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How New Issues Become Polarized: Partisan Triggers and Subsystem Shopping in Early AI Policymaking

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ABSTRACT

Early AI policymaking in the United States appeared bipartisan, but subsequent developments raise the question of whether AI policy will become more polarized over time. To examine how partisanship takes root around novel policy issues, we perform a mixed-methods study, analyzing survey data from 129 state legislators in 44 states and performing four case studies featuring legislative debates over enacted AI regulation in Idaho, Colorado, and Illinois. We articulate four potential partisan triggers that shape the emergence of issue polarization: (1) competing problem definitions, (2) preferred policy tools, (3) stakeholder participation, and (4) issue placement in policy subsystems, and we introduce the concept of subsystem shopping. Flexibility and compromise in subnational AI policymaking were initially common due to uncertain issue ownership over diverse problem definitions, the presence of disrupted industries, and deference to nonpartisan expert voices, which enabled subsystem shopping towards less controversial policymaking. However, bipartisan windows narrowed as AI became anchored in party-owned domains, lobbying became more coordinated, and "soft" areas of initial legislative consensus hardened into disputes over more robust policy tools. These developments offer insights into how nascent policy domains can initially sustain bipartisan cooperation, and why it may erode unless actors work to preserve it.

1 | Introduction

Despite persistent high levels of partisan polarization in the United States, policymaking on artificial intelligence (AI) between 2017 and 2022 offered bipartisan opportunities for action. The U.S. House and Senate AI Caucuses (founded in 2017 and 2019) and numerous congressional committees expressed a shared sense of urgency around AI and focused on core issues that crossed party lines. Between 2019 and 2022, state legislatures also introduced nearly 150 AI-related bills (Maslej et al. 2024), some developing robust bipartisan support across red, blue, and purple states. Since 2022, however, there are indications that the windows for bipartisan cooperation are fewer and further between. Recent public opinion data shows growing partisan divides on AI governance (Dreksler et al. 2025), while federal developments—from the evolution of the AI Safety Institute (renamed the Center for AI Standards and Innovation) to US statements at the 2025 Paris AI Action Summit—reveal a shifting policy landscape.[1] AI policy has moved from greater bipartisan cooperation in its early years to more contested partisan terrain.

Why did early AI policymaking avoid partisan polarization? How did actors navigate this emergent issue without clear partisan signposts? What conditions opened windows for bipartisan action, and what forces may ultimately close these

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windows? Finally, what lessons from this earlier moment can help actors seeking to navigate—or open—opportunities for cross-party cooperation on AI policy or other emerging issues?

To answer these questions, we look to subnational AI policy between 2019 and 2022. In the face of federal gridlock and inaction, states began to fill the void by considering over 150 pieces of legislation addressing the use of AI and algorithmic tools in a range of areas. While some set the stage for further information gathering on AI development, others offered more substantive regulation focusing on specific use cases. Much of early state legislation targeted public sector uses of AI, but with an expanding focus on the private sector, and penetration across numerous policy subsystems (DePaula et al. 2024; Parinandi et al. 2025) such as insurance pricing or automated vehicles. We use a mixed-methods approach to study this formative period in AI policymaking. In particular, we survey state legislators about their attitudes on AI, and we also develop case studies of state legislative passage targeting AI usage in various sectors. The survey and case studies jointly allow us to evaluate both what legislators thought and how they behaved when confronted with AI policy choices during the early period of AI policy development. To interpret evidence from the survey and case studies, we employ a framework of potential partisan triggers: (1) competing problem definitions, (2) preferred policy tools, (3) stakeholder participation, and (4) issue placement in policy subsystems.

Evidence from both methods indicates early broad-based bipartisan support for AI policy, including on ostensibly more controversial types of regulation. These windows for bipartisan action opened due to AI policy's status as a nascent policy issue lacking an existing policy subsystem, established partisan cues, clear problem definitions, settled coalitions or even stakeholders, and an obvious institutional home. This created flexibility that disrupted industries and other policy entrepreneurs could strategically use. Our evidence reveals that AI maintained bipartisan appeal precisely because entrepreneurs successfully navigated this interpretive flexibility. They mobilized credible bipartisan voices (especially academics), proposed flexible policy tools, framed problems in ways that didn't trigger established partisan reflexes, and avoided situating AI in existing highly polarized subsystems.

Instead, entrepreneurs engaged in what we call *subsystem shopping*: the strategic pursuit of policy goals in whichever existing subsystem offers the most favorable political terrain. That is, interpretive flexibility around an emergent issue, along with AI's nature as a cross-cutting topic, allowed for strategizing beyond venues and at the level of policy subsystems themselves. However, as AI policy matures into a domain in its own right, partisan fissures appear to be crystallizing, with debates around problem definitions, policy tools, and stakeholders. Understanding this early period of AI policy not only informs future governance efforts around AI, but also provides important insights into the maturation of policy subsystems more broadly.

2 | Partisanship and Nascent Policy Subsystems

Recent public opinion research indicates both shared and divergent preferences on AI across party lines. While Rainie et al. (2022), O'Shaughnessy et al. (2023), and others find evidence of partisan divides in public opinion about adopting or regulating certain uses of AI, the nature and substantive importance of these differences are less clear. For instance, Zhang and Dafoe (2019) find that Democrats are more supportive of general AI development (p. 5), yet party is not significantly associated with perceptions that AI governance is an important issue (p. 94). Concerns about data security, autonomous weapons, hiring bias, and regulation of social media platforms often cross party lines. However, Democrats appear more supportive of government regulation, and patterns in media coverage suggest emerging partisan frames, with left-leaning outlets more likely to emphasize risks related to facial recognition technology, while right-leaning outlets are more likely to promote security benefits and warn about authoritarian abuses by foreign actors (Shaikh and Moran 2022). Meanwhile, certain key attitudes toward AI have developed in the context of highly polarized debates about policing and racial justice (Brewer et al. 2022; Sippy et al. 2025). Yet, surprisingly, Democrats report they are more willing to support police use of AI for controversial purposes like predictive policing, despite lower trust in police generally (Schiff et al. 2025). Finally, early aggregate research on state-level AI policy adoption suggests that partisanship and ideology at the individual legislator level play a growing role in the politics of AI policy, while unified party government does not appear to explain adoption of legislation compared to structural factors like unemployment and inflation (Parinandi et al. 2024).

These apparent contradictions reflect AI's status as a novel policy problem. In the early period of 2019–2022, AI represented an emerging issue without a clear definition, with critical challenges spanning multiple policy subsystems, and without its own existing policy subsystem. The Advocacy Coalition Framework suggests that established policy problems feature relatively stable coalitions with clear beliefs and problem frames (e.g., Sabatier 1987; Weible et al. 2011). In contrast, coalitions around novel policy problems and in nascent policy subsystems are "in an embryonic stage, which are poorly, if at all, differentiated" (Pozzi et al. 2024, p. 562) with some actors developing shared beliefs while others have indeterminate goals or values. This instability enables unexpected political alignments (Baumgartner and Jones 1991) and potentially more compromise or collaboration as actors are forming policy preferences and beliefs (Fidelman et al. 2014; Sabatier and Jenkins-Smith 1999).

Relatedly, a critical but underexplored dimension for understanding the maturation of policy subsystems pertains to how partisan cues emerge around novel policy problems. The early period of subnational AI policy development provides insights, as AI issues experienced both bipartisan consensus and partisan debates as they were situated within a range of policy subsystems across multiple states. We study how such partisan dynamics unfolded around AI policy, and we draw from the policy process literature to organize our analysis around four interconnected elements that can each either activate or suppress partisan divisions: problem definitions, policy tools, stakeholders, and subsystem attachment.

First, there is persistent conflict surrounding the identification, selection, and framing of policy problems, or ***problem definitions***. Problem definitions serve a variety of functions, shaping or narrowing the scope of policy solutions (Dan Wood and Doan 2003) and ultimately policy outcomes (Dery 2000; Rochefort and Cobb 1994). At the macro level, AI has been framed in relation to economics and innovation; international relations including military and technological competition; and ethical, social, or human rights considerations (Bareis and Katzenbach 2022; Imbrie et al. 2021; Schiff et al. 2022). At the sectoral level, in domains like criminal justice or welfare, AI has been seen divergently as a *solution* to underlying problems of human inefficiency and access or a *compounding factor* that may exacerbate bias and dilute transparency (Hall and Ellis 2023; Weinberg 2022). Finally, at the individual use case level, AI tools like robotic surgery, lethal autonomous weapons, or industrial robots have been similarly framed as both tools for public safety and as societal threats (Lawless and Sofge 2017; Moradi and Levy 2020; Nissim and Simon 2021; Watts and Bode 2023). Importantly, different problem definitions may activate different policy preferences and values, which can contribute to polarization. For example, defining AI as a novel problem could avoid activating partisan cleavages, while framing AI as exacerbating or solving existing problems may tie AI to existing policy subsystems and party-owned issues or values. Importantly, 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 the process (Rhinard 2010), enabling issue expansion or containment, coalition building, or favorable venue shopping (Schattschneider 1960).

