

State Procurement of AI: Diffusion, Collaboration, and Policy Implementation

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Abstract

State agencies translate policy responsibilities into requests for technological capabilities through procurement. This paper examines whether their pursuit of artificial intelligence follows patterns of interstate influence. I construct a public-source dataset of 269 initiatives across 50 U.S. states between January 2017 and May 2026, classified by policy domain. Event-history models examine states' first pursuit of AI and first entry within particular domains, while count models examine procurement volume. I find no consistent evidence that accumulated activity among geographic or political peers predicts faster first entry. Some peer measures are associated with procurement volume, while repeated regional procurement shows no clear additional association with entry or activity. Documentary accounts identify professional exchange, collaborative development, and experience carried by vendors as possible pathways of influence. These findings position procurement as a setting for studying policy implementation and suggest closer attention to the relationships through which agencies encounter and develop technological capabilities.

1 Introduction

New federal work requirements from H.R. 1 put pressure on states to change how they administered food and medical assistance. In 2025, Maryland’s Department of Human Services warned that verifying compliance could overwhelm existing processes, increase caseworker workloads, and lead to wrongful benefit terminations. The department sought an artificial intelligence assistant from technology vendor Nava to help residents upload and correct documents used to verify work requirements for the Supplemental Nutrition Assistance Program (SNAP) and Medicaid. The project was designed for use beyond Maryland. Its plan designated Maryland as the initial implementation site, with other states and the District of Columbia able to observe development, influence the design, and consider using the tool in their own programs. The American Public Human Services Association would organize this collaboration through an advisory committee, peer learning, and shared implementation guidance.¹

Procurement is the process through which governments seek and obtain the goods and services they need to carry out public responsibilities, and its records show how agencies can translate policy into requests for specific capabilities. For example, in September 2023, California Governor Gavin Newsom signed an executive order directing state agencies to consider opportunities to procure and use generative AI (Newsom 2023). The following January, the state sought a generative AI solution for health care facility inspections, explicitly identifying the executive order as a basis for the request (California Department of General Services and California Department of Technology 2024). Following these requests across policy domains (such as health and human services, transportation, and education) makes it possible to examine where AI enters government and how agencies’ choices relate to what other states are doing.

I construct a dataset from public sources covering 269 initiatives across all 50 states to

¹Maryland Department of Human Services, PBIF Signed Agreement, Exhibit Two, pp.13–14; statement of work with the American Public Human Services Association, pp.1–2; revised Nava statement of work, p.1.

acquire or fund AI capabilities between January 2017 and May 2026. Procurement postings, agency documents, and materials obtained through public records requests establish what agencies sought and when they acted. I organize these initiatives by policy domain and examine both a state’s first recorded pursuit of AI and its first recorded pursuit within a particular domain. I also examine the volume of activity, allowing governments to return for further AI procurements after their initial entry. The analysis compares activity among states that share a border, belong to the same region, or have similar political characteristics.

I find no consistent evidence that accumulated procurement elsewhere predicts earlier first AI entry or earlier entry into a new policy domain. Exploratory comparisons reveal positive associations between procurement volume within policy domains and prior activity among politically similar states. These patterns do not establish that agencies learned from or copied one another. Following the mixed-methods approach of Robles & Mallinson (2024), I examine procurement records directly to identify accounts of how agencies encountered particular AI tools. One example comes from vendor Acusensus, whose AI camera systems were sought for traffic enforcement and data collection. Georgia’s procurement records describe learning about North Carolina’s experience through a professional meeting and include information supplied by the vendor. The paper places these forms of evidence alongside one another to examine both the emergence of administrative demand and the relationships through which governments encounter AI tools. In doing so, it brings agencies’ pursuit of technological capabilities into the study of policy diffusion and implementation.

2 Procurement Demand and Interstate Influence

Seeking an AI tool is in itself an administrative choice about how a public responsibility should be carried out. A human services agency might seek faster review of eligibility documents, while a transportation agency might seek better detection of unsafe driving. Translating those concerns into a request typically requires officials to specify both the work they want

a system to perform and the conditions under which it would be used. As Mulligan & Bamberger (2019) argue, choices embedded in machine-learning systems can shape policy through decisions about goals, risk, and discretion; procurement documents provide a direct record of the capabilities an agency has chosen to pursue. The release of a solicitation makes that demand public, even while vendor selection and implementation remain unresolved.

Similar demands can emerge across states even when agencies make their decisions independently. Policy diffusion research distinguishes conditions within a state from the influence of choices made elsewhere (Berry & Berry 1990). Agencies responsible for the same programs may confront common federal requirements, workload pressures, or new products offered by the same vendors. Their ability to respond can also depend on funding, technical staff, and the systems already in place. These conditions provide an explanation for why procurement activity might cluster across states without one state’s decision influencing another’s. They also mean that the relevance of another state’s experience depends on the policy problem: an earlier AI purchase in transportation may offer little guidance to officials deciding how to process benefit claims. Examining procurement within policy domains narrows the comparison to agencies confronting more closely related responsibilities.

