inclined to favor a limited product safety regime (Kovacev, 2020; Marchant & Gutierrez, 2022). Debates between precautionary and pro-innovation approaches, or between the importance of shorter-term ethical concerns versus longer ones are common (Andreesen, 2023; Baum, 2017). These solutions attach to existing preferences regarding political values, the appropriate scope of government

[6] While terms including: definitions, issue or policy frames, narratives, and still other concepts as applied to policy problems could apply here, we select "policy problems" for parsimony.

action, the value of private versus public sector governance, and the prospects for beneficial versus harmful AI, amongst numerous other factors. Indeed an ongoing debate is whether AI is itself the 'fix' to social ills or primarily represents another problem that itself demands solutions (Katzenbach, 2021).

Contestation over which policy solutions or policy mixes are technically feasible, politically or publicly acceptable, or compatible with existing policy subsystems (Bicket & Vanner, 2016; Majone, 1975; Todt, 2011) is thus another important dimension in the framework.

## Actors

Actors, the power they exert, and the dynamics between them constitute a staple of how policy images and subsystems are shaped, and how policy change occurs. Classic typologies distinguish formal from informal actors, or interest groups from the public and government (Gilens & Page, 2014). Policy theories likewise nearly universally include the role of actors, whether as individuals, tightly-knit organizations, or loosely-knit coalitions in their explanation of the policy process (Sabatier, 1991; Rozbicka & Spohr, 2016). Policy scholarship identifies groups of actors ranging from policy entrepreneurs to policy communities to epistemic communities to transnational advocacy networks and much more (Miller & Demir, 2017; Neshkova & Huo, 2018). Indeed, Grossman (2012) identifies as many as 1,300 policy actors identified in books and articles in the second half of the 21st century. Research related to these stakeholders often articulates the structure of the actor groups, the roles and activities undertaken, and avenues for exerting power and influence (Marshall et al., 1985; Richardson, 2000. Indeed, stakeholders are responsible for making choices around issue framing, venue selection, lobbying, and ultimately adopting an implementing policy (Behmke, 2016; Tarlea, 2018).

In the context of AI policy, scholarship has likewise begun to unpack the roles and activities of industry actors, civil society, the general public, the media, and AI researchers and experts, amongst other actors (Deshpande & Sharp, 2022; Justo-Hanani, 2022; Schiff, 2022). Central debates surround the extent which the AI policy agenda is being shaped by experts, given its status as a highly complex, technical domain (Schiff, 2023), how to foster meaningful public participation (Buhmann & Fieseler, 2021; Seger et al., 2023), what strategies policy entrepreneurs are employing to influence policymakers (Schiff & Schiff, 2023), and how policymakers are weighing trade-offs between civil society advocacy and industry lobbying (Tallberg et al., 2023).

Much of this literature has helpfully drawn on prior conceptions of stakeholder activity, but even more remains unknown about the composition, power, and effectiveness of different stakeholders. Our framework therefore attends to the possibility that different stakeholders active at the state level could exert more or less agency to shape a particular policy image, frame AI along a certain partisan perspective, or leverage existing relationships and power pathetic policymakers.

## Subsystems

Relatedly, strong policy preferences can attach to existing policy sectors through the policy regimes and images that are dominant in a given policy subsystem (Baumgartner & Jones, 1991). Subsystems that are sufficiently controlled by a standing policy image or set of actors may be termed a policy monopoly. Sectors can thus serve as structural focal points (Ringe, 2005) which channel liberal against conservative perspectives (in a simple, bipartisan context) around sectors such as criminal justice, education, taxation, and foreign policy (Nicncic & Ramos, 2010). Moreover, sectors that are more salient and accessible to the public may receive heightened attention from policymakers as well (Wlezien, 2004), rendering those sectors more  (or less) prone to conflict and less capture by interests or technocrats. For example, Horowitz and Kahn (2021) find that amongst local US policymakers, Republicans are less supportive of AI used in autonomous vehicles and surgery compared to Democrats, while there is bipartisan support around natural disaster planning.

An open question is whether AI could at the micro scale or within individual policy subsystems, disrupt those subsystems or cut across them, creating new cross-sector issue networks. For instance, the uptake of AI tools or narratives surrounding AI policy could make activity in a certain policy subsystem more favorable (e.g., social safety net supports to deal with labor disruption, increased STEM education) or less favorable (e.g., social media platforms, targeted advertising, autonomous weapons). Some actors may seek to explicitly preserve existing policy images or utilize the stability of those images to cast AI solutions in a positive or negative light, such as using AI tools to preserve public safety in a criminal justice or national security context (O'Carroll, 2023), or letting trusted medical professionals have agency over AI systems they adopt (Sand et al., 2021).

Importantly, political cleavages are not only attached to entire sectors. Existing policy 'sub-images' associated with long-standing partisan disagreement may characterize sectoral debates handily. That is, Democratic and Republican may have clearly carved out and competing stances on criminal justice reform, environmental regulation, or racial politics that are instrumental in how they interpret AI. As Crosson et al. (2024) highlight in one of the few studies on state-level AI politics, legislators with a liberal ideology are more inclined to support legislation focused on consumer protection. Politicization attached to policy subsystems constitutes the final dimension of our framework. In key ways, policy subsystems are reflective of all of the prior dimensions of the framework: problems, solutions, and stakeholders.

Table 1: Conceptual Framework

| | **Description** |
|---|---|
| **Problem Definitions** | The framing of which problems matter in the AI policy domain, e.g.,: ethical, economic, geopolitical; connected to novel or familiar social issues; narrow or broad in scope |
| **Tools** | The nature of proposed and popular policy solutions, e.g., technical or social, abstract or concrete, uncontroversial or controversial |
| **Actors** | The types of actors prominent in shaping policy, e.g., experts, industry, civil society, and the strategies and power they exert |
| **Subsystems** | The attachment of AI to existing or new policy images; the venues, problems, solutions, and stakeholders associated with AI policy activity |

Table 1 summarizes the components of our conceptual framework. While not comprehensive, and while developed with a special focus on the US context, may serve as a useful starting point for understanding the lines along which partisanship may or may not emerge.

# Methodology

Our study makes use of a mixed-methods research design, combining an online survey of state legislators in 44 states conducted in late 2021 to early 2022 with case studies of AI-related legislation in three states–Idaho, Illinois, and Colorado–from 2019 to 2022. We couple broader, general insights from the survey with in-depth specifics and process tracing details from the case studies to characterize early developments in state-level AI policymaking. The sections below describe the methodology for both components of the study.

## Survey of Legislators

### Survey Administration and Sample

In December 2021, we sent out emails to 7,355 state legislators–all state legislators for whom we could identify an email address–with an invitation to complete an online survey through Qualtrics on state AI policy. This email campaign was a follow-up to a prior study (Schiff & Schiff 2023) in which we partnered with an AI-focused think tank, The Future Society, to send information about AI via email to state legislators and to host a webinar for state legislators on AI policy. The email campaign for the current study began on December 14, 2021, the day after the webinar for state legislators. In order to increase the response rate, we sent out reminder emails after one month (in January 2022) and after two months (in February 2022), times of the year during which many state legislatures are in session.

In total, 129 legislative offices participated in the survey (response rate of about 2%), with 44 states represented.[7] Despite the small response rate–typical for studies of state legislators–the sample is fairly representative of the full population of state legislators as shown in Table 2, except that there are slightly more Republicans in our sample. Further demographic information about the sample is displayed in the appendix.