Second, partisan polarization can be associated with proposed ***policy tools***, instruments, or solutions. With respect to AI, 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; Trengove et al. 2022). Some policy actors argue for sweeping protections, or enhanced social safety net initiatives like a universal basic income funded by a new robot tax, while others are inclined to favor a limited product safety regime (Kovacev 2020; Marchant et al. 2020). The site of rulemaking or oversight embedded within a solution can trigger competing political commitments around considerations like the size of government, deference to the market, or regulatory capture. Preferences over policy tools thus understandably can reflect long-standing commitments, values, and strategic priorities. Contestation over which policy solutions or policy mixes are technically feasible, politically or publicly acceptable, or compatible with existing policy subsystems (Bicket and Vanner 2016; Majone 1975; Todt 2011) could push AI towards bipartisan or party-based support.

Third, policymaking involves inclusion of various ***stakeholders*** with distinct, often conflicting, goals and values. In the AI space, this includes policy actors from industry, civil society, the general public, the media, and researchers and experts (Deshpande and Sharp 2022; Justo-Hanani 2022; Schiff 2022). Central debates surround the extent to 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 and Fieseler 2021; Seger et al. 2023), what strategies policy entrepreneurs are employing to influence policymakers (Khanal et al. 2024; Schiff and Schiff 2023), and how policymakers are weighing trade-offs between civil society advocacy and industry lobbying (Tallberg et al. 2023). Within this burgeoning field, questions remain about the composition, power, and effectiveness of different stakeholders. Further, different stakeholders active at the state level could exert more or less agency, and be perceived as more or less acceptable (e.g., credible or aligned) to one or both major parties. Mobilizing bipartisan voices (such as credible academics) can maintain cross-party support, while relying on partisan-associated advocates (civil rights groups, tech executives) can trigger opposing coalition responses.

Finally, policymaking often occurs within ***policy subsystems***, involving dominant problem definitions or policy images, existing coalitions of actors, and favored policy solutions or tools. The particular policy subsystems that are connected to debates over AI (e.g., criminal justice, labor, and education) may have a strong influence on the extent to which partisan cues are activated. Sectors that are more salient and accessible to the public may receive heightened attention from policymakers (Wlezien 2004), rendering those sectors potentially more prone to partisan conflict and less subject to capture by interests or technocrats. For example, Horowitz and Kahn (2021) find bipartisan support among local policymakers for AI use in natural disaster planning, while Parinandi et al. (2024) find partisan divides related to consumer protection at the state level. Extant party ownership matters also: Democrats and Republicans may have clearly carved out and competing stances on issues like criminal justice reform, environmental regulation, consumer protection, and racial politics that could be instrumental in how they interpret AI (Horowitz and Kahn 2021). Party-owned issues mean some sectors serve as structural focal points (Ringe 2005) which channel liberal against conservative perspectives (in a simple, bipartisan context) around criminal justice, education, taxation, foreign policy, or other topics (Nincic and Ramos 2010).

The interaction between these four elements creates opportunities for what we call "subsystem shopping," the strategic effort by policy entrepreneurs to frame issues, select tools, and mobilize stakeholders to align an issue with a favorable policy subsystem. Policy subsystems provide the organizing institutional logic for how problem definitions, policy tools, and actors ultimately converge. For issues like AI, characterized by interpretive flexibility, there may be no single, obvious existing subsystem in which to pursue policy goals, though this remains an open question (Lemke et al. 2023). Entrepreneurs may find it useful to attach or detach an ambiguous policy issue like AI to a mature, more predictable subsystem, like education, immigration, or criminal justice. In some cases, entrepreneurs may find it prudent to develop an entirely new subsystem altogether. This concept of subsystem shopping offers one important way to understand how AI policy entrepreneurs can achieve bipartisan support: by strategically selecting subsystems that offer the most favorable political terrain while avoiding domains marked by partisan conflict.

This concept is related to, but differs from, venue shopping (Baumgartner and Jones 1991; Pralle 2003). Like venue shopping, strategic subsystem shopping behavior is likely driven by factors such as prospective alignment, likelihood of success, and organizational resources, as well as over-time policy learning (Holyoke et al. 2012; Pralle 2006). Yet while venue shopping is about strategic institutional placement, often with respect to particular legislation for example, subsystem shopping is about the interpretive policy space within which an issue is situated. We expect subsystem shopping to be especially relevant for other novel policy issues (Ley and Weber 2015; Kaunert and Léonard 2012), which lack settled boundaries, viable tools, and clear ownership. Broad, cross-cutting issues should also be more susceptible to such strategic interpretation. AI serves as a useful test case given its breadth and potential attachment to multiple existing subsystems.

3 | Methodology

Given our theoretical expectations regarding how partisan cleavages may emerge around novel policy issues, we turn to an empirical examination focused on AI policymaking in the U.S. states. 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 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 and partisan dynamics in state-level AI policymaking. Such an approach allows us to consider both what legislators *believe* about AI governance and how they *act* when faced with specific proposals and active stakeholders.

3.1 | Survey of State Legislators

In December 2021, we sent out emails to 7355 state legislators 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 and Schiff 2023). In total, 129 legislative offices participated in the survey (a typical response rate of about 2%), with 44 states represented.[2] Despite the modest response rate, the sample is fairly representative of the full population of state legislators, as shown in Table 1, except that there are slightly more Republicans in our sample.[3]

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. (2023) study of public and expert opinion for validity and comparability. Our survey instrument (see Appendix C) obtained consent from participants,[4] provided a definition of AI adapted from Zhang and Dafoe (2019), and then proceeded to ask questions about AI knowledge and preferences.

TABLE 1 | 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
Prop. female	0.32	0.31
Average tenure (in years)	5.51	6.13
Average state Squire Index[8]	0.20	0.22
Number of legislators	129	7,355

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 competing problem definitions related to AI, such as possible tradeoffs between concerns about AI ethics and human rights against innovation and global AI leadership. Finally, the survey asked about legislators' AI regulatory preferences and priorities, including questions about specific use cases, policy tools, and influential stakeholders with respect to AI.

In presenting the results of the survey, we include descriptive statistics as well as p-values based on t-tests and regression analyses to assess differences in subgroup responses, primarily between Democrats and Republicans. We additionally use principal component analysis (PCA) to identify underlying dimensions driving state legislators' opinions on AI policy across a range of survey questions (see Appendix D).

3.2 | State Case Studies

To complement the survey data, we conducted case studies of AI regulation in state legislatures between 2019 and 2022 to explore when problem definitions, actors, and proposed policy tools trigger partisan attachments in legislative debates across various sectors. The study drew from the database of the National Conference of State Legislatures, initially identifying 19 possible cases of enacted AI legislation between 2019 and 2022. We focused on regulatory measures, as government regulation constitutes a key divide between contemporary parties and presents a 'tough case' for bipartisan action. In contrast, the political stakes are lower for non-regulatory measures, such as those that merely create task forces.

We focused on enacted measures for theoretical and practical reasons. Enacted measures allow us to investigate how partisan considerations interact with other factors to produce policy outcomes, rather than proposals that are symbolic or underdeveloped bills that will come to fruition in subsequent legislative sessions. Enacted bills have richer empirical records such as committee and floor deliberations, stakeholder testimony, and voting records across multiple stages (e.g., committee, floor, conference committee) to assess party influence on decision making. Our analysis focuses on tracing the processes through which partisan dynamics unfold during legislative consideration, not simply on whether bills pass or fail. The partisan patterns we identify in enacted cases—including instances where partisan potential remained unrealized—provide insights into the mechanisms of partisan activation that would be present (though less observable) in failed cases as well. Only considering enacted bills does introduce some limitations to our findings, which we discuss in our conclusions.

Based on these criteria, we identified four cases from the five instances of enacted AI regulation between 2019 and 2022.[5] The four selected cases offer strategic variation for testing our theoretical framework: "Pretrial Risk Assessment" (Idaho 2019), "Employment Decisions" (Illinois 2019 and 2021), "Insurance Pricing" (Colorado 2021), and "Facial Recognition" (Colorado 2022). These cases provide analytical leverage through variation in both partisan voting patterns and theoretical explanatory factors. Partisan voting ranges from unanimous bipartisan support (Idaho Pretrial risk assessment) to broad bipartisan support transitioning to emerging partisan divisions (Illinois employment decisions over time) to emergent partisanship (Colorado facial recognition) to straight party-line voting (Colorado insurance). This variation allows us to examine the conditions under which AI policy triggers or avoids partisan conflict. The cases also vary across key explanatory factors: different subsystem attachments—criminal justice (Idaho), labor/employment (Illinois), consumer protection/insurance (Colorado 2021), and civil rights/privacy (Colorado 2022); both public sector AI use (Idaho, Colorado facial recognition) and private sector regulation (Illinois, Colorado insurance); different political contexts in terms of party control, including Republican supermajority, Democratic supermajority, and Democratic control without supermajority; and within-state comparisons across subsystems (Colorado) and with policy tool evolution over time (Illinois). Together, these cases allow us to trace how entrepreneurs navigated problem definition, actor mobilization, tool selection, and subsystem attachment to produce varying levels of partisan conflict. The state case studies are summarized in Figure 1.