Earlier procurement elsewhere can give officials a concrete example of an AI application and a potential supplier. Learning occurs when agencies use information about those choices and their consequences to reassess a capability’s value or feasibility (Shipan & Volden 2008, Gilardi 2010). A procurement notice may convey only that another agency is pursuing a tool, while professional meetings, demonstrations, or continuing exchanges may supply information about its performance. Repeated procurements may also make a capability appear increasingly viable or expected, creating pressure to revisit an earlier decision to wait. If these signals matter, greater prior activity among relevant peers should be associated with earlier first AI procurements, earlier entry within particular policy domains, and greater procurement activity.

Interstate influence can also begin before a government has implemented a system that

others can evaluate. Research on collaborative innovation describes how public agencies and other participants can jointly develop new solutions (Sørensen & Torfing 2011, Schulze 2024). States might help define a problem, identify desired features, or take part in a shared pilot before deciding whether to acquire the resulting tool. Maryland’s planned advisory group illustrates this possibility: prospective users were to help shape the system, with Maryland designated as its initial implementation site. The first recorded acquisition may therefore occur within a process already involving several governments. Procurement timing and the development of interstate relationships can describe different stages of the same effort to build administrative capability.

Procurement records can also reveal the considerations behind agencies’ choices. Following the mixed-methods approach of Robles & Mallinson (2024), I examine these records alongside the statistical analysis to better identify the pathways through which diffusion may occur. Table 1 presents examples consistent with four mechanisms discussed in policy diffusion research: competition, emulation, learning, and coercion (Shipan & Volden 2008). Virginia’s Lottery describes protecting its market position, while its Department of Social Services identifies systems elsewhere as models for fraud prevention. Georgia reports encountering North Carolina’s experience with Acusensus through a professional meeting, and Idaho connects its program-integrity request to federal compliance pressures. These accounts provide evidence about the influences agencies themselves identify, complementing the broader patterns examined in the statistical analysis.

TABLE 1: ILLUSTRATIVE DIFFUSION MECHANISMS IN STATE PROCUREMENT

Mechanism	Illustrative procurement	Summary
Competition	Virginia Lottery iLottery procurement (2026)	The Lottery seeks to preserve its position as the highest-grossing and highest-per-capita U.S. iLottery program while expanding market share against other online gaming options.
Emulation	Virginia Department of Social Services fraud-prevention procurement (2024)	The procurement identifies fraud-detection systems used by the SEC, IRS, CMS, and commercial providers, then states that Virginia needs a similar system for benefits integrity.
Learning	Georgia Acusensus procurement (2024)	The documentation reports that North Carolina presented Acusensus-supported distracted-driving results to southeastern leaders at a Motor Carrier Safety Assistance Program Commanders Meeting before Georgia’s procurement.
Coercion	Idaho Department of Health and Welfare program-integrity procurement (2026)	The procurement ties a search for AI-enabled monitoring and improper-payment detection to recent federal actions, funding scrutiny, and heightened expectations for benefit-program compliance.

Note: Idaho’s August 2026 request falls after the modeled period.

The states from which officials draw information need not be the same for every procurement. Shared borders and regional ties can create opportunities for contact and expose agencies to similar administrative problems. Professional associations and vendors can also connect officials working in the same policy area across greater distances (Robles & Mallinson 2024, Desmarais, Harden & Boehmke 2015). Political similarity, including a governor’s party or a state’s political preferences, may make another state’s choices appear more relevant or acceptable. Learning is selective, however, and similar preferences can also lead officials to pursue similar technologies independently (Gilardi 2010). Geography and political similarity therefore identify possible sets of relevant peers, whose prior procurement activity can be compared with a state’s own decisions.

Entry and continued procurement also represent different administrative decisions. Diffusion research distinguishes a government’s initial adoption from later expansion of its involvement (Boehmke & Witmer 2004). A state may seek an AI tool in a policy area once, then return to renew a service, expand its scope, or pursue another application. Recurring activity elsewhere can sustain the visibility of AI capabilities and repeatedly place them before officials who have yet to act. Under this framework, a peer’s second or third procurement remains relevant even after its first request has been recorded. Distinguishing the number of peer states that have acted from their additional procurements makes it possible to ask whether continued activity adds pressure beyond the spread of initial entries. Plainly speaking, the expectation is that as peers seek AI for additional applications, its growing salience increases pressure on states that have yet to pursue it (Boushey 2010).

3 Data and Measurement

I constructed a dataset of 269 state initiatives to obtain or fund AI capabilities between January 2017 and May 2026, covering all 50 states. Agentic AI systems performed a substantial share of the search and document collection under my direction, searching public procurement portals, agency websites and archives, locating supporting attachments, and assisting with public records requests. Searches used terms such as artificial intelligence and machine learning in notices and available supporting documents, supplemented by searches for named systems and procurement identifiers. Missing materials were pursued through archive searches and requests to the responsible agencies. I established the scope and inclusion rules and reviewed disputed cases. This assistance made an extensive collection effort feasible for a single researcher. For each initiative, the available identifiers, source links, date evidence, and obtained materials were retained, providing an audit trail between the analytic observations and their supporting evidence.