Table 2: Comparison of Survey Sample to Full Population of State Legislators

| Demographic | Survey Sample | Full Population |
|---|---|---|
| Prop. Lower Chamber | 0.71 | 0.73 |
| Prop. Democrat | 0.33 | 0.45 |
| Prop. Independent | 0.02 | 0.01 |
| Prop. Republican | 0.65 | 0.54 |

[7] No state legislators from California, Delaware, Indiana, Nevada, New Jersey, and Texas participated.

| | | |
|---|---|---|
| Prop. Female | 0.32 | 0.31 |
| Average Tenure (in years) | 5.51 | 6.13 |
| Average State Squire Index | 0.20 | 0.22 |
| Number of Legislators | 129 | 7,355 |

### Survey Design and Analysis

In constructing the survey instrument, we drew on prior studies of public opinion on AI and used many of the exact survey questions from the O'Shaughnessy et al. (2022) study of public and expert opinion for validity and comparability. Our survey instrument obtained informed consent from participants[8], provided a definition of artificial intelligence (AI) adapted from Zhang and Dafoe (2019), and then proceeded to ask questions about AI knowledge and preferences.

The survey asked about legislators' prior AI knowledge and involvement, as well as opinions on AI generally, such as whether the benefits of AI outweigh the risks. In addition, the survey asked about prominent competing problem definitions emerging around AI, such as regarding the importance of AI ethics and human rights concerns on one hand and innovation and global AI leadership on the other hand. Finally, the survey asked about legislators' AI regulatory preferences and priorities, including with regard to specific use cases and policy tools, and which stakeholders legislators would prefer to "listen to" regarding AI. The full survey instrument is included in the appendix.

In presenting the results of the survey, we include descriptive statistics as well as p-values based on t-tests or regression analysis to assess differences in subgroup responses, primarily Democrats versus Republicans. We additionally use principal component analysis (PCA) to identify the underlying dimensions driving state legislators' opinions on AI policy across a range of survey questions. This provides more comprehensive insight into which combinations of values and problem definitions may be structuring legislators' AI attitudes, as well as whether partisanship is a key dimension.

## State Case Studies

To complement the aggregate and self-reported evidence in surveys, we conducted case studies looking at the passage of AI legislation in states in the formative period 2019 to 2022. These cases provide an opportunity to see how state legislators' attitudes on AI translate into action on particular issues and in particular political contexts. This allows us to address questions about key forces that might open, and close, bipartisan windows for action on artificial intelligence. Cases included successful passage of legislative regulation of specific uses of AI. Excluded from consideration were legislation that developed additional bodies or called for further study of AI. We also excluded measures that encouraged AI development generally or called for including AI education into state curriculum or universities. Finally, because of the long existing history of state legislative involvement in regulating autonomous vehicles we did not consider action addressing AVs.

During this time period, there were five cases of legislative activity across three states of trailblazing AI regulations: Colorado (2021, 2022), Idaho (2019), and Illinois (2019 and 2021). These cases address four unique uses of AI across

[8] Our study was deemed exempt by the IRBs at Emory University and Georgia Institute of Technology.

public and private sectors: insurance pricing, facial recognition; pretrial release risk assessment; and AI use in hiring processes. Across these five legislative histories, we have two cases of bipartisan passage, one case of partisan passage with a party line vote, and two cases of emergent partisanship where a small block of senators from one party opposed the measure.

Table 3: Summary of State Case Studies

| **State-Year** | **Use Case** | **Vote** |
| --- | --- | --- |
| Idaho 2019 | Pretrial risk assessment | Bipartisan |
| Illinois 2019<br><br>Illinois 2022 | Hiring process, notification<br><br>Hiring process amendments, testing | Bipartisan<br><br>Emergent partisanship |
| Colorado 2021 | Insurance industry | Partisan |
| Colorado 2022 | Facial recognition | Emergent partisanship |

For each case we look at the legislative history of the bill. We reviewed all committee and floor votes. We analyzed testimony and speeches that were part of hearings and deliberations in the committees and chambers. We also conducted contextual research on key participants for each measure.

We introduce each case study briefly below before presenting our findings, organized along the lines of our conceptual framework emphasizing policy problems, solutions, stakeholders, and policy subsystem.

## Idaho “Pretrial Risk Assessment….”

In 2019, Idaho became the first state to enact legislation targeting the use of AI for pretrial risk assessment. The Idaho law mandated that “all documents, data, records, and information used by the builder to build or validate the pretrial risk assessment tool and ongoing documents, data, records, and written policies outlining the usage and validation of the pretrial risk assessment tool shall be open to public inspection, auditing, and testing.” The law further clarified that there would be no exception based on trade secrets or intellectual property claims. The law targeted the fundamental problem of transparency in automated decision making and AI systems.[9] As an early actor, some saw Idaho as “an exemplar for states committed to using algorithms in pretrial sentencing while retaining the notions of fairness and due process.” (Epic p. 11)

The sponsor of the bill, Representative Greg Chaney (R), was Vice Chair of the House Judiciary, which would be the first to consider the bill. Representative Chaney was supported in this effort by the American Bail Coalition. Other stakeholders involved included prosecuting and defense attorneys, and civil liberty organizations. The Republican dominated legislature passed this first of its kind regulatory legislation

[9] Of note, the bill was originally broader and also sought to ensure through validation that systems were free of bias. However, questions about the definition of bias and who bore the duty and the costs of validation led to this portion being removed to ensure that something was accomplished in the legislative session.

addressing the use of AI in the legal system unanimously in both chambers.[10] From this case, we observe key lessons about the regulatory tools and sectoral targets that may draw bipartisan support. In particular, the passage of this measure in Idaho highlights two important elements in AI regulatory politics: the defining role of private industry in the particular sector being targeted for regulation; and the importance of academic specialists in problem definition around emerging technology. This case can thus be used in conversation with other state cases addressing other sectors to provide lessons on how debates over technology may map onto partisan interests as these emerging issues become more regularized.

## Illinois

In 2019, Illinois passed a law, the first in the country to address the use of artificial intelligence in hiring practices, focusing on AI applied to video interviews. The law required the candidate be notified and explained the basics of the system, and it limited who could view the video and permitted the candidate to request destruction of the video. The 2019 bill focused on transparency and notification passed in Idaho with bipartisan support. In 2021, the state legislature passed an amendment to require companies who utilize AI to eliminate candidates at initial stages of the hiring process to gather and report statistics on race to the state. The state would then be able to see if such systems presented problems of bias and discrimination.

There was no enforcement mechanism attached to the self-reporting and no indication of what would be done with the information. This additional step, still not regulation but an attempt to study the use of such systems did, however, develop more resistance, resistance that was along party lines. The Illinois senate passed the measure 43 to 11. All eleven in opposition were Republican Senators, while four Republicans supported the measure. In the house, the vote was 112 in support with five Republican representatives voting against the proposed legislation. This was a small fraction of the Republican delegates who generally voted overwhelmingly in support of the bill; however, we do see possible emergent partisanship.

## Colorado

Colorado passed two important pieces of legislation, one addressing the use of AI in the insurance industry and a second considered the use of facial recognition and AI by public entities. In 2021, Colorado became the first state to legislatively address the challenges of monitoring the insurance industry in the wake of the big data algorithmic revolution by requiring self-testing and self-reporting. Insurance agencies are required to test their tools to ensure they do not unfairly harm protected classes.[11] The 2021 legislation extended this requirement explicitly to AI systems used for similar purposes. This trail blazing piece of legislation passed along party lines.[12]

[10] (The House in Idaho during the session had 56 Republicans and 14 Democratic members. The Senate had 28 Rs and 7s Ds).