For each case, we looked at the legislative history of the associated bills, reviewed all committee and floor votes, analyzed testimony and speeches that were part of hearings and deliberations in committees and chambers, and conducted contextual research on key participants for each measure. Contrasting cases of bipartisan action with those with more party-driven votes on enacted regulatory measures provides fertile ground for exploring the problem framings, stakeholder involvement, tools, and sectors that trigger the partisan identities of state legislators when discussing AI.

4 | Results

The subsections below present evidence across the survey and case studies with respect to the four components of our theoretical framework: problem definitions, policy tools, stakeholders, and subsystems. For brevity, for the first three components (problem definitions, policy tools, and stakeholders), we focus primarily on a single case to enable a richer presentation of evidence, but Appendix E provides additional information on other cases. The last subsection on subsystems includes details from multiple cases.

4.1 | Problem Definitions

Based on the survey results, we find bipartisan policymaker 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 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*. Moreover, a full 96% of the state legislators that we surveyed said that they support the *careful management* of AI.

State legislators also reported a shared concern for social and ethical risks. 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.” Here, 73% of legislators (76% of Democrats and 70% of Republicans) chose the latter 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.

We do, however, observe partisan differences on some survey questions. For example, Republicans were somewhat more likely than Democrats to indicate that regulating the development and use of AI will “stifle innovation” ($p = 0.09$). Nonetheless, the survey and PCA results (presented in Appendix D) suggest that there may be a bipartisan coalition possible around regulating AI due to shared concerns of AI's risks and ethical impacts despite some differences on topics like innovation or risk aversion.

The cases echo survey findings of bipartisan support for addressing ethical and social risks of AI broadly. When those

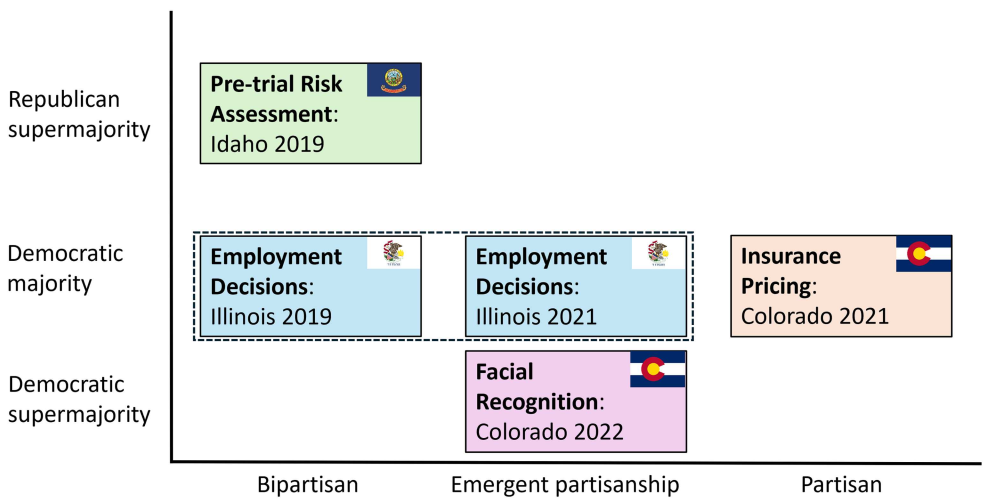

FIGURE 1 | Summary of state case studies. *Note:* Left-right dimension indicates partisanship; vertical dimension indicates party control. Colors indicate case studies. Flags indicate states. Majority refers to greater than 50% support, and supermajority refers to a filibuster-proof majority.

risks are specified, however, some develop bipartisan support, while others trigger partisan attachments. For instance, across the case studies, there is broad salience and bipartisan support for addressing the problems of privacy and transparency. When legislative debates centered on questions about equity or fairness, though, existing frames regarding racial equity were transposed to the debates over AI and stirred partisan votes.

In 2019, Idaho became the first U.S. state to regulate the use of AI in **pretrial risk assessment** legislatively. HB 118 mandated public inspection of all documents related to AI risk assessment tools, with no exceptions for trade secrets. Idaho's Republican-dominated legislature unanimously passed legislation limiting the ability of businesses to shield their risk assessment technology from public scrutiny. Initially, proponents argued the bill addressed fairness and transparency, but when facing pushback, they pivoted to emphasizing transparency alone.

In the House Judiciary, Rules and Administration Committee 2019, supporters argued that algorithmic risk assessments were a doorway for racial bias. Opponents of the bill like Representative Hartgen countered that racial bias along dimensions like "nationality" did not exist. Mark Manweiler, also opposing the bill and representing the Idaho Association of Criminal Defense Attorneys, argued that the current bail system—what risk assessment would help replace, was a fundamentally unfair system. He testified that financial bias in the current bail system was more important than "a theoretical potential problem" with algorithms, calling technology concerns speculative while bail problems were real. The bill, then, was a "solution in search of a problem" and was preventing bail reform that would correct a real problem of bias.

In response to these concerns, proponents shifted to the problem of transparency. Representative Chaney (R), the sponsor of the bill, responded to Hartgen's assertions that these systems did not consider race or nationality, and said the main concern with AI is that there is "no way to know how much weight is placed on a given factor." Similarly, 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."

In the sponsor's closing remarks at the hearing, Rep Chaney concurred with this alternative problem definition, one more conducive to opponents of the bill who disputed the bias-focused framing: "At a minimum we need transparency.... at a minimum we need to see inside the black box." After a narrow passage out of the committee, Rep Chaney said he would be willing to work with others to amend the bill to focus on transparency. The bill was amended to remove any requirement that the risk assessment tools be shown to be free from bias. Instead, the bill that received bipartisan support in the House and Senate only required public access to data, reflecting the viability of the more conducive transparency problem definition over the contested framings of fairness.

We witness similar dynamics in the other three cases as in the Idaho case. The Illinois legislature moved from bipartisan support in 2019 of a bill that focused on transparency and privacy when using AI in the hiring process, to a 2021 partisan debate and emergent partisan vote on an amendment that re-centered the problem of bias. Likewise, a 2021 debate in Colorado about the use of AI in insurance decisions centered on discrimination of protected groups. In addition to debates about the extent of the problem of racial bias in insurance, there was contestation around the role of AI in creating that problem. Partisan divisions made a vibrant appearance in testimony, emphasizing competing racial projects and resulted in a party line vote on the bill. The subsequent year, the Colorado legislature considered regulation on facial recognition where racial discrimination was only one of a number of social and ethical problem definitions discussed. This bill passed with bipartisan support including with support of some of the vocal opponents of regulation of AI use in insurance just the year before.

From the survey and case studies, we see certain problem frames open policy windows for broad bipartisan action on AI. State legislators can reach across the aisle when AI policy discussions pertain to *general* "social and ethical risks" as challenges or to a broad sense of unknown consequences of AI. Additionally, questions about transparency can generate bipartisan support. However, if policy entrepreneurs highlight more specific problems connected to party-owned issues, such as racial justice, the survey and case studies suggest politicians will respond to party cues. Bipartisan action is more likely if technology is framed as creating a novel problem (e.g., the black box problem) rather than exacerbating known and already-polarized problems. Given these findings, there may be a temporary but important window for bipartisan action on AI while AI's problematization remains vague. While utilizing a less well-specified problem definition may undermine other policy goals like successful implementation, for minimally *initiating* regulation of AI, lack of specificity may be a strategy.

4.2 | Policy Tools

Building on the findings regarding problem definition, the survey suggests bipartisan agreement on more general policy tools, such as approaches for baseline 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 legislation, with no difference in support across parties ($p = 0.20$). Both parties also have similar levels of support for providing funding for AI research and development ($p = 0.62$).

Yet, partisan cleavages emerge when policy tools implicate the size of government or involve contrasts between public and private sector oversight. Republican legislators are about 31 percentage points less supportive of increasing government capacity and expertise in AI than Democratic legislators ($p = 0.002$). We also see evidence of partisan differences in preferences for more formal regulation of AI: while 67% of Democrats favor hard governance (formal government regulation) and only 33% favor soft governance (less formal government oversight), 38% of Republicans favor hard governance, 53% favor soft governance, and 8% favor industry self-regulation. Finally, we also find partisan divisions for policy tools that implicate certain contentious policy domains. For example, regarding hypothetical legislation to encourage greater immigration of high-skill STEM workers, Republicans express much lower support than Democrats ($p = 0.03$).

The case studies illuminate the role of policy tools in determining support for the regulation of AI. In 2019, Illinois became the first state to address the use of AI in **employment decisions**. HB 2557, requiring notification and consent of candidates if a company used AI to review interview videos, passed with bipartisan support. In 2021, a proposed amendment (HB 53) requiring reporting of statistics on race for companies who use AI in hiring showed emerging Republican opposition.