Each observation represents a distinct state initiative to obtain or fund an AI-related

capability. Eligible records include requests for information, competitive solicitations, sole-source notices, state-issued AI grant calls, and documented state grant applications for defined AI projects. Collection concentrated on procurement opportunities, so the inventory is not an exhaustive census of AI-related grants. Duplicate postings, amendments, and later award documents were linked to their originating initiative. A subsequent procurement was counted separately when it represented a distinct request, such as a new lease or expansion, preserving recurring demand without counting the same initiative more than once.

The institutional scope covers state agencies and central state university systems, excluding individual university campuses, local governments, and the District of Columbia. References to artificial intelligence, machine learning, or natural language processing in buyer-issued materials qualified as evidence of AI relevance, including optional capabilities within a broader procurement. Records seeking named AI products or services directly supporting their implementation were also eligible following review of the supporting evidence. A general claim that a vendor offered AI was insufficient unless the record connected that capability to what the agency sought, which would reflect the actual behavioral aspect of seeking AI-related tools.

All analyses use calendar months. For solicitations and notices, timing follows the original release date. Where an exact day was unavailable but the issuance month could be established, I retained month precision rather than assigning an artificial date. The dataset contains 267 records dated to the day, one dated to the month, and one assigned month for a grant application.²

Document availability was assessed separately from eligibility and timing. Some initiatives have original solicitations and supporting attachments, while others are documented through official notices, agency correspondence, or later records describing the request. Missing attachments did not automatically exclude an otherwise eligible, dated initiative. It could, however, limit how precisely the requested capability or policy domain could be identified. I

²The grant application is assigned to August 2025, the final month of a documented application window running from July 17 to August 16. The actual submission month is unconfirmed.

retained source-availability and date-precision information so that these limitations remained visible in the analytic records.

Policy domains identify the substantive area of government activity that the requested capability serves, such as health and human services, transportation, or education and workforce development. Classification follows the documented program and intended use rather than the technology alone or the name of the purchasing office. For example, AI used to review Medicaid eligibility belongs to health and human services, while a government-wide employee administration system belongs to general government. The analysis uses nine domains, including an Other category for initiatives that fit none of the substantive domains or lack sufficient information for a specific assignment. Eighteen initiatives were assigned to this category.

I adapted the separation of focused summarization and subsequent scoring in Benoit, de Marchi, Laver, Laver & Ma (2026) to the procurement records. Available substantive documents were converted to readable text, using optical character recognition for scanned pages. For document collections with overlapping text, exact repeated passages were consolidated while preserving their source locations and surrounding context. GPT-6.1 Sol then generated a structured summary for each initiative covering four elements: the agency and intended users, the requested AI capability, the stated purposes of the request, and the substantive policy setting. The instructions required the model to distinguish the AI component from the broader deliverable, required capabilities from optional features, and proposed activities from documented implementation. Summaries linked substantive claims to source passages and recorded missing or ambiguous information.

For each of the 269 initiatives, OpenAI’s Decisions API, using GPT-6 Luna, received the complete four-part summary and the policy-domain coding instructions. The classifier selected a domain and returned probabilities across the available categories. Researcher-coded reference labels were withheld from these requests. I retained the model predictions and probabilities separately from the reference labels and subsequently reviewed assignments,

allowing agreement to be assessed before using the classifications in the analysis.

I assessed the classifier against a gold-standard reference set of 80 initiatives that I coded from the available original source documents. Sixty cases supported development of the coding instructions and summary procedure, while twenty additional cases provided a subsequent evaluation. Disagreements prompted review of source documents and clarification of coding rules before classification of the full dataset. All reference coding was completed by a single researcher.

Decisions matched my policy-domain labels in 57 of the 60 development cases (95 percent). In the subsequent evaluation, it matched 16 of 20 cases (80 percent). Following source review and refinement of the coding instructions, classification of the full dataset matched the revised reference labels in 76 of 80 cases (95 percent). The final rate measures agreement after iterative refinement of the procedure and reference labels, rather than accuracy on an independent sample.

4 Research Design

I organized the initiatives into monthly panels covering all 50 states from January 2017 through May 2026. Two outcomes capture entry into AI-related procurement. The first identifies the month of a state’s first observed AI initiative in any policy domain. The second identifies its first observed initiative within each domain. A state contributes observations to the general first-entry analysis through the month of its first initiative. For domain-specific entry, each state remains under observation separately within each domain until its first initiative there or the end of the study period. Multiple initiatives in the same first month constitute a single entry event.

I also measured procurement activity as the number of distinct initiatives in each state-month and each state-domain-month. Months without a recorded initiative were coded as zero in these panels. These counts include both initial and subsequent initiatives, capturing

how administrative demand accumulates beyond first entry. A separate exploratory analysis examines activity only in months after a state’s first initiative within a domain. That analysis begins in the following month, excluding the initial entry month from the measure of subsequent activity.

For each state and month, I measured peer exposure using the cumulative number of initiatives previously recorded in other states during the study period. The measures average those counts across the relevant comparison states, with weights determined by the geographic or political relationship being examined. Exposure for general entry and statewide activity includes initiatives across all policy domains, while domain-specific analyses use only initiatives in the same domain. Only initiatives dated to earlier months contribute, and a state’s own initiatives are excluded. Both a peer state’s first initiative and its subsequent requests contribute to exposure, capturing recurring activity alongside the spread of first entry.