[11] Partnering with the insurance industry to submit their own testing was essential; while the insurance commission may have had existing the authority, limited in house technical expertise, a rapidly shifting technological landscape, and a breadth of different uses of big data and AI systems meant it was possible for the insurance commission to conduct such tests themselves.

[12] The Colorado House passed the bill 21 to 23 in a straight party line vote. The senate passed it 21 to 14 a largely party line vote with only one Democrat voting against the measure and one Republican voting for the bill.

During the next legislative session, the state legislature took up the issue of state use of facial recognition[13] and passed legislation with three main parts: the first called for a pause on any new acquisition of AI tools by law enforcement and public schools, the second established a working group to develop policy around the use facial recognition by state and local agencies, and the last established an interim regulatory regime to govern use of AI tools by schools and law enforcement agencies. Voting on this bill was governed less by partisanship than the previous vote over insurance regulation. AI's use in facial detection and recognition split the Republican Party. In the senate, seven Republicans voted against the bill and five voted in favor of the bill. All Democrats voted for the bill. In the house, nine Republicans joined the house Democrats voting for the bill, and 14 Republicans voted against the bill. Comparisons between the legislative histories of the early Colorado moves to address the use of AI in both the public and private sector reveal important dynamics about party influence in debates over technology policy.

# Results

## Problem Definitions

### Evidence from the Survey

Based on the survey results, we find bipartisan agreement on several general themes, values, and problem definitions related to AI. First, we find bipartisan agreement on urgency: 65% of state legislators responded that it is better to start regulating AI now, rather than wait, with no significant differences between the parties ($p$ = 0.43). In addition, 64% of legislators (70% of Democrats surveyed and 61% of Republicans surveyed) indicated that they would support legislation on *privacy*, suggesting another shared priority and value. Moreover, a full 96% of the state legislators that we surveyed said that they support the *careful management* of AI.

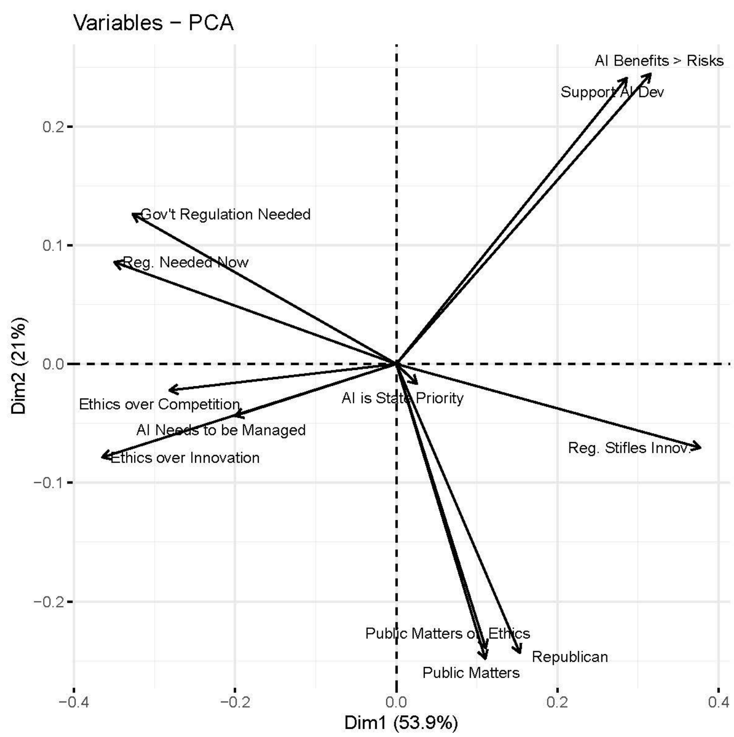
State legislators also indicated a shared concern for social and ethical risks when forced to select between competing problem definitions. We asked legislators to choose between the view that "AI's benefits for innovation are tremendous; any social and ethical risks will not be too difficult to address" and the view that "AI's social and ethical risks are a major concern; efforts to innovate need to consider these issues more seriously." Of the 103 legislators that answered this question, 73% (76% of Democrats and 70% of Republicans) chose the perspective that social and ethical risks are a major concern. Thus, the general problem of social and ethical risks elicits similar levels of concern across parties. However, when those risks are differently specified, partisan differences begin to emerge. In a forced choice between global AI

[13] Oregon was the first state to address facial recognition in law enforcement through legislation. Since then over a dozen states have adopted some kinds of restrictions ranging from an almost near total ban in Vermont to state laws ensuring it cannot be the sole basis for arrest. In 2020, New York became the first state that banned the use of facial recognition in schools, until the state education commissioner could study and report the use of such technology in school. Like other well touted and publicized early activity on AI, the New York ban appeared to be more hype than reality. When the ban was passed civil liberties groups and others suggested New York was a leader in civil rights, and a first in the nation. However, the impact of the legislative ban was not clear. Schools were left without guidance on purchasing different kinds of security technology and with vendors selling camera dependent tools and no enforcement, the moratorium was less than complete, and the inclusive and expansive study seems to have not happened as imagined. https://nysfocus.com/2023/03/28/facial-recognition-schools-new-york; https://www.nyclu.org/en/news/ny-ignoring-ban-facial-recognition-schools. The ban expired in July of 2022 and the future of facial recognition in New York schools is unclear.

leadership and respect for human rights, 70% of all respondents chose the perspective emphasizing respect for human rights. While majorities in both parties still signal greater concern for human rights over the race for AI leadership, Democrats do so by a much wider margin (83%) than Republicans (64%).

We see similar results when we use principal component analysis (PCA)[14] to explore the underlying dimensions explaining state legislators' responses across survey questions. The PCA results indicate that two key components explain about 75% of the total variation in legislators' responses, and Figure 2 graphically represents how the survey measures map on to these top two dimensions. The first component, explaining 53.9% of the total variation across survey questions, corresponds to a dimension emphasizing the tension between 1) innovation on one hand and 2) ethics, regulation, and careful management on the other hand. Noticeably, partisanship (Republican identification) is not a prominent part of this dimension. Instead, Republican identification relates to the second component, explaining 21% of the variation in responses, that also incorporates support for AI development, AI benefits, and attention to public input. The PCA results suggest that there may be a (bipartisan) coalition possible around regulating AI due to shared concerns for AI risks and ethical impacts emphasized by legislators of both parties across a variety of related questions.

Figure 2: Dimensions Underlying State Legislators' Opinions on AI Policy




Nonetheless, we also observe partisan differences on other survey questions. For example, on a question about support for hypothetical legislation to encourage more immigration of high-skill STEM workers, Republicans indicate much lower support than Democrats ($p$ = 0.03). Additionally, Republicans were

[14] For the PCA, we use a correlation matrix based on 12 survey questions, with a subset of 91 legislators who answered all 12 questions. The 12 survey questions represent the key themes driving our survey design. Support for AI in distinct use cases is strongly correlated with general support for AI development, so we omit use case specific questions.

somewhat more likely than Democrats to indicate that regulating the development and use of AI will "stifle innovation" ($p = 0.09$).

## Examples from the Case Studies

The state cases initially echo survey findings for potential bipartisan support of addressing ethical and social risks of AI. The problems that moved legislatures across the aisles to act were privacy, lack of transparency, and general lack of knowledge about the technology prior to widespread deployment. Yet other social or ethical dilemmas from AI usage, however, were a barrier to bipartisan support for action. When legislative debates centered on ongoing problems in the policy community regarding equity or fairness, popular transposed frames surrounding racial equity stirred partisan action. In each state, Idaho, Illinois, and Colorado, we witness multiple, sometimes competing problem definitions. In each, we see the broad salience of privacy and transparency, but alongside the political challenges of framing the problems around fairness and racial equity, which constituted a challenge in developing robust bipartisan support.