The 2019 bill 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. Representative Williams (D), in an attempt to overcome a possible partisan divide, stressed the particular tool, notification, as something uncontroversial that should be adopted across technological domains and supported by policymakers across parties. As Representative Davidsmeyer (R) concurred, this soft governance approach was critical to his support: "Okay. So what your bill does…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). The bill passed the Illinois legislature with bipartisan support.

Yet two years later, an amendment proposed that businesses using AI as a sole determinant to offer in-person interviews needed to report the race and ethnicity of applicants, interviewees, and hires to the state Department of Commerce and Economic Opportunity. These specifics of the policy tool became central in the debate. Representative Wheeler (R), in the Cyber Security Data Analytics Committee, argued that the new requirements would be only a minimal burden to businesses, highlighting 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" (Cyber Security and Data Analytics Committee 2021). However, some saw a reporting requirement, even with no enforcement mechanism, as an unacceptable burden on small business owners. The final vote showed an emerging partisan divide over a policy that required only testing and reporting, with no enforcement provisions, with a small block of Republicans voting against the measure in the House and the Senate.

The other case studies also show the unique, although not determinative, analytic leverage of considering policy tools to understand partisan triggers. In the Colorado discussions about AI and insurance pricing, broad debates over the best tool for addressing racial discrimination—the market or government regulation—contributed to a party line vote. In Idaho, the bill targeting pretrial release risk assessments originally sought to require validation that systems were "free of bias." However, technical and logistical feasibility about this validation process resulted in contention over the proposed tool, while notification and consent were softer tools that garnered broad bipartisan support.

Overall, the survey data show that Democrats favor hard governance approaches and Republicans favor soft ones. The case studies further 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. Democrats appear to support weaker tools when stronger regulation seems unlikely to be successful, as in the early Illinois legislation around hiring. For Democrats, then, this might serve as a first attempt to build a more robust policy mix, or "dipping our toe in the water" as described by Rep Wheeler. Alternatively, for Republicans, this collegiality might represent a strategy to provide tacit endorsement of the use of AI and to fend off more robust policy tools. As Representative Flowers (D) argued, notification alone might fail to address racial discrimination while ironically providing employers with the cover to use AI systems. In that sense, bipartisanship related to AI tools could be reflective of a pseudo-consensus that may not hold up over time as more detailed regulation is considered.

4.3 | Stakeholders

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–from most to least important 'to listen to' for AI policy in general, for policy issues related to ethical/social implications, and for policy issues related to security/economic competitiveness. Legislators' responses mostly indicate partisan differences, with one possible area of agreement.

The largest partisan difference concerns attention to industry stakeholders, reflected in a different average ranking of importance (from 1 to 7). 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 ($p = 0.05$).

Yet an interesting 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* ($p = 0.05$, and on average ranked 3rd vs. 2nd), Democrats and Republicans were similarly willing to seek input from academics on *specific* policy issues related to both ethical/social implications ($p = 0.99$, and both parties on average ranked in 2nd spot) and policy issues related to security/economic competitiveness ($p = 0.88$, and both parties on average ranked in 3rd spot).

Both the power of industry actors in AI policy for Republicans and the cross-partisan influence of academics are seen in the two Colorado cases. First, a 2021 battle over the use of AI in **insurance pricing** in Colorado was a "classic" contest between industry on the one side and consumer protection and civil rights groups on the other. Colorado became the first state to address the challenges of monitoring insurance pricing in the wake of AI advances through legislation by requiring self-testing and self-reporting, though without enforcement.

Testifying in opposition to the bill or asking for radical amendments and exclusions were end users of the AI products: 10 insurance associations, two chambers of commerce, and two individual insurance agents. Testifying in support of the bill included twelve civil rights, consumer rights, or economic justice organizations. Meanwhile, no academic witnesses were present. S 169 passed on a party line vote over the opposition of Republicans.

The following year in Colorado, S 113, regulating **facial recognition**, passed with more Republican support. This measure paused acquisition of AI tools by law enforcement and public schools, established a working group to develop policy for regulating facial recognition, and established an interim regulatory regime. The witness list for the 2022 Colorado debate on facial recognition may provide clues as to why this hard governance bill did not develop unified Republican opposition seen in the previous year's debate on AI. Testimony on effectiveness and bias in facial recognition 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 restricting purchasing of facial recognition systems.[6] Meanwhile, industry witnesses opposing a moratorium and the creation of a state centralized regulatory regime for facial recognition represented the *developers* of the AI products (not its end users as in the insurance pricing case). Only two witnesses testified in opposition, 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.

Yet, AI developers were isolated in their opposition to regulation, lacking consistent support from end users, and their testimony did not result in moving legislators to oppose the regulation. Users of the technology both supported and opposed, or were absent from the debates. A representative from the Colorado Association of Chief of Police encouraged a pause on further acquisition until regulations and trustworthy end user guidance were in place. In contrast, the Executive Director of the Colorado Information Sharing Consortium, David Shipley, noted that facial recognition tools when "used according to reasonable law and policy" could increase public safety and help with civil rights. Ultimately, the presence of divided end users led to passage of a strong regulatory measure, with the Republican party divided rather than united in opposition.

Notably, the debate over pretrial risk assessment in Idaho highlights the power of well-organized industries that might be disrupted by AI to *drive* regulatory action, rather than resist it. Pretrial risk assessments, such as the ones regulated in the Idaho law, are key to the bail reform movement's aims and a threat to bail insurance companies who depend on individuals not being released pretrial. Jeff Clayton, Executive Director of the American Bail Coalition, a trade organization of bail insurance companies, was central to the drafting and amending of this bill, testifying at the committee hearings, and supporting Rep Chaney as a key policy entrepreneur. (Rep Chaney was subsequently prominently featured on the state page of the American Bail Coalition website.) This exemplifies how disrupted industries may not only favor regulatory action, contrary to common assumptions, but also that they may be more well prepared for coordinated messaging and lobbying efforts compared to new AI entrants like Clearview in Colorado.

In sum, there are several important takeaways regarding stakeholders' presence and the prospects for bipartisanship in AI policymaking. First, inclusion of academics can promote bipartisanship in some instances. Our findings suggest that state legislators from both parties were willing to consult academics on more narrow issues, such as those pertaining to social/ethical risks of AI or national security/competitiveness. This was especially common in the context of public sector regulation, more common in early AI policymaking (DePaula et al. 2024), where private sector interests are less present.

Second, we find that, while industry stakeholders competing with civil society may polarize state legislators along party lines in a traditional sense (Parinandi et al. 2024), politics may unfold differently when industry stakeholders also represent disrupted businesses. End users could encourage Republican lawmakers to *resist* government action when the proposed measures threatened business practices, but disrupted industries—typically more established and effective in the legislative process—could also nudge Republican lawmakers to *support* government regulation to protect their interests. This might align Republican and Democratic lawmakers, at least on de minimis regulation. Republican responsiveness to industry actors, then, can cut both ways in this critical period of AI development as some industries are being disrupted by the new technology. As such, resistant end users amongst disrupted industries may encourage bipartisan action in the politics of AI policy, especially when developers are absent or uncoordinated. However, this may change as AI developers or other new entrants cultivate a more effective 50 state lobbying strategy. These findings suggest that policy entrepreneurs can strategically mobilize different coalitions to either activate or suppress partisan responses, with academics and disrupted industries offering particular opportunities for bipartisan coalition-building in nascent policy subsystems.

4.4 | Subsystems

While the preceding subsections each highlight one dimension of possible partisan activation, these dynamics do not operate in isolation. Rather, they unfold within specific (established or nascent) policy subsystems, which shape and are shaped by how issues are framed, which tools are proposed, and which stakeholders engage. The subsystem context therefore provides a natural point of integration. For instance, in both Idaho's pretrial risk assessment and Colorado's facial recognition cases, bipartisan coalitions formed around transparency, yet the subsystem context shaped which stakeholders were mobilized and how problems were framed. Similarly, soft governance tools enabled initial consensus in both employment regulation in Illinois and insurance oversight in Colorado, but the partisan durability of that consensus varied depending on the policy arena and industry structure.