I defined geographic peers using two relationships: membership in the same U.S. Census region and adjacency between states. The regional measure uses the Northeast, Midwest, South, and West, assigning equal weight to the other states within each region. The adjacency measure assigns equal weight to neighboring states.³ Regional analyses include all 50 states. Comparisons involving adjacency use the same 48 contiguous states because Alaska and Hawaii have no adjacent U.S. states. I examined regional and adjacent-state exposure separately and together within this common sample.

I measured ideological similarity using state citizen-ideology estimates from 2016, before the observation period. The scores were rescaled between zero and one, and similarity was defined as one minus the absolute difference between two states’ scores. After excluding each state from its own comparison group, I normalized these weights to sum to one. States with more similar citizens therefore contribute more to the weighted average of earlier initiatives. The weights remain fixed throughout the study, so procurement activity does not determine

³The adjacency definition includes point contact at Four Corners. An alternative specification uses shared borders only.

which states are treated as ideologically similar. These analyses cover January 2017 through May 2026, with comparisons involving adjacency restricted to the 48 contiguous states.

A second political measure identifies peers through the governor’s party affiliation in the previous calendar year. Other states with governors from the same major party receive equal weight. For each year, these weights apply to the peer states’ entire prior initiative histories, including initiatives issued under earlier governors. The measure therefore captures prior activity among states with a shared lagged partisan affiliation, rather than activity undertaken exclusively by governors of that party. Party-based analyses cover January 2018 through May 2026 and use the 48 contiguous states to permit comparisons with geographic exposure. States and state-domain pairs that had already entered before 2018 remain outside the corresponding first-entry risk sets.

I estimated Cox proportional hazards models for first entry, relating prior peer activity to the rate at which states issue their first observed AI initiative. Time is measured in monthly intervals from January 2017, and the baseline hazard allows the underlying entry rate to change over the study period without imposing a particular trend. The domain-specific models allow a separate baseline hazard for each policy domain while estimating a common association between peer exposure and entry across domains. I report hazard ratios, which describe differences in the entry rate among states that have not yet entered. A ratio above one indicates faster entry at higher exposure, while a ratio below one indicates slower entry.

For monthly procurement activity, I estimated Poisson pseudo-maximum-likelihood models with fixed effects. The statewide models include state and calendar-month fixed effects, accounting for stable differences between states and changes common to all states in a given month. The domain-specific models instead include state-domain and domain-month fixed effects, comparing changes within each state and domain after accounting for monthly changes shared by states in that domain. The same specification is used for the exploratory analysis of activity after domain entry.⁴ Exponentiated coefficients describe

⁴Poisson estimation removes groups with no initiatives or only one observation. Additional separation checks remove observations that prevent finite estimates in the post-entry models.

proportional differences in expected initiative counts. For both model families, I report 95 percent confidence intervals using standard errors clustered by state. These models estimate associations between peer activity and administrative demand; shared pressures and uneven source coverage remain possible explanations for those relationships.

The main first-entry models account for population size, technology-related economic activity, citizen ideology, Census region, partisan control, and fiscal reserves. Partisan controls identify Republican governors, Republican legislative control, and divided legislative control. Population enters in logarithmic form, and fiscal reserves are measured as rainy-day fund balances relative to general-fund spending. The activity models use the same economic, ideological, partisan, and fiscal controls, with their fixed effects absorbing stable geographic differences. Smaller first-initiative specifications provide a comparison given the limited number of entry events.

Population estimates come from the U.S. Census Bureau, economic measures from the Bureau of Economic Analysis, fiscal reserves from the National Association of State Budget Officers, and partisan control from the National Conference of State Legislatures. The technology-related economic measure combines information industries, computer systems design, and miscellaneous professional, scientific, and technical services as a share of state gross domestic product. Population and fiscal reserves are measured in the preceding calendar and fiscal years, respectively. The economic measure also uses the preceding year, except that the 2026 observations retain the latest complete industry data from 2024. Citizen ideology comes from the American Ideology Project (Warshaw & Tausanovitch 2022), using estimates standardized within the 2016 wave for 2017 through 2021 and within the 2020 wave thereafter. Partisan controls use annual snapshots held constant within each year, including a March 2017 snapshot for that year, so they do not capture the exact month of political transitions.

I report estimates for a one-standard-deviation increase in peer exposure, using the conditional exposure scale described in the results for political activity models. In additional regional models, I separated the share of peers that had begun AI procurement from the

volume of their subsequent initiatives. This distinguishes wider participation among states from recurring demand among states that had already entered. It also allows the analysis to examine whether those two patterns have different associations with a state’s own procurement behavior.