In Idaho, sponsors and proponents of legislation targeting the use of AI in pretrial risk assessments began with two central policy problems: fairness and transparency. The former posited that risk assessments were less fair than bail, a central thread in the broader debate over bail reform. The latter focused on black box systems making critical decisions, a new policy problem centered on new technology. Vice Chairperson Chaney (R) introduced the bill using a popular cultural referent, the film *Minority Report*. Rep Chaney discussed the dystopian world where individuals are punished for crimes they did not commit, stressing the two problems embedded in the movie the legislation would address: "the first was that it was unconstitutionally punishing people that were doing no wrong, and number two they were hiding errors that occurred." (House judiciary committee cite)

Opponents focused on the problems of bias. Mark Manweiler representing the Idaho Association of Criminal Defense Attorneys testified against the bill, trying to tie it into debates about bail reform and decentering questions about the technology itself as speculative. He noted that pretrial risk assessment is "common sense" and had been used exclusively in the federal government since 1984 and in Idaho for juveniles. He did not address the question of transparency, but instead focused on competing claims about fairness:

> One thing the bill does not address is the financial bias of the current system we have in Idaho which allows rich people to post million dollar bails and poor people who are arrested for vagrancy or drunk in public or violating a park curfew and they are homeless and they have a $300 bail and they sit in jail [at taxpayers' expense]... That's much more important in our view, the financial bias with the bail system that we have, than a theoretical potential problem if some of these counties decide to go to algorithms. … This isn't a problem yet in our state anyway (February 19, 2019)

Manweiler contested then that there was a problem of fairness that pre-trial risk assessment would solve and called this bill favoring regulation of AI assessments a "solution in search of a problem." This echoed a previous exchange in the committee when a member argued there was not a problem with racial bias in Idaho. Rep Hartgen noted: “The pretrial release programs that I am familiar with in one of the larger counties, I guess I have never noticed that a bias is on nationalities but more on if they actually live in the community if they are a flight risk…criminal record in the past” (February 7, 2019). Opponents also argued that the problem of racial bias was intractable.

In response to such challenges, proponents did not sustain a defense of the importance of addressing bias but pivoted to the problem of transparency. In response to Rep Hartgen’s direct challenge that pretrial risk assessment did introduce special problems related to race, Chaney did not provide evidence that racial bias was a concern but instead shifted to a transparency frame. He noted that the main concern is that there is “no way to know how much weight is placed on a given factor under the current system.” Similarly, when confronted with challenges about the “solubility” (Peters 2005) of the problem of bias, Jeff Clayton, the executive director of the American Bail Coalition and a strong proponent of the bill, stressed problems with “trade secrets” and “black box technology.” He noted, “Transparency is the heart and most important piece of this bill. Regardless if you can come up with some solution to racial bias or not. Let academics, let people who are able to do this work do it. If it’s an open source system, you’ll get the information you want. And so if you don’t do anything, do that” (February 19, 2019). In the sponsors closing remarks, Rep Chaney concurred saying “At a minimum we need transparency. I think the definitions of bias are ready to move forward but at a minimum we need to see inside the black box.”

The rest of his closing remarks crafted a problem definition to have broader appeal, part of an issue expansion strategy. He situated the problem of risk assessment not solely as associated within problems within the criminal justice system, but instead regarding general questions about technology and society:

> The desensitization of our culture towards technology and the pervasiveness of big data is remarkable. What we’ve come to accept. What are we going to come to accept in criminal justice? What are we going to get desensitized to?... When I think about all the things that desensitize us [lifts cell phone here], not only about using technology but sharing information, not only things people say about themselves, things people say about each other we’re fine being under surveillance we invite surveillances. When I think about the other ways our culture is becoming increasingly desensitized and then I think about any sort of nonchalant attitude towards constitutional violations being shrouded in technology and being acceptable because it is being wrapped in technology, I realize that if we are indifferent to constitutional violations or the risk of it today because its’ out of sight out of mind and it works. What will be like in 2054?

After a narrow passage out of the committee, Rep Chaney said he would be willing to work with others to amend the bill before it came to the floor to focus on transparency. The bill was amended to remove any requirement that the risk assessment tools be shown to be free from bias. The bill that received bipartisan support in the house and senate only required public access to data.

We witness similar dynamics in Illinois and Colorado. The Illinois legislature moved from its 2019 bipartisan support of a bill that focused on questions about transparency and privacy to a 2021 partisan debate and vote on a bill that centered the problem definition on bias in the hiring industry. In Colorado, the 2021 debates similarly centered on the degree to which AI in insurance decisions could lead to discrimination and bias against protected classes, and the votes on the bill likewise demonstrated emerging partisanship. The subsequent year, the legislature considered regulation on facial recognition where racial discrimination was only one of a number of competing frames among a range of social and ethical risks. This bill passed with more bipartisan support including with support of some of the vocal opponents of the insurance bill the year before.

The differences between the two Colorado cases are telling. The debates over regulation of the use of AI in the insurance industry centered competing understandings of race and discrimination. The bill covered other protected groups such as surrounding gender identity, sexual orientation, and disability status; however, the majority of the testimony addressed concerns about racial discrimination and centered on competing racial projects. Supportive witnesses and sponsors of the bill spoke about structural racism and systemic inequality, pointing to previous racist practices such as redlining, over-policing, or job discrimination that affected current data points used by many insurance systems such as credit scores and neighborhood crime rates. Proponents also noted that big data in other sectors have been shown to have racial bias due to training on data generated from a society steeped in racial discrimination.

Opponents of the bill countered the concerns about systemic racism by focusing on intentional acts of discrimination, a central tenet of color blind conservatism. One senator critical of the legislation asked an insurance provider:

> To you, Mr. Martinez since you work with a lot of different ethnic groups, especially people who speak Spanish, have you ever had your clients come to you and say 'geez, I feel discriminated against because I speak Spanish or because of my race.' Do you have people that come to you and complain to you about this all the time?

All three insurance agents present quickly and emphatically testified that they had never witnessed the use of protected categories in the industry and that customers had not expressed concerns about discrimination. The bill passed the house and the senate on a party line vote.

During the next legislative session however, the Colorado legislature, with bipartisan support, passed a law requiring a pause on acquiring facial recognition systems by public entities and instituted an interim regulatory regime for existing systems. While the new tools in the insurance industry focused on an old problem, regulating discrimination in the insurance industry, facial recognition did not have an evident precursor to frame the debate. Witnesses and representatives throughout the hearings tried on a range of framings from other domains such liberty vs. security, regulation vs. innovation, demanding racial justice in policing vs. supporting police; and protecting victims vs. criminal justice reform.

None of the attempted transposed frames fully stuck as the hearing demonstrated representatives were ultimately grappling with just understanding the technology, and understanding what policy problem they were addressing. Was the problem unreliable readings or the unequal distribution of error rates? Was the problem children's privacy? In this emergent policy domain, one that had not been entrenched in partisan battles nor drenched in business interests (yet), there were a variety of different problem definitions and a number of different frames.

Notably, in the absence of a dominant partisan frame, given an emergent technology and an emergent justice issue, academic witnesses proved important to help representatives try to walk through some of the challenges of problem definition for this new regulatory area. Academic witnesses also told representatives that Colorado was among the trailblazers in this field and as such was developing new standards. Here, acting on procurement questions in the public sphere could put Colorado ahead in the technology race. Despite possible association with clearly partisan polarized issues (e.g., support of police and victims vs. rights of the accused; reduction in technological progress due to government interventions) this “cutting edge” legislation on facial recognition did not have a single dominant party frame.