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 2 below shows the percentage of state legislators by political party that responded that the risks of AI would outweigh the benefits in particular use cases.[7] 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

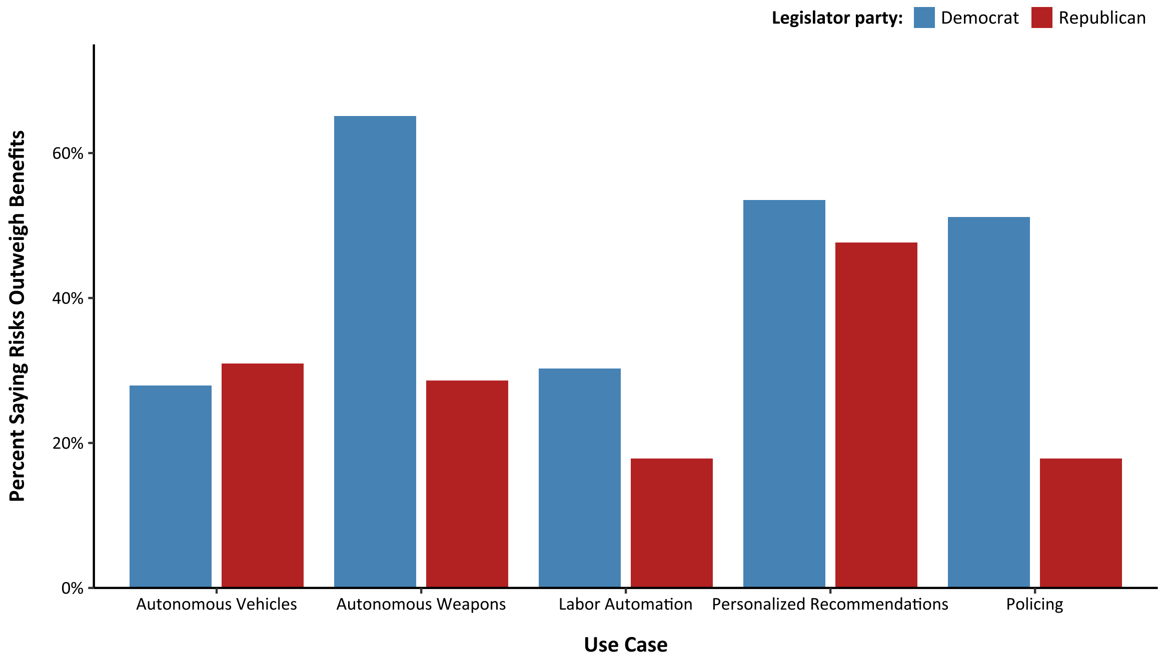

FIGURE 2 | Perceived risk by use case for Democrat and Republican state legislators.

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

However, there is also evidence of partisan divisions in Figure 2 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% vs. 18%, respectively) and in military use of autonomous weapons (65% vs. 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. Politicization related to AI's disruption of labor is worthy of continued study.

The case studies also indicate that the regulatory sector or subsystem matters to understand the degree to which partisanship will drive debates on AI governance. The debate over **facial recognition** regulation in Colorado shows the surprising way public sector use of AI can disrupt existing subsystem dynamics. Debates over regulation of use of AI in the private insurance industry just a year earlier in the state 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. While questions about crime and policing generally have deep partisan cleavages, the combination of this subsystem with another—education—helped to dislodge this debate from the partisan trappings of the criminal justice sector. This development suggests that subsystem location can have dramatic impacts on AI policymaking and demonstrates subsystem shopping in practice; entrepreneurs strategically combined education and law enforcement avoiding the partisan dynamics of a pure criminal justice regulation.

On the issue of **pretrial risk assessment** in Idaho, a bipartisan coalition ultimately formed despite encompassing law enforcement as well. In part, this was due to articulation of a policy subsystem that was about 'public sector use of AI,' rather than about the criminal justice subsystem per se. A representative of the ACLU gave testimony about a 2017 lawsuit against the state of Idaho for Medicaid decisions informed by algorithms. This incident in the health subsystem spurred interest from legislators who had earlier expressed opposition to regulation of pretrial risk assessment. The convincing example of difficulties the state encountered using technology in service distribution highlights how framing this as part of an evolving domain about *public sector use of AI* was vital to generating unanimous support for this bill, particularly given the high salience of civil liberties in the public sector.

Bill sponsor Cheney (R) attempted to disconnect the problems of risk assessment from criminal justice subsystem issues, and instead push towards an image of AI policymaking that targets technology and society more broadly:

> *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]... 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... What will [it] be like in 2054?*
>
> (House Judiciary, Rules and Administration Committee 2019)

We see the cultivation of an emerging and overarching AI-specific policy strategically to alter partisan dynamics in Illinois as well. In 2019, Representative Williams (D) argued for notification and consent for **employment decisions** by centering shared concerns about surveillance and data in other arenas.

As a result of AI's interpretive flexibility as an object of policy, we suggest that AI policy issues are capable of being attached to multiple subsystems, a concept we term "subsystem shopping." In turn, the prospects for inheriting the characteristics of an existing subsystem and its attendant polarization (or lack thereof) are unsettled. Choice of problem framings, actors, and tools can move the debate from a polarized subsystem to a more neutral one, or even a new subsystem emphasizing AI governance, featuring a unique constellation of AI-specific actors, problems, and discourse.

5 | Discussion

In this study, we theorize about the emergence of partisan politics around novel policy issues, and we assess empirical evidence on early state-level AI policymaking. We examine four cases of subnational legislative activity along with survey data from state legislators from 2019 to 2022. While interpretive flexibility around AI as a novel policy issue created strategic opportunities for policy entrepreneurs to build early bipartisan consensus, often by enabling subsystem shopping, we also document the emergence of partisan divisions. We offer four takeaways about partisanship and nascent policy domains.

First, novel policy issues and nascent policy domains create temporary windows for bipartisan action through interpretive flexibility over problem definitions, policy tools, stakeholders, and subsystem attachment. During AI policy's formative period, we observe bipartisan consensus on the need to start regulating AI now, on the importance of shared values for areas like privacy and transparency, and on the need to consult academics (on specific issues, and in public sector settings). Certain formulations of problem definitions, particular proposed policy tools, types of engaged stakeholders, and the policy subsystems to which issues are attached can foster broad bipartisan support, while other trajectories within each of those elements can serve as partisan triggers. For instance, general concerns about shared risks enabled bipartisan agreement in Idaho and Colorado, while more specific equity-focused frames, as seen in the insurance and hiring cases, activated partisan divides. Figure 3 summarizes our findings regarding which policy process factors opened windows for bipartisan agreement on AI policy and which closed windows.

Second, bipartisan support, like agreement on soft governance tools, may represent pseudo-consensus on approaches to emerging technologies like AI. While Republican and Democratic lawmakers hold different views about the appropriate formality of regulation, both were able to agree on light-touch policy tools like basic information and consent, as seen in Illinois's hiring law and Idaho's transparency-focused bill on pretrial risk assessment. Yet, this agreement masks deeper dissensus. Our findings suggest that Republicans may (only) favor regulation in some contexts because it provides implicit endorsement for use of AI in a certain setting (e.g., AI in hiring) or because it presents a relatively low regulatory burden (e.g., only transparency requirements) that might enable favorable path dependencies. Meanwhile, Democrats may (only) favor this modest regulation because they see it as the only legislation that is able to succeed or as a steppingstone to more detailed and robust regulation. As shown in Figure 3, then, soft governance tools can enable bipartisan agreement, but robust or redistributive tools considered subsequently may serve as partisan triggers. Initial bipartisanship on AI policy or around other novel issues, then, may overstate the degree of actual or longer-term consensus.

Third, industry dynamics in nascent domains or around emerging technology can create unexpected coalition opportunities. We highlight that industry can play a protective, pro-regulatory role, contrary to a simple industry versus civil society dynamic.

	Factors Favoring Bipartisan Agreement	Factors Favoring Partisan Divisions
Problem Definitions	General or collective risks; novel, technical features of AI; shared values like transparency and privacy	Group-specific risks; tech exacerbation of existing problems; contested projects like racial equity and fairness
Tools	Soft governance as initial consensus; providing information, assessing risk	Hard vs. soft governance; independent auditing or enforcement
Stakeholders	Academic experts, especially for public sector uses; industry disrupted by AI in favor of protective regulation	Contestation between supportive industry end users and skeptical civil society representatives
Subsystems	When debates supersede policy subsystems or open door for a new AI subsystem; public sector use of AI	When debates pertain to existing, polarized policy subsystems; private sector use of AI

FIGURE 3 | Factors shaping bipartisan or partisan pathways in AI policy.

Critically, private sector actors may *support* regulations because new proposed uses of AI threaten existing private sector interests (e.g., AI risk assessment disrupting the cash bail industry in Idaho) who tend to benefit from greater lobbying capacity, expertise, and relationships. In contrast, novel AI entrants such as developers may lack these capacities, expecting their end users to serve as advocacy proxies. However, end users may have fewer uniform interests compared to developers; they may be concerned about inheriting risks from developers and accordingly amenable to regulations that protect their downstream use of AI.

Fourth, subsystem shopping enables strategic positioning around novel issues and in nascent domains. Indeed, across the cases we studied, policy entrepreneurs attempted to associate AI with subsystems aligned with their goals, in some cases attaching AI to or detaching it from more contentious domains. For example, bipartisan support for regulating facial recognition in Colorado emerged when the issue was framed through both education and law enforcement subsystems, rather than solely criminal justice. Similarly, in Idaho, proponents of transparency in pretrial risk assessment emphasized AI as a general governance challenge rather than a partisan criminal justice reform issue. As reflected in Figure 3, we also witnessed efforts to articulate novel, technical problems associated with AI (e.g., when promoting transparency in pretrial risk assessments in Idaho) and to center shared values and problem definitions. These strategies could serve to place AI into a new cross-sectoral subsystem dominated by a new policy image, one with its own actors, discourses, and coalitions. Future research should investigate subsystem shopping around other novel issues and in other cross-sectoral domains, as well as examine how subsystem attachments stabilize over time. Key questions include the conditions that enable successful shopping and how this strategy interacts with coalition building to shape long-term policy trajectories and partisan polarization.