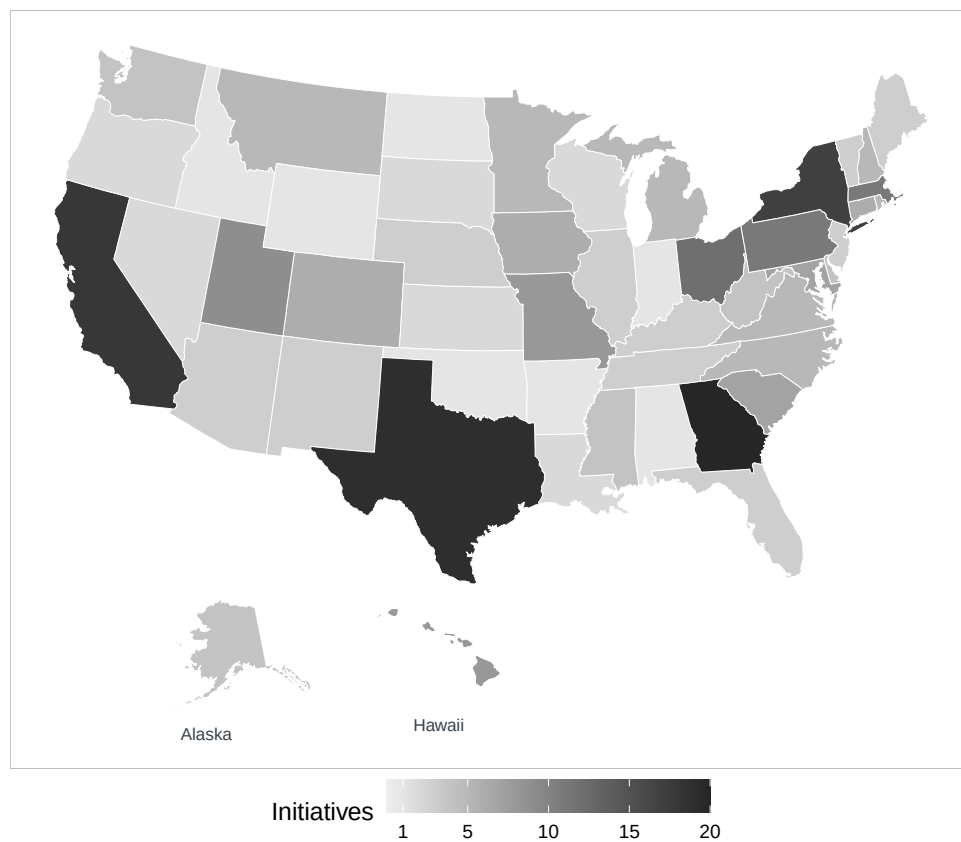
I assessed the sensitivity of domain-entry findings to starting the analysis in 2018, ending it in 2025, and uncertainty in policy-domain classification. The classification check excluded uncertain initiatives from peer exposure and stopped following affected states before their first uncertain record. I also checked whether the entry models’ assumption of stable relationships over time was supported, and estimated alternatives allowing selected control relationships to change. These checks help distinguish findings that persist across reasonable specifications from those that depend on particular modeling choices.

5 Findings

Recorded AI procurement activity increased substantially during the study period, rising from four initiatives in 2017 to 76 in 2025. A further 39 initiatives were recorded during the first five months of 2026. By the end of 2022, 26 states had issued at least one observed initiative; all 50 had done so by May 2026. These patterns show both broader state participation and increasing procurement activity, although differences in historical source coverage may also affect the observed trend. Figure 1 shows the geographic distribution of these initiatives, while Figure 2 shows the accumulation of states issuing a first observed AI initiative.

The initiatives span a range of administrative responsibilities. Health and human services accounts for the largest number, with 53 initiatives, followed by general government with 44, education and workforce with 36, and transportation and infrastructure with 35. Even the largest domain represents only about one fifth of the dataset. Across the nine domains, states had issued a first observed initiative in 162 of the 450 possible state-domain combinations. National reach therefore coexists with substantial variation in the policy areas where states

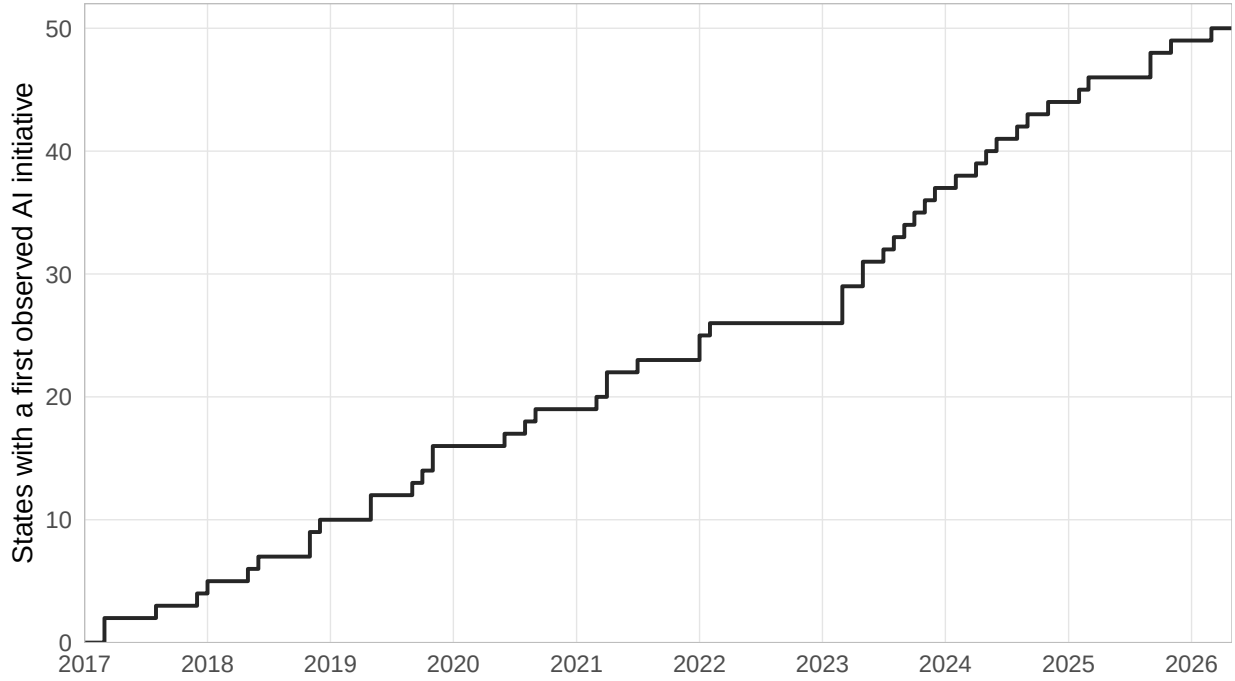
FIGURE 1: AI PROCUREMENT INITIATIVES BY STATE