## Summary of Findings

To summarize, the survey and case studies suggest four lessons about problem definition and partisanship. First, state legislators may be able to reach across the aisle when AI policy discussions pertain to general risks, rather than more specified problems. Actors across parties recognize social and ethical risks as challenges that need to be addressed through careful management of AI. Second, bipartisan action seems more likely if technology is framed as creating a *new* problem rather than exacerbating old or existing problems. Third, if policy entrepreneurs highlight problems connected to party-owned issues, such as immigration, racial equity, or market competition, the survey and case studies show that politicians will respond to party cues over potentially shared concerns about AI. Fourth, key values that are not tied to a party, specifically privacy and transparency, are powerful motivators for bipartisan legislation on AI. This willingness to embrace collective frames suggests that collective, social harms of AI may be easier to address in a bipartisan fashion than risks to subgroups.

Given these findings, there may be a temporary but important window for bipartisan action on AI. In general, a less well-specified problem definition may undermine other kinds of policy goals, but for minimally initiating regulation of AI, lack of specificity may be a strategy. The broad-strokes agreement on dangers related to AI, but lack of agreement on specific problems, is due in part to a prevailing vague problem definition that emphasizes that the dangers of AI are ‘not well known.’ While there is still much disagreement among developers, researchers, and the public about the scale and character of AI risks, there might be continued success for measures targeting general threats of AI.

# Tools

## Evidence from the Survey

The survey also provides some evidence regarding the policy tools or solutions that state legislators would support. Building on the findings regarding problem definition, we see bipartisan agreement on general approaches for information-gathering and research. For example, 45% of state legislators indicate that they would support legislation “requiring companies to perform risk assessments for certain AI products.”

This is the second highest area of agreement on legislation after privacy, and we find no difference in support across political parties ($p = 0.20$). Both parties also have somewhat similar levels of support for providing funding for AI research and development ($p = 0.62$).

Yet, similar again to problem definitions, partisan cleavages emerge when policy tools implicate the size of government or involve contrasts between the public and private sector. For example, Republican state legislators are about 31 percentage points less supportive of increasing government capacity and expertise in AI[15] than Democratic state legislators ($p = 0.002$). We also see evidence of partisan differences in preferences for formal government regulation of AI: Republicans are about 18 percentage points less supportive ($p = 0.15$). While 67% Democrats favor hard governance (formal government regulation) and 33% favor soft governance (less formal government oversight and monitoring), 38% of Republicans favor hard governance, 53% favor soft governance, and 8% favor industry self-regulation.

## Examples from the Case Studies

The Idaho and Illinois cases illuminate that widespread support is affected by the policy tools under deliberation. In Idaho, the bill targeting pretrial release risk assessments originally sought to require validation that systems were "free of bias." However, questions about the operationalization of freedom from bias, technical feasibility about such validation, as well as who bore the duty and the costs of validation led to this portion being removed, ensuring that the measure could pass the Republican dominated legislature. Notification and consent were the alternative tools that could garner broad bipartisan support.

We see a similar shift in Illinois between the bipartisan passage of the law addressing the use of AI in the hiring process, and the amendment to that law the subsequent year. Representative Andrade (D) introduced the bill to require notification to employment candidates about the use of AI. The bill was passed out of the House Labor and Commerce committee with no debate and no witnesses. Once the bill landed on the house floor, debate highlighted the importance of certain policy tools to generate bipartisan support. The sponsor and others in favor of the bill repeatedly noted this legislation simply required notification.

Some skepticism emerged from Democrats who favored hard governance instead. Rep Flowers (D) believed notification would not address racial discrimination and would ironically provide employers with the cover to use AI systems, increasing usage and therefore discrimination. Andrade noted another bill he introduced that proposed stronger regulatory tools but was held up in committee. In contrast, Republicans supported this soft governance approach. Representative Deavidsmeyer (R) provided clarity about the policy solutions being forwarded: "Okay. So what your Bill does, is it requires now, instead of just being able to do it without letting anybody know, it requires them to let the individual know who's being interviewed…So, so this is a good, you know, personal protection Bill, right?" (p. 40) To further stress how notification was a critical policy tool in a range of settings that involve technology, and should therefore engender bipartisan support, Rep Williams (D) stated:

[15] Between 2019 and 2022, five capacity building measures were passed in legislation, one of which was vetoed. VT H410, 2021; WA, S 5092, 2021; NJ S2723, 2020; CA A 485, 2019; CA A.B. 594 (vetoed).

> Great. So you're saying all this Bill does is provide notice that data's being collected. I just will note for my friends on the Republican side….Note on the other side of the aisle, I'm very intrigued by the fact that you are concerned about a simple notification of collection of private personal data. If you're concerned about that, I have a great Bill on geolocation you might be interested in...I would just encourage all of you to take a look a little deeper when we're talking about advancing technology and ask yourself the question, what is this data being used for? How is it being used? And are people even aware that it is being utilized and collected? (p. 42)

Rep Williams, in an attempt to overcome a possible partisan divide, stressed the particular tool, notification, as something that should be adopted across technological domains and supported by policymakers across parties. The bill passed the Illinois legislature with bipartisan support.

Two years later, an amendment to the previously passed legislation required that any business who used AI as a sole determinant in offering in-person interviews to report the race and ethnicity of applicants who are and are not offered an interview and of those who were hired. Data would be sent to the state Department of Commerce and Economic Opportunity who would receive, analyze and report on the collected data. Representative Wheeler in the Cyber Security Data Analytics Committee argued that the tool was a limited one that did not place a burden on businesses. He noted that there was no application, fee, or certification but simply reporting of some basic data. He described the policy tool as modestly "dipping our toe in the water" to help understand "how AI can be used in the hiring process and using it fairly so that people are [not] disadvantaged by it." However, some representatives still saw this additional regulation as a potential burden on small business owners. The final vote showed an emerging partisan divide over a policy that required only testing and reporting with a small block of Republicans voting against the measure in the house and the senate.

In Colorado, a debate over the best approach to handle the problem of racial discrimination in insurance, government regulation or the market, contributed to a party line vote. Opponents of the proposed bill argued that a competitive market was the best way to take care of discrimination in insurance. Insurance agents, they contended, would want to secure business by offering rates that were lower than their competitors'. If risks were indeed falsely inflated, a customer could respond to this discrimination by shopping around in the market. Such an analysis was used to counter witnesses who provided personal testimony of encountering discrimination in the insurance industry, noting that the corrective should not be government intervention but continued encouragement of the private market.[16]

One senator asked an insurance agent if they would be willing to follow up with any individual who presented a story of discriminatory treatment to secure them better rates. This was meant to illustrate that agents are incentivized to offer lower rates that legitimately matched risks, minimizing the chance of discrimination. Additionally, the bill's proposed policy solution would cause more problems than it solved, according to critics. First, the required reporting would in fact *open* the doorway for discrimination by

[16] Senator Liston: "And to you Mr. Martinez since you are bilingual, which is great, when you speak to a Spanish Speaking person and they have questions or are concerned about their one policy that might be a little more expensive, uh and they come to you or vice a versa you can go to them do you ever say look I can shop around for you and I can find you a better policy at a cheaper price … so you are more than willing to work with your clients and encourage them to shop around … because you want to retain them as a client is that correct?"

requiring agents to collect data about protected categories such as religion, race, gender, and sexual orientation. Second, this policy tool would lead to other unintended consequences such as market instability and driving up rates. This strong government intervention passed without Republican support.[17]

### Summary of Findings

In both the Illinois case and the Colorado case, we see tools like reporting and monitoring can introduce expected party line concerns as the issue of the burdens on businesses arise. This however is dependent on the stakeholders present and perceived stringency of the tool. Without an effective business lobby, reporting requirements can develop bipartisan support as seen in the Colorado case we explore below. That is, while surveys suggest that Democrats favor hard governance approaches and Republicans favor soft ones, the case studies demonstrate that soft governance functions as a ‘lowest common denominator’ that can generate bipartisan support. This is evident in the bipartisan support of consumer notification and consent requirements. As in the Illinois case above, there are indications that Democrats will support industry reporting when stronger regulation seems unlikely to be successful. For Democrats, this might serve as a first attempt to build a more robust policy mix. For Republicans, this might serve as a strategy to provide tacit endorsement of the use of AI even when more robust policy solutions may never come into play.