Our study is also subject to several limitations that future research may be able to improve upon. First, the time period and regional focus under consideration are limited, as are the number of cases and respondents, raising questions about reliability and generalizability over time. Second, our focus on enacted measures means we cannot directly observe cases where partisan triggers may have prevented policy adoption. Our findings should be interpreted as illuminating how partisanship shapes successful AI policy development, rather than explaining the full universe of partisan effects on AI policymaking. However, understanding how partisan dynamics operate within successful policy development provides crucial insights into the mechanisms of partisan attachment. Our cases reveal the mechanisms through which partisan attachments form and influence policy content—insights that can inform hypotheses about partisan effects in failed cases, different levels of government, and investigations of continued development in this emerging policy landscape. Finally, as our survey and case study evidence are limited to only AI policy, we cannot speak to whether the partisan triggers we identify hold for other policy domains or the extent to which subsystem shopping occurs for other novel policy issues. We encourage further research on these topics.

6 | Conclusion

Our analysis reveals that the early bipartisan consensus on AI policy resulted not from the technology's inherent characteristics, but from strategic choices by policy entrepreneurs operating within the temporary interpretive flexibility of a nascent policy domain. As that flexibility narrows and partisan cues crystallize, the challenge for future AI governance will be whether policymakers can apply these lessons to craft new windows of cooperation or whether AI will follow the familiar path toward partisan entrenchment. The stakes of this trajectory extend well beyond AI to encompass how democratic societies navigate technological change in an age of political polarization. These insights have growing relevance as technological change accelerates—from biotechnology and quantum computing to space governance and climate engineering—each potentially following similar trajectories from bipartisan cooperation to partisan division.

Our findings also extend recent theoretical explorations into emerging subsystem dynamics. Ingold et al. (2017, 2023) discuss when a nascent subsystem might absorb or spin off policy issues. While this study focuses especially on the role of beliefs and actor coordination, our work further elaborates the role of partisanship as it pertains to problem definition and solution acceptability in this process. Additionally, we suggest that strategic and contingent choices by entrepreneurs and industries through subsystem shopping will drive that process. This emphasis echoes other recent research by Lemke et al. (2023) arguing that agendas converge in nascent subsystems when issues and instrument priorities likewise converge. The concept of subsystem shopping provides a new lens for understanding how policy entrepreneurs navigate partisan terrain around ambiguously-defined, novel policy issues, with implications extending beyond technology policy to any crosscutting issue lacking a clear institutional home.

While the bipartisan window on AI policy may be closing, there are nevertheless forward-looking insights for those interested in shaping AI policy. Disrupted industries, which can push towards consensus for government action, will adapt or even disappear over time. Scattershot lobbying of developers that allows for bipartisan action have become more coordinated and sophisticated. And the broad range of "unknown risks" of AI which can lead to deference to academics and government regulatory exploration, will become—or at least feel—more concrete. That said, the lessons from what opened windows of cooperation, such as careful subsystem shopping and shared problem framings, could be guides to those that want to develop bipartisan cooperation even as the political context shifts. In a time of heightened party polarization and closely divided government, the degree to which AI becomes a locked-in partisan issue will be key to the development of those policy paths, with both national and international implications. The future looks very different if AI governance becomes a party-owned issue or if current debates build a narrative of consensus on the fundamental project of AI policy. Understanding the components of the policy process that can trigger cooperation or partisan conflict is essential for explaining, and shaping, future developments in AI policy.

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

Endnotes

[1] Vice President Vance noted "I'm not here this morning to talk about AI Safety, which was the title of the conference a year ago. I'm here to talk about AI opportunity."

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

[3] For further demographic information see Appendix B.

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

[5] See Appendix A. We excluded the fifth case—Alabama's facial recognition legislation—due to limited access to legislative materials and its duplication of Colorado's facial recognition case.

[6] The power of academic witnesses to open bipartisan windows is also supported by other evidence, such as when a computer science professor testifying in Idaho played a key role in the pretrial risk assessment debate, as well as in the survey where both Democrats and Republicans expressed a willingness to listen to academics about the risks of AI.

[7] 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.

[8] The (adjusted) Squire Index (Squire 2017) assesses the professionalism or capacity of state legislatures, deriving from measures of legislative staff, session length, and member pay.

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Appendix A

Case Study Selection

Table A1

As part of our case study selection and analysis, we aimed to center legislation with a specific focus on AI. As such, we excluded from consideration bills that simply mention "artificial intelligence" or "machine learning" if this reference was primarily in the service of a different area such as budgets or education.

We also excluded two other types of legislation that may have implications for AI policy: autonomous vehicles and data privacy. Between 2017 and 2022, 47 states considered around 650 pieces of legislation about autonomous vehicles. About 60 pieces of legislation passed during this time, many of which were about platoon trucks, budget issues, testing, and modifying requirements for licensing or cars. Many also built on previous legislation. Similarly, while data privacy implicates AI, it extends beyond AI technology to include many forms of technology.

Of the 19 enacted measures specifically targeting AI between 2019 and 2022, the majority either encouraged innovation and education, or focused on studying or building state capacity that would allow for future regulation. There were six bills that passed legislatures during these years that developed new regulatory regimes. We examined five of those. At the time of writing, Alabama did not have enough accessible information to compare with the other state legislative efforts.

Appendix B

Additional Details on Legislator Sample

Figure B1

TABLE A1 | Bills passed in U.S. state legislatures addressing AI 2019–2022.

State	Year	Bill number	Approach	Summary
AL	2022	SB 56	Regulate	Requires that facial recognition is not the only basis for arrest
*CO	2022	S 113	Regulate	Regulates state use of facial recognition and establishes a commission to continue study
*IL	2021	H 53	Regulate	Amends Interview Act and requires reporting on demographic info for automation of granting of job interviews
IL	2021	H 645	Study	Future of Work Task Force focused on questions about emerging technologies and AI
VT	2021	H 410	Capacity Building	Creates a Division of Artificial Intelligence within an existing agency on digital services
WA	2021	S 5092	Capacity Building	Develops a work group to oversee state use of automated decision tools
AL	2021	S 78	Study	Establishes the Alabama Council on Advanced Technology and Artificial Intelligence
*CO	2021	SB 169	Regulate	Prevention of discrimination insurance
MS	2021	HB 633	Encourage	Calls for a computer science curriculum that includes AI
NJ	2020	S 2723	Encourage/Capacity Building	Allows Chief Technology Officer to evaluate annually the use of AI in service provision
UT	2020	SB 96	Encourage	Develops a deep technology initiative for higher education
AL	2019	SJR 45	Encourage	Commends tech and growing AI industry
AL	2019	SJR 71	Study	Establishes commission on AI
CA	2019	AB 485	Study/Capacity Building	Requires local agencies to report on AI job loss
*ID	2019	HB 118	Regulate	Requires notification of use of pretrial risk assessment algorithms
*IL	2019	H 2557	Regulate	Requires informing applicant when AI is used to screen candidates for employment
NY	2019	S 3971	Study	Establishes commission
TX	2019	SB 64	Encourage	Encourages all agencies to consider AI utilization (in broader bill on cybersecurity)
VT	2019	H 16	Study	Establishes a commission to study AI

Note: The final selected cases are indicated with *s.