Notes: January 2017–May 2026; 269 initiatives.

have publicly sought AI capabilities.

FIGURE 2: STATES ISSUING A FIRST OBSERVED AI INITIATIVE



Notes: Cumulative state count, January 2017–May 2026.

Table 2 shows no consistent association between earlier AI procurement among geographic peers and faster first entry. For a state’s first AI initiative, both regional and adjacent-state estimates have wide confidence intervals that accommodate slower or faster entry. The lower point estimates therefore offer little basis for concluding that peer activity delays entry. Diagnostics also raise concerns about treating relationships in the regional general-entry model as constant over time.

For first entry within a policy domain, the regional and adjacent-state estimates are closer to no association. Their hazard ratios are 0.94 and 1.04, respectively, with both confidence intervals including one. Including both geographic measures together did not reveal a clear positive relationship. The regional findings were also similar when the analysis began in 2018, ended in 2025, or accounted for uncertain classifications. These geographic measures therefore provide no consistent evidence that states entered a policy domain more rapidly following procurement activity elsewhere in their region or among adjacent states.

TABLE 2: GEOGRAPHIC PEER ACTIVITY AND FIRST AI PROCUREMENT ENTRY

	First AI initiative		First initiative in domain	
	(1) Region	(2) Neighbors	(3) Region	(4) Neighbors
Prior AI initiatives: regional peers	0.45 (0.06, 3.56)		0.94 (0.79, 1.11)	
Prior AI initiatives: neighboring states		0.80 (0.38, 1.65)		1.04 (0.91, 1.18)
State population (logged)	1.06 (0.63, 1.78)	1.13 (0.70, 1.82)	1.47*** (1.17, 1.84)	1.49*** (1.19, 1.87)
Technology-related share of state GDP	1.81** (1.19, 2.74)	1.75* (1.06, 2.87)	1.17 (0.89, 1.53)	1.27 (0.97, 1.66)
Citizen ideology (state score)	1.55 (0.80, 2.97)	1.70 (0.77, 3.77)	1.02 (0.65, 1.58)	1.16 (0.74, 1.80)
Midwest (vs. South)	0.58 (0.18, 1.85)	0.66 (0.22, 1.96)	1.05 (0.62, 1.77)	1.17 (0.73, 1.88)
Northeast (vs. South)	2.67 (0.40, 18.01)	2.13 (0.45, 10.05)	2.26* (1.06, 4.79)	2.41* (1.13, 5.13)
West (vs. South)	2.05 (0.91, 4.61)	1.61 (0.66, 3.94)	1.53 (0.86, 2.74)	1.38 (0.75, 2.55)
Republican governor	0.99 (0.49, 1.99)	0.96 (0.48, 1.92)	1.27 (0.87, 1.86)	1.26 (0.85, 1.85)
Republican-controlled legislature	0.59 (0.15, 2.33)	0.51 (0.12, 2.18)	1.23 (0.67, 2.26)	1.14 (0.62, 2.09)
Divided legislative control	0.84 (0.18, 3.86)	0.79 (0.17, 3.58)	1.80 (0.96, 3.36)	1.73 (0.91, 3.30)
Rainy-day reserves / general-fund spending	0.94 (0.76, 1.18)	0.94 (0.73, 1.21)	0.97 (0.78, 1.19)	0.95 (0.76, 1.20)
States	50	48	50	48
First AI entries	50	48	162	156
Monthly observations	2,990	2,829	45,337	43,412
Partial log likelihood	-139.5	-132.1	-574.1	-544.7

Notes: Cox hazard ratios with state-clustered 95% intervals; continuous predictors are standardized. * $p < .05$, ** $p < .01$, *** $p < .001$.