## Actors

### Evidence from the Survey

In the survey, we asked state legislators to rank seven stakeholders–civil society and advocacy groups, members of the public, private companies, intergovernmental or international actors (e.g., United Nations, European Union), the federal government, academic researchers and think tanks, and the media–according to their importance for 1) AI policy in general, 2) policy issues related to ethical/social implications, and 3) policy issues related to security/economic competitiveness. State legislators’ responses mostly indicate partisan differences, with one possible area of bipartisan agreement.

The largest partisan difference concerns attention to industry stakeholders. Republican state legislators consistently ranked private companies an entire standard deviation higher in importance ($p < 0.001$) compared to Democratic state legislators. Moreover, while Republicans were relatively more likely to seek input from members of the public ($p = 0.03$), Democrats were more likely to seek guidance from the federal government ($p = 0.06$), intergovernmental actors ($p < 0.001$), and academics ($p = 0.05$).

A possibility for bipartisan agreement concerns the consultation of academics for more specific purposes. While Republicans were less likely to indicate that they would listen to academics generally ($p = 0.05$),

[17] While debate over the tools did come up in Colorado, with a complex and indeterminate problem frame, and the lack of an effective business lobby, the debate over tools did not gain much traction. The Colorado bill proposed a pause on new acquisition of facial recognition systems and a task force to develop an interim regulatory regime to deal with the problem of bias and discrimination in facial recognition. One of the two opposing witnesses stressed that this tool was the equivalent of a ban. The representative from the Security Industry association noted the similarity with a Washington law that was so complex that no one applied for a permit and therefore functioned as a prohibition. He suggested that a task force would be good but that the regulation would decrease innovation and therefore public safety.

Democrats and Republicans may be similarly willing to seek input from academics on policy issues related to ethical/social implications ($p = 0.99$) and policy issues related to security/economic competitiveness ($p = 0.88$).

## Examples from the Case Studies

The two legislative debates in Colorado a year apart had different constellations of stakeholders and different levels of partisan voting. The 2021 battle over the use of AI in insurance was a faceoff between industry on the one side and consumer protection and civil rights groups on the other. Testifying in opposition to the bill or asking for radical amendments and exclusions were 10 insurance associations, two chambers of commerce, and two individual insurance agents.[18] Testifying in support of the bill included twelve civil rights, consumer rights, or economic justice organizations. [19] As questions about the technology only appeared on a few occasions in the house and senate committee sessions, [20] no academic witnesses were present for what ended up as a party line vote.

In 2022, the smaller witness list for the debate on facial recognition included a different cohort of stakeholders. Industry witnesses opposing the legislation represented the developers of the AI products and not the end users. These developers were limited in their number and capacity, and confronted a different and also modest set of opposing stakeholders. Two witnesses testified in opposition to the bill, a representative from the Security Industry Association and a woman from Clearview AI. Clearview AI, one of the largest providers of AI security technology founded in 2017, did not have a long history of lobbying and government affairs. The representative from Clearview spoke about her personal experience as a victim of sex trafficking. She noted that facial recognition technology can alleviate the horrific abuse she experienced. She emphasized the rights of victims to be identified and that perpetrators deserved to be identified. She did not present evidence on the effectiveness of facial recognition to these ends or discuss the technology or use of it more broadly. Notably, vendors of AI were not present as witnesses in the other cases, including the Colorado case regulating insurance. However, when present in this case, they were isolated in their opposition to regulation and their testimony did not result in moving legislators to oppose the regulation.

Testimony on the technology and possible concerns about its effectiveness and bias came from academic witnesses, the most numerous type of participants in the bill's hearings. All six academics spoke or submitted testimony in favor of the bill. Users of the technology also supported the bill.[21] The power of academic witnesses to open up bipartisan windows is also evident in the role played by a computer science professor in the Idaho case and indicated in the survey data where both Democrats and Republicans expressed a willingness to listen to academics about the risks of AI.

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[18] Insurance Information Institute; American Property Casualty Insurance Association, The Aurora Chamber of Commerce, Denver Metro Chamber of Commerce, National Association of Mutual Insurance Companies, American Council of Life Insurers, and individuals who owned insurance agencies.

[19] Supportive witness testimony came from Colorado Organization for Latina Opportunity and Reproductive Rights, Colorado Center on Law and Policy, Colorado Children's Campaign, Colorado Consumer Health initiative, Consumer Reports, New Era (an advocacy organization that works towards youth empowerment economic justice), Center for Economic Justice, One Colorado (an advocacy organization for LGBTQ Coloradans), The Bell Policy Center (which promotes economic mobility in Colorado), Consumer Federation of America, and, once some confusion on an accidental removal of disability from the list of protected categories was clear up, The Colorado Cross Disability Coalition.

[20] The insurance commissioner was the one individual who raised questions that pertained to the specific challenges of the new technology and regulating it.

[21] Of note, one of the main targets of the bill, schools, did not have any witnesses providing testimony in favor or against the legislation.

A representative from the Colorado Association of Chief of Police suggested a pause on further acquisition until a regulatory regime could be established that would ensure users had needed guidance. In contrast, the executive director of the Colorado Information Sharing Consortium, Mr. Shipley, noted that facial recognition tools when "used according to reasonable law and policy" would increase public safety and help with civil rights. Shipley also applauded the sponsors for being receptive to the views of stakeholders. Yet absent from the discussion was a broad set of vendors or any civil rights or justice advocacy organizations. Ultimately, the presence of supportive end users opened a door for this strong regulatory measure, the most comprehensive of the cases studied here, to divide rather than unite the Republican party in opposition.

In Idaho, a coalition of industry, the academy, and civil rights organizations from both the right and the left supported this measure. The Idaho Freedom Foundation, a far right leaning organization, joined the ACLU in giving this legislation a positive rating.[22] The history of the bill suggests the power of well-organized interests as policy entrepreneurs who cultivated an opening for this regulation. Risk assessments, such as the ones regulated in the Idaho law, are key to the growing bail reform movement and a threat to bail insurance companies, as they would enable more individuals to be released from detention pre-trial without paying bail.

Jeff Clayton, the executive director of the American Bail Coalition, and the Executive Director of the American Bail Coalition, a trade organization of bail insurance companies, testified at the key committee meeting. Rep Chaney also reported later that Clayton had worked with him on drafting and amending the bill. Representative Chaney was subsequently prominently featured on the state page of the American Bail Coalition website. This case suggests policy entrepreneurs look to disrupted over prospected industries when considering the coalition building and industry involvement in the politics of AI. Of note here, no representatives from vendors of risk assessment programs were present. The industry being disrupted, the bail bondsman, was the pro-active force trying to stop the risk assessment snowball.