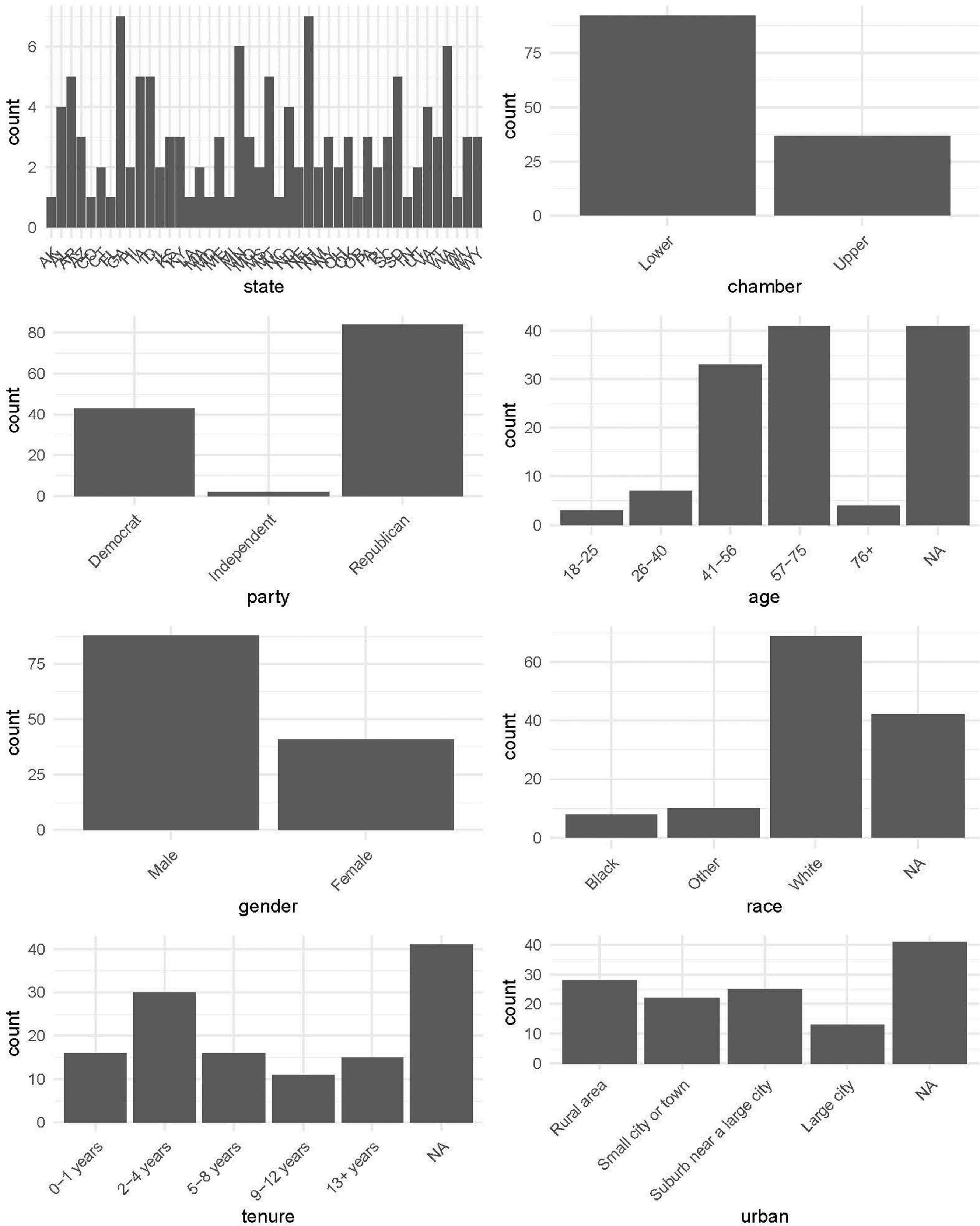

FIGURE B1 | State legislator demographics. *Note:* demographic data obtained via publicly-available information or survey responses.

Appendix C

Survey Instrument

1. Are you a United States state-level policymaker (State Senator, State Representative) or staff member/representative of a policymaker's office? [Yes, No].
2. What is your affiliation or position? [Open-ended].
3. Thank you for your willingness to participate in the survey about policymaker attitudes about artificial intelligence (AI). It should take no more than 3–5 min. Your responses will only be made available at an aggregate level; they will not be tied to you as an individual or your office. We will share a final report with survey takers who are interested. [Instructions].
4. Artificial intelligence (AI) refers to computer systems that perform tasks or make decisions that usually require human intelligence. AI can perform these tasks or make these decisions without explicit human instructions. Today, AI has been used in applications such as: identifying people from their photos, diagnosing diseases like skin cancer and common illnesses, blocking spam email, helping run factories and warehouses, and predicting what one is likely to buy online. Some important issues related to AI include: self-driving vehicles, facial recognition, social media algorithms, and industrial robotics. [Instructions].
5. How much have you heard about artificial intelligence (AI) before today? [Nothing at all, A little, A moderate amount, A lot].
6. How much has your state government focused on addressing AI policy (e.g., hearings, legislation, task forces) in the last few years? [Not at all, A little, A moderate amount, A lot, Don't know/unsure].
7. How much have you, personally, been involved in AI policy efforts (e.g., hearings, legislation, task forces) in the last few years? [Not at all, A little, A moderate amount, A lot].
8. Select all of the activities you've participated in related to AI policy:
   - Followed AI policy issues (in research, media, reports, webinars, etc.).
   - Communicated with constituents (e.g., emails, newsletters) about AI policy.
   - Met with individuals or groups advocating, lobbying, or interested in AI policy.
   - Participated in a committee or task force that has addressed AI policy.
   - Voted on legislation related to AI policy.
   - Proposed or sponsored legislation related to AI policy.
   - Other (please briefly describe).
9. *Thinking about society generally, the benefits of AI outweigh the risks [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree].
10. *I support the development and use of AI [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]
11. *AI should be carefully managed [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree].
12. *Even if neither is exactly right, which comes closest to your view:
    - AI's benefits for innovation are tremendous; any social and ethical risks will not be too difficult to address.
    - AI's social and ethical risks are a major concern; efforts to innovate need to consider these issues more seriously.
13. *Which of the following issues seems more pressing:
    - Ensuring that the United States remains the global leader in AI research and innovation.
    - Ensuring that the development and use of AI respects key human rights and ethical values.
14. *Generally speaking, how much should AI be considered a priority for state governments, compared to other policy topics like healthcare, education, immigration, environment, etc.? [Much lower priority, Lower priority, Equal priority, Higher priority, Much higher priority].
15. *Who do you think it is most important for policymakers to listen to regarding AI policy? Please rank the following actors from most (1) to least (7) important by clicking and dragging:
    - Civil society and advocacy groups.
    - Members of the public.
    - Private companies.
    - Intergovernmental or international actors (e.g., United Nations, European Union).
    - Federal government.
    - Academic researchers and think tanks.
    - The media.
16. *For policy issues related to ethical and social implications of AI, who do you think it is most important for policymakers to listen to? Please rank the following actors from most (1) to least (7) important by clicking and dragging:
    - Civil society and advocacy groups.
    - Members of the public.
    - Private companies.
    - Intergovernmental or international actors (e.g., United Nations, European Union).
    - Federal government.
    - Academic researchers and think tanks.
    - The media.
17. For policy issues related to national security and economic competitiveness implications of AI, who do you think it is most important for policymakers to listen to? Please rank the following actors from most (1) to least (7) important by clicking and dragging:
    - Civil society and advocacy groups.
    - Members of the public.
    - Private companies.
    - Intergovernmental or international actors (e.g., United Nations, European Union).
    - Federal government.
    - Academic researchers and think tanks.
    - The media.
18. *Which comes closest to your view:
    - Private companies should be allowed to regulate their own behavior regarding AI with little government oversight.
    - Governments should monitor, oversee, and provide incentives, but not formally regulate AI.
    - Governments need to step in to regulate AI formally.
19. *Which comes closest to your view:
    - Regulating the development and use of AI is necessary to minimize social and ethical risks.
    - Regulating the development and use of AI will stifle innovation Which comes closest to your view:
20. *Which comes closest to your view:
    - It is too soon to regulate AI; we don't know enough about it yet.
    - The risks of waiting to regulate AI are too large; we should start regulating AI now.
21. Which of the following types of legislation would you support or like to see introduced in your state? Select all that apply.
    - Legislation regulating facial recognition in certain contexts.
    - Legislation requiring companies to perform risk assessments for certain AI products.
    - Legislation requiring social media platforms to regulate content.
    - Legislation regulating AI-generated misinformation (such as deepfake videos or images).
    - Legislation to protect individuals' data privacy.

- Legislation to restrict the use of algorithms in hiring or college admissions decisions.
- Legislation to provide funding for AI research and development.
- Legislation to encourage more immigration of high-skill STEM workers.
- Legislation to increase the supply of high-skill STEM workers (such as training more AI researchers).
- Legislation to increase government capacity and expertise in AI.
- Other (please briefly describe).