TABLE 3: POLITICAL PEER ACTIVITY AND FIRST AI PROCUREMENT ENTRY

	First AI initiative		First initiative in domain	
	(1) Ideology	(2) Same-party	(3) Ideology	(4) Same-party
Prior AI initiatives: ideological peers	0.07 (0.001, 7.46)		0.63 (0.18, 2.22)	
Prior AI initiatives: same-party governors		0.99 (0.15, 6.68)		0.87 (0.59, 1.29)
State population (logged)	1.04 (0.62, 1.74)	1.29 (0.77, 2.15)	1.47*** (1.18, 1.83)	1.53*** (1.22, 1.92)
Technology-related share of state GDP	1.77** (1.19, 2.64)	1.74 (1.00, 3.04)	1.17 (0.89, 1.53)	1.24 (0.95, 1.63)
Citizen ideology (state score)	1.29 (0.59, 2.82)	1.71 (0.83, 3.55)	0.97 (0.63, 1.51)	1.16 (0.77, 1.75)
Midwest (vs. South)	0.85 (0.34, 2.11)	0.66 (0.24, 1.80)	1.08 (0.65, 1.81)	1.14 (0.69, 1.89)
Northeast (vs. South)	1.83 (0.43, 7.84)	0.86 (0.22, 3.38)	2.22* (1.05, 4.71)	2.21* (1.10, 4.44)
West (vs. South)	1.83 (0.83, 4.04)	1.61 (0.59, 4.39)	1.49 (0.82, 2.68)	1.32 (0.73, 2.39)
Republican governor	0.92 (0.45, 1.87)	1.23 (0.52, 2.91)	1.24 (0.84, 1.83)	1.24 (0.81, 1.92)
Republican-controlled legislature	0.63 (0.16, 2.50)	0.30 (0.08, 1.12)	1.23 (0.67, 2.25)	1.02 (0.58, 1.81)
Divided legislative control	0.88 (0.20, 3.91)	0.98 (0.24, 3.99)	1.79 (0.96, 3.31)	1.71 (0.93, 3.16)
Rainy-day reserves / general-fund spending	0.94 (0.74, 1.18)	0.98 (0.76, 1.26)	0.96 (0.78, 1.19)	0.95 (0.76, 1.18)
States	50	44	50	48
First AI entries	50	44	162	152
Monthly observations	2,990	2,275	45,337	38,250
Partial log likelihood	-139.3	-115.9	-574.0	-529.3

Notes: Cox hazard ratios with state-clustered 95% intervals; continuous predictors are standardized. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 3 shows that earlier activity among politically similar states was also not consistently associated with faster first entry. In the first-initiative models, the ideological estimate is below one but very imprecise, while the partisan estimate is close to one. Within policy domains, both political estimates have confidence intervals that accommodate slower or faster entry. Adding geographic exposure does not reveal a consistent positive political relationship. Political similarity therefore offers little support for explaining faster first entry in this dataset.

Table 2 shows that larger states enter new AI policy domains at higher rates. A one-standard-deviation increase in logged population is associated with a 47 percent higher monthly rate of domain entry in the regional model (95 percent confidence interval: 17–84 percent higher, $p < .001$). Table 3 shows a similar population association in the political-peer models. For general AI entry, the clearer relationship concerns the state’s economic composition. An increase of roughly four percentage points in the technology-related share of state GDP is associated with an 81 percent higher monthly rate of issuing a first AI initiative in the regional model (95 percent confidence interval: 19–174 percent higher, $p = .005$). Larger states thus seem to seek AI in new policy areas earlier, while states with larger technology-related sectors appear to issue their first AI request earlier.

The regional model in Table 2 also estimates a 126 percent higher monthly rate of domain entry for Northeastern states than for Southern states (95 percent confidence interval: 6–379 percent higher, $p = .034$). The wide interval leaves substantial uncertainty about the size of this regional difference. Citizen ideology, partisan control, and fiscal reserves show no consistent associations in the main entry or activity models. These estimates provide little basis for a general claim that Republican-led states or states with larger fiscal reserves pursue AI earlier or more frequently. The extreme control estimates in the smaller post-entry samples remain too unstable for substantive conclusions.

Table 4 shows a positive relationship between neighboring states’ procurement and statewide AI procurement volume. A one-standard-deviation increase in accumulated activity among neighboring states is associated with about 50 percent more expected monthly initiatives. This association remains positive when regional exposure enters the same model. The regional estimate, however, is not statistically significant. The neighboring-state finding therefore suggests an association with procurement volume, despite the absence of a consistent relationship with faster first entry.