Finally, the limited 2019 bill requiring notification of the use of AI in hiring practices did not elicit any serious resistance or support from outside interest groups. In one house committee, hearing there were three witnesses who registered support of the measure, two representing the Chamber of Commerce. This indicated that business not only did not find this regulation to be troubling but perhaps, even as the Democratic representatives feared, saw it as favorable to business interests. Through non-intrusive notification requirements, businesses felt more confident in the implicit state endorsement of the use of AI for interview vetting.

## Summary of Findings

In sum, there are several important takeaways regarding the stakeholders consulted and prospects for bipartisanship in AI policymaking. First, consulting academics can promote bipartisanship in some instances. The case studies show that academic testimony was instrumental for questions of public sector use of AI (e.g., in Idaho and the Colorado facial recognition case), but much more limited, or even non-present, when private sector use of AI is considered (e.g., in Illinois and the Colorado insurance case). Somewhat similarly, from the survey, we see that state legislators from both parties were willing to

[22] https://idahofreedom.org/house-bill-118-pretrial-risk-algorithms/

consult academics on more narrow issues, such as those pertaining to social/ethical risks of AI or national security/competitiveness, both arguably primarily related to public sector concerns and values.

Second, and in contrast, we find that industry stakeholders may polarize state legislators, unless industry stakeholders represent disrupted businesses. Based on the survey, and compared to Democratic state legislators, Republican state legislators were significantly and substantially more likely to highly rank private companies as key stakeholders. This may lead to party line voting, especially when civil rights groups conflict with industry representatives.[23] While this basis for division is perhaps the most straightforward, in line with findings by Crosson et al. (2024), the case studies suggest additional nuance. In particular, we saw that private industry stakeholders encouraged Republican lawmakers to *resist* government action when the proposed measures threatened business practices. However, disrupted industries could also effectively nudge Republican lawmakers to *support* government regulation to protect their interests. This could potentially align Republican and Democratic lawmakers, at least on de minimis regulation.

Finally, it is important to note that AI developers and vendors were noticeably absent from the case studies in this early period of state-level AI policymaking. Only in the Colorado facial recognition case was a vendor representative brought in as a witness, and in that case, the witness acted more as a personal or individual witness. This may be due to the limited experience of new AI companies and tech start-ups in lobbying state governments, to a desire to minimize attention, or to other reasons not examined here. As AI companies grow and as generative AI vendors proliferate, however, we expect these dynamics to change. Attention should be devoted to a potentially increasing role of AI developers and vendors in policymaking, with currently unknown impacts for promoting, or detracting from, bipartisanship.

# Subsystems

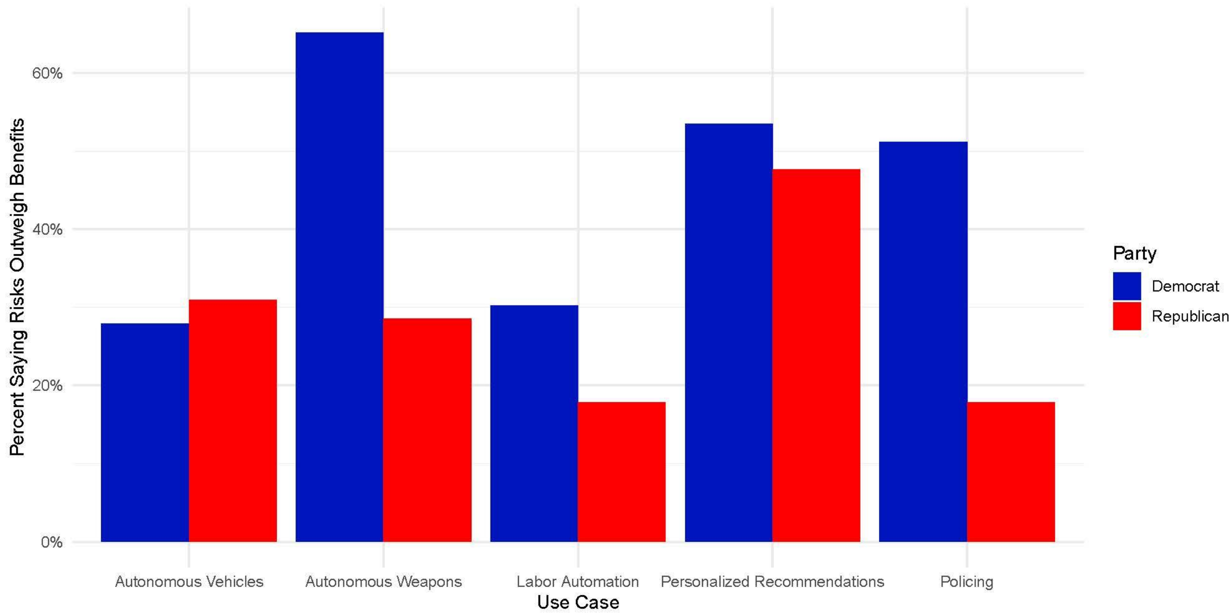
## Evidence from the Survey

In the survey, we find evidence of both bipartisan agreement and emergent partisan divisions over AI used for specific applications or in particular policy subsystems. Figure 1 below shows the percentage of state legislators by political party that responded that the risks would outweigh the benefits[24] of AI in particular use cases. There is bipartisan agreement on a relatively high level of risk involved in personalized recommendations (e.g., on social media platforms), with 53% of Democrats and 48% of Republicans responding that the risks outweigh the benefits. There is also bipartisan agreement on greater benefits and lower risks for autonomous vehicles (only 28% of Democrats and 31% of Republicans indicated greater

[23] This finding is dependent on a context in which racial politics are highly salient and divide the parties. While racial politics is a central constitutive element of US politics across history, some/most moments the political parties compromise on questions of racial liberation to advance other priorities (e.g. Katznelson 2006), attempting to brush under the rug the questions about race. In the contemporary political moment, party polarization with a sorting along racial lines has resulted in a public salience of racial bias for the Democratic party that can be tapped into by civil rights groups effectively. This is seen in the legislative debates in Colorado on systemic racism and the insurance industry.
[24] Either that the risks would outweigh the benefits and use should be discouraged, or that the risks would outweigh the benefits and there is a need for careful management and/or regulation. The question was posed symmetrically for all AI applications.

risks over benefits). That is, bipartisanship can manifest in overall support for an AI policy measure, or in overall opposition.

Figure 1: Perceived Risk by Use Case for Democrat and Republican State Legislators




However, there is also evidence of partisan divisions in Figure 1 as well. Most clearly, Republican and Democratic state legislators are divided over the risk-benefit trade-offs involved in AI use for defense and law enforcement purposes. Democrats were much more likely than Republicans to perceive risks over benefits in police use of AI (51% versus 18%, respectively) and in military use of autonomous weapons (65% versus 29%, respectively). There may also be emergent partisan divisions over labor automation (30% of Democrats indicating that the risks outweigh benefits compared to 18% of Republicans), but the differences are less stark.

## Examples from the Case Studies

The case studies indicate that the regulatory sector or subsystem matters to understand the degree to which partisanship will drive debates on AI governance. Public sector use of AI may open up possibilities for bipartisan support more than private sector use. Additionally, disruption of cleavages in existing policy subsystems is key for altering any partisan dynamics present in the policy subsystem, a key finding of this study.

The Colorado cases show the surprising way public sector use of AI can disrupt existing subsystem dynamics. Regulation of use of AI in the private insurance industry tapped into long standing cleavages with Democrats supporting and Republicans opposing regulation, resulting in a party line vote. Debates over restricting public use of AI and facial recognition systems in schools and by law enforcement, however, did not result in a party line vote for Republicans. In brief, highly salient questions about crime, policing, and control generally have deep partisan cleavages. The splitting of the Republican party on facial recognition regulation suggests the debate over technology created a disruption in the policy subsystem such that policy decisions on AI regulation were not trivially attached to the existing policy images in criminal justice and policing.