22. Which resources would help you to address AI as a policymaker? Please rank the following from most (1) to least (3) important.
    - Expert information explaining how AI works and its impacts on society.
    - Connections to other legislators and organizations interested in AI policy.
    - Examples or stories about how AI has impacted individuals and society.
23. Now we would like to know how you think AI should be used in a few specific applications. We will provide you with short descriptions of cases where AI has been used. After each we will ask you a question about your views. [Instructions].
24. Some police departments use AI to predict where crime is likely to occur, helping them decide where to deploy their resources. But civil rights groups and some researchers argue that these AI systems simply increase arrests in minority neighborhoods without actually reducing crime. Which comes closest to your view on the benefits versus risks of AI used in policing?
    - Risks outweigh benefits; development and use should be discouraged.
    - Risks outweigh benefits; needs careful management and/or regulation.
    - Benefits outweigh risks; needs careful management and/or regulation.
    - Benefits outweigh risks; development and use should be encouraged.
25. AI systems are likely to automate many tasks. Some think that these AI systems will make work less tedious and produce higher standards of living. Others believe that these AI systems will increase unemployment and inequality. Which comes closest to your view on the benefits versus risks of AI used in automating labor?
    - Risks outweigh benefits; development and use should be discouraged.
    - Risks outweigh benefits; needs careful management and/or regulation.
    - Benefits outweigh risks; needs careful management and/or regulation.
    - Benefits outweigh risks; development and use should be encouraged.
26. Lethal autonomous weapons controlled by AI systems could improve our national security while putting fewer service members in danger. But some worry that AI-powered weapons could be dangerous or lead to a reckless arms race. Which comes closest to your view on the benefits versus risks of AI used in autonomous weapons?
    - Risks outweigh benefits; development and use should be discouraged.
    - Risks outweigh benefits; needs careful management and/or regulation.
    - Benefits outweigh risks; needs careful management and/or regulation.
    - Benefits outweigh risks; development and use should be encouraged.
27. 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. Which comes closest to your view on the benefits versus risks of AI used in self-driving cars?
    - Risks outweigh benefits; development and use should be discouraged.
    - Risks outweigh benefits; needs careful management and/or regulation.
    - Benefits outweigh risks; needs careful management and/or regulation.
    - Benefits outweigh risks; development and use should be encouraged.
28. 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. Which comes closest to your view on the benefits versus risks of AI in product, news, and content recommendations?
    - Risks outweigh benefits; development and use should be discouraged.
    - Risks outweigh benefits; needs careful management and/or regulation.
    - Benefits outweigh risks; needs careful management and/or regulation.
    - Benefits outweigh risks; development and use should be encouraged.
29. Finally, we'd like to ask some questions about you. Only aggregate, anonymous results will be reported, and answering these questions is very helpful to us. [Instructions].
30. What is your age? [18-25, 26-40, 41-56, 57-75, 76 +].
31. What is your gender? [Male, Female, Other].
32. What is your race? (Please select the category below that best describes you) [White, Black or African American, Asian or Pacific Islander, Hispanic, American Indian or Alaska Native, Other race or ethnicity].
33. Generally speaking, where would you place yourself along the political spectrum? [Strong liberal, Lean liberal, Moderate, Lean conservative, Strong conservative].
34. How long have you served in the state legislature? [0-1 years, 2-4 years, 5-8 years, 9-12 years, 13+ years].
35. What type of community do you primarily represent? [Rural area, Small city or town, Suburb near a large city, Large city].
36. Would you like to receive the final anonymous report summarizing the results of this study? If so, put your e-mail address below. [Open-ended].
37. Is there anything else you wish to share about AI policy, e.g., work you have done, resources that would help you, thoughts about policy issues related to AI? [Open-ended].

Note: Questions marked with * were used as part of principal component analysis, along with political party, available via additional administrative data not asked directly in the survey.

Appendix D

Principal Component Analysis Results

Figure D1

We see similar results when we use principal component analysis (PCA) to explore the underlying dimensions explaining state legislators' responses across survey questions. 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, indicated in Appendix C, represent the key themes driving our survey design. For example, support for AI in distinct use cases (e.g., transportation, healthcare) is strongly correlated with *general* support for AI development, so we omit use case specific questions.

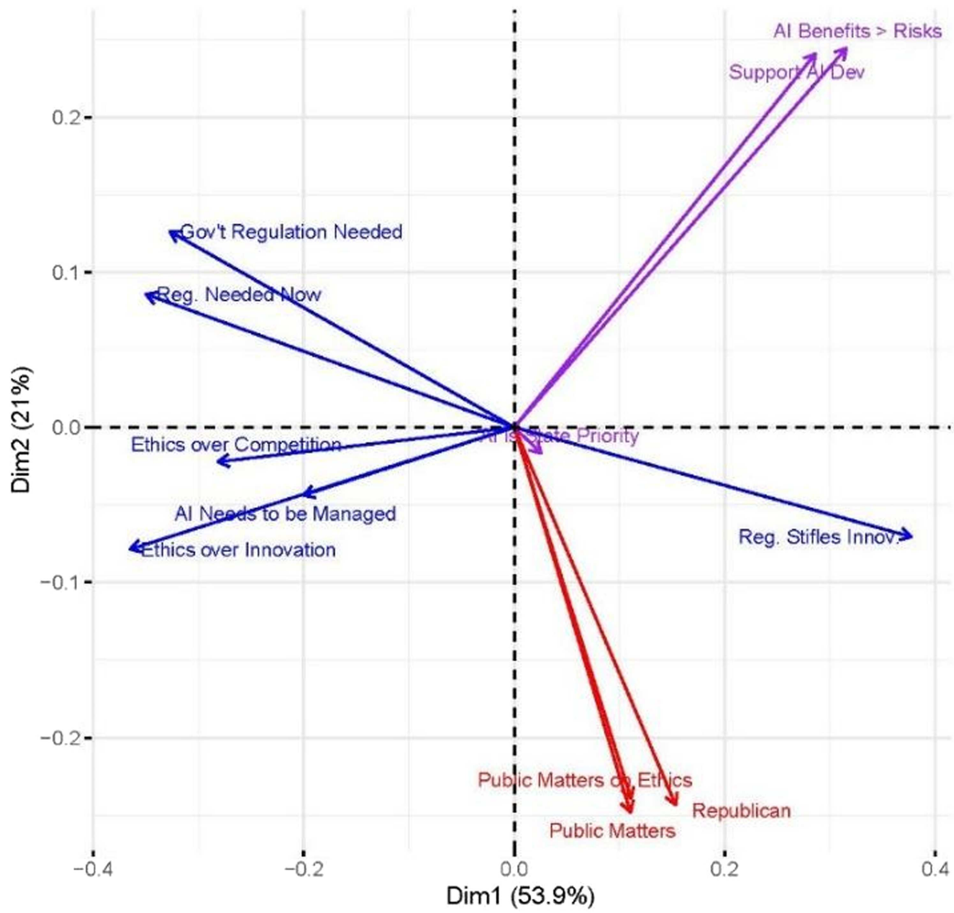

FIGURE D1 | Dimensions underlying state legislators' opinions on AI policy. *Note:* Dimension 1 (blue) represents the tension between innovation and ethics/regulation; Dimension 2 (red) is associated with partisan identification and preferences for public input. Variables in purple load similarly on both components.

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. Variables in blue map primarily onto the first dimension, variables in red map primarily onto the second dimension, and variables in purple map relatively strongly onto both dimensions.

The first component, explaining a sizable 53.9% of the total variation across survey questions, corresponds to a dimension emphasizing the tension between innovation, on one hand, and ethics, regulation, and careful management on the other hand. Noticeably, partisanship is not a prominent part of this dimension. That is, preferences for ethics versus innovation were not strongly associated with partisanship. Yet, partisanship *is* reflected in the second component (explaining 21% of variation in responses) related to Republican identification and preferences for public input, which suggests that partisanship is still relevant despite not driving state legislators' main considerations.

Appendix E

Additional Evidence From Case Studies

Problem definitions. We witness similar dynamics in the other three cases as in the Idaho case. The Illinois legislature moved from bipartisan support in 2019 of a bill that focused on transparency and privacy when using AI in the hiring process, to a 2021 partisan debate and emergent partisan vote on an amendment that re-centered the problem of bias. Likewise, a 2021 debate in Colorado about the use of AI in insurance decisions centered on discrimination of protected groups. In addition to debates about the extent of the problem of racial bias in insurance, there was contestation around the role of AI in creating that problem. Partisan divisions made a vibrant appearance in testimony, emphasizing competing racial projects and resulted in a party line vote on the bill. The subsequent year, the Colorado legislature considered regulation on facial recognition where racial discrimination was only one of a number of social and ethical problem definitions discussed. This bill passed with bipartisan support including with support of some of the vocal opponents of regulation of AI use in insurance just the year before.

Policy tools. In addition to findings from the Illinois case, the other case studies also show the unique analytic leverage of considering policy tools to understand partisan triggers. In the Colorado debate over insurance pricing, broad debates over the best tool for addressing racial discrimination—the market or government regulation—contributed to a party line vote. In Idaho, the bill targeting pretrial release risk assessments originally sought to require validation that systems were "free of bias." However, technical and logistical feasibility about this validation process resulted in contention over the proposed tool, while notification and consent were softer tools that could garner broad bipartisan support.

Policy stakeholders. Main findings regarding the Colorado cases are mirrored in the 2019 Illinois bill requiring notification and consent for use of AI in hiring, for which there was no 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. Business not only did not find this regulation to troubling, but may have even (as the Democratic representatives feared) have seen it as *favorable* to business interests. Through nonintrusive notification requirements, businesses could feel more confident in the implicit state endorsement of the use of AI for job candidate vetting. This evidence echoes the importance of focusing on disrupted versus disrupting industries in AI, and the presence of within-party debate, rather than treating the private sector as a simple Republican-aligned block acting in opposition to Democratic-aligned civil society groups.

Appendix F

Bipartisanship in Federal Legislation

For example, the landmark CHIPS and Science Act passed the Senate 64-33 with a 243-187 vote in the House. The following pieces of AI legislation all also had bipartisan support: 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).