The Idaho case, also within the crime and policing policy subsystem, may provide clues as to why this was the case. In Idaho, a bipartisan coalition was able to be formed around government use in a sector where civil liberties are highly salient, pretrial detention. The sponsor of the bill called for support of this legislation by drawing on specific values that were central to the policy subsystem at hand. Representative Chaney noted the challenge presented to core values and that the introduction of technology would be especially concerning here as compared to other sectors:

> Constitutional violations shouldn't be seen as okay just because they are wrapped up in a computer program and hidden from sight. Individual rights are the priority in our criminal justice system, not efficiency. We are intentionally inefficient in this country because we don't want a system that gets it right on average. We believe in a system that gets it right for each and every defendant to the degree possible. (Feb 19th House committee hearing)

Within the domain of bail policy, state Republicans traditionally support a maintenance of some form of monetary bail while state Democrats frequently have been at the forefront of removing reliance on cash bail and reducing pretrial detention.[25] An opponent of the bill, a defense attorney, attempted to situate the question about pretrial risk assessment tools within that policy debate:

> There's basically a trend a snowball rolling down the hill in our country that eventually everybody is going to have either a no bail pure pretrial release system or their going to have some hybrid form of that and the people in the bail bond industry are not stupid they know that so they are the people really pushing this bill… and this is a preemptive strike by the bail bond industry to try and get your attention and get you leaning against what's coming.

If consideration of this bill was only shaped by its connection to the criminal justice and specifically bail policy subsystem, bipartisan support and support of organizations like the ACLU (who are strong supporters of bail reform) would be difficult to explain. Instead, the testimony from representatives from the ACLU connected the question of risk assessment tools not simply to the bail policy debate but to broader questions about the use of AI by the government. A representative of the ACLU gave testimony about a 2017 lawsuit against the state of Idaho for Medicaid decisions informed by algorithms. This spurred interest from legislators who had earlier expressed opposition to regulation of risk assessment. Using an example of difficulties the state encountered using technology in a different public sector shifted this bill from wholly within the criminal justice policy subsystem to the policy subsystem on public sector use of AI. The bill passed with bipartisan, unanimous support.

## Summary of Findings

In summary, we find highly polarized state legislator opinions on AI use in policy subsystems with historically strong and currently salient partisan cleavages: defense and law enforcement. On the other hand, there may be bipartisan agreement regarding regulation, or lack thereof, for other policy subsystems. Legislators of both parties generally view autonomous driving advancement as on balance

25

beneficial, but view recommender systems for domains like news and social media as more concerning[26] (even if for dissimilar reasons). In these cases, technical considerations may become more front and center. Yet, a notable feature of AI policy is that regulation can apply to both the public and private sectors. Regulation in the public sector context can serve to disrupt existing partisan dynamics and engender more bipartisan support, whereas regulation of the private sector tended to align with existing actor interests and partisan cleavages. However, AI policy issues are capable of being attached to multiple subsystems, meaning the prospects for inheriting the characteristics of that subsystem and subsequently polarization remain unsettled until a policy image becomes more dominant.

# Conclusion

[Future research directions, testable hypothesis… somewhere]

In this study, we ask a central question in the early days of AI policy: to what extent, in the long which lines, might AI become polarized? To provide insight, we examine four cases of legislative activity in three US states, and data from a survey of state legislators from the period of 2019-2022. Our findings, and associated conceptual framework, summarized in Table 4, help make the argument that partisan cleavages might emerge with relation to competing problem definitions, proposed policy tools, impactful actors, and the policy subsystems to which AI issues are attached.

Table 4: Conceptual Framework and Prospects for Polarization

| | **Bipartisan Agreement** | **Partisan Divisions** |
|---|---|---|
| **Problem Definitions** | General, related to technical features of AI; transparency and privacy | Specific, related to existing policy subsystems; racial equity and fairness |
| **Policy Tools** | Providing information, assessing risk | Hard vs. soft governance |
| **Stakeholders** | Experts; industry disrupted by AI | Business or advocacy groups utilizing AI |
| **Policy Subsystems** | When debates supercede or disrupt policy subsystems; public sector use of AI | When debates pertain to existing policy subsystems; private sector use of AI |

[26] For reference, our survey used the following language regarding self-driving cars: "AI-powered self-driving cars could save lives by reducing traffic accidents caused by human error. But some are concerned that the AI systems in self-driving cars are vulnerable to malfunctioning or being hacked." As for automated recommendation systems: "Using data collected from user behavior, AI systems can provide free and helpful recommendations about products, news, or social media content. But some worry that this can undermine individual privacy and lead to misinformation and political polarization."

First, our evidence points to some areas of general agreement. There is interestingly bipartisan agreement on the need to start regulating AI now, on the importance of risks for areas like privacy, on the importance of consulting academics, and in the use of low cost policy tools like transparency. Moreover, we find that bipartisanship is more likely in this emerging domain when AI is framed as introducing new, technical problems, rather than attached to existing policy subsystems; or when it is attached to shared value frames surrounding areas like privacy and transparency, rather than more controversial ones surrounding issues like racial justice. Finally, because AI is used prominently in the public sector, without as much engagement by private interests, regulatory discussions centering the public sector tended to stand apart from the comparable discussions that might take place in the private sector subsystems, creating an opportunity for novel or disruptive subsystem development.

In contrast, AI policy appears to follow along partisan lines when attached to existing politicized subsystems, such as related to law enforcement or immigration, where Democrats might favor more consumer protection and where Republicans might perceive more benefits than risks. For subsystems without this kind of politicization, such as autonomous vehicles, technical considerations and academic expertise matter more. Our findings also indicate that Republicans do favor consulting industry stakeholders, suggesting that these actors may have increasing power to the extent that they increase their lobbying presence and skill.

However, even the participation of the private sector is not straightforward. For example, we found cases where core developers were not engaged in policy discourse, but users of AI systems were. In some cases private sector actors favored regulation, contrary to a simple binary where developers and users of AI want to minimize regulation. Our findings suggest that they may favor regulation in some contexts because it might help provide implicit endorsement for use of AI in a certain setting (e.g., AI in hiring), because it might present a relatively low level of regulation (e.g., only transparency requirements) that might create favorable path dependencies, or because a new proposed use of AI might threaten existing private sector interests (e.g., AI risk assessment disrupting the cash bail industry). Overall then, even with deference to private sector actors in private sector contexts, the position of these actors or sympathetic legislators is not necessarily obvious. Like in other domains, ultimate outcomes may depend on, for example, contests between different private sector actors.

While problem definitions, policy tools, and stakeholders each appear to play a role in the politicization of AI, policy subsystems are most fundamental. To the extent that policy entrepreneurs are able to attach certain AI issues to subsystems with the dominant policy images by advancing or discrediting certain framings or tools or actors, they may succeed in leveraging the extant dynamics of those subsystems. On the other hand, there may yet be an opportunity for policy entrepreneurs to invoke a variety of different subsystem dynamics, and to disrupt them by centering broadly shared values, technical novelty, and the expertise of independent actors like academics. Policy entrepreneurs may benefit by picking policy subsystems in which there is a favorable existing image drawn, constituting a unique type of venue shopping, or to try to create a new subsystem and identify its central images and values. Indeed, the diverse activity witnessed in the case studies may represent variable efforts by different actors to try strategies. In an evolutionary process, which strategies succeed and which fail may come to shape the ultimate images and subsystems associated with different AI uses.

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