Table 4 also shows positive but less conclusive geographic activity estimates within policy domains. Neither the regional nor the neighboring-state estimate is statistically

TABLE 4: GEOGRAPHIC PEER ACTIVITY AND AI PROCUREMENT VOLUME

	Statewide activity		Activity within domain	
	(1) Region	(2) Neighbors	(3) Region	(4) Neighbors
Prior AI initiatives: regional peers	1.47 (0.58, 3.71)		1.27 (0.94, 1.71)	
Prior AI initiatives: neighboring states		1.50** (1.12, 2.01)		1.20 (0.89, 1.62)
States	50	48	50	48
AI initiatives	269	257	269	257
Monthly observations	4,000	3,792	4,032	3,750
Controls (Table A4)	Yes	Yes	Yes	Yes
Fixed effects	State Month	State Month	State-domain Domain-month	State-domain Domain-month
Log likelihood	-848.8	-804.0	-912.3	-865.5

Notes: PPML count ratios per peer-activity SD, with state-clustered 95% intervals. * $p < .05$, ** $p < .01$, *** $p < .001$.

significant. The clearest geographic activity relationship consequently concerns states' total AI procurement volume, without establishing that they are seeking capabilities in the same policy areas as their neighbors. Because these models count both initial and later initiatives, they also leave open whether peer activity is associated specifically with procurement after first entry.

TABLE 5: POLITICAL PEER ACTIVITY AND AI PROCUREMENT VOLUME

	Statewide activity		Activity within domain	
	(1) Ideology	(2) Same-party	(3) Ideology	(4) Same-party
Prior AI initiatives: ideological peers	1.21** (1.06, 1.37)		1.68*** (1.44, 1.95)	
Prior AI initiatives: same-party governors		1.07 (0.93, 1.22)		1.17* (1.04, 1.33)
States	50	48	50	48
AI initiatives	269	253	269	253
Monthly observations	4,000	3,648	4,032	3,621
Controls (Table A4)	Yes	Yes	Yes	Yes
Fixed effects	State Month	State Month	State-domain Domain-month	State-domain Domain-month
Log likelihood	-844.6	-790.3	-867.3	-843.1

Notes: PPML count ratios per conditional exposure SD, with state-clustered 95% intervals. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 5 shows positive associations between politically similar states’ prior procurement and activity within policy domains. The table reports exposure differences scaled to the variation remaining after adjustment for other predictors and fixed effects. Over one such standard deviation, prior activity among states with governors from the same party is associated with about 17 percent more expected monthly initiatives in the same domain. This relationship remains positive and statistically significant when regional and neighboring-state activity enter the model together. The statewide partisan estimate, however, is not statistically significant. The corresponding ideological contrasts are associated with about 21 percent more statewide initiatives and 68 percent more initiatives within a domain.

These contrasts make the estimates easier to interpret without changing the models or their statistical significance. Ideological exposure varies little after adjustment for common trends and other predictors, so a whole-panel standard deviation would represent a much larger contrast than the differences supporting those comparisons. Appendix K documents the reporting scales. Political similarity may reflect shared priorities and pressures, and these exploratory associations do not identify whether agencies learned from one another.

TABLE 6: REGIONAL PARTICIPATION, REPEATED PROCUREMENT, AND AI ACTIVITY

	(1) First AI initiative	(2) First in domain	(3) Domain activity
Regional peers with prior AI activity (share)	0.18* (0.04, 0.78)	0.82 (0.64, 1.05)	1.36* (1.02, 1.83)
Repeat AI initiatives among regional peers	0.61 (0.12, 3.03)	1.05 (0.90, 1.22)	1.02 (0.78, 1.32)
States	50	50	50
First AI entries	50	162	
AI initiatives			269
Monthly observations	2,990	45,337	4,032
Controls (Table A4)	Yes	Yes	Yes
Fixed effects			State-domain Domain-month
Log likelihood	-137.3	-573.3	-911.4

Notes: Hazard ratios (1–2) and count ratios (3) per peer-exposure SD, with state-clustered 95% intervals.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 6 separates wider regional participation from peers’ repeated procurement, revealing no consistent relationship with faster first entry. The estimates for peers’ subsequent

initiatives are not statistically significant for either a state’s first AI initiative or its first initiative within a policy domain. Broader regional participation is associated with slower general first entry, although diagnostics raise concerns about the model’s assumption that relationships remain constant over time. Neither component is statistically significant for entry within a policy domain.

Table 6 shows a positive and statistically significant association between broader regional participation and procurement volume within policy domains. A one-standard-deviation increase in the share of regional peers that have entered is associated with about 36 percent more expected monthly initiatives. The estimate for peers’ subsequent initiatives is close to one and is not statistically significant. These findings do not confirm that repeated procurement among regional peers adds pressure for further action.

Restricting the analysis to months after a state’s first initiative within a domain produces mixed findings. The regional and partisan estimates are not statistically significant, while the ideological estimate remains positive and statistically significant. After removing observations that prevent finite estimates, these models retain only 97 initiatives across 30 states, or 90 initiatives across 28 states in the partisan comparison. The remaining samples cannot separately estimate the partisan controls, and several other controls remain imprecise, limiting what these comparisons establish about continued procurement. Appendix O reports the post-entry estimates and full activity-model coefficients.

6 Acusensus and Vendor-Mediated Diffusion

A closer examination of procurement records can identify pathways that the aggregate measures do not capture. Acusensus’s Heads-Up Real Time system is designed to use AI to identify potential mobile phone and seat belt violations from camera images and send that information to enforcement officers. I examine this case because a Georgia procurement record explicitly identifies how officials became aware of the technology, as well as preserving

information provided by the vendor (Georgia Department of Public Safety 2024). It offers an opportunity to examine how professional exchange and commercial promotion enter the same procurement process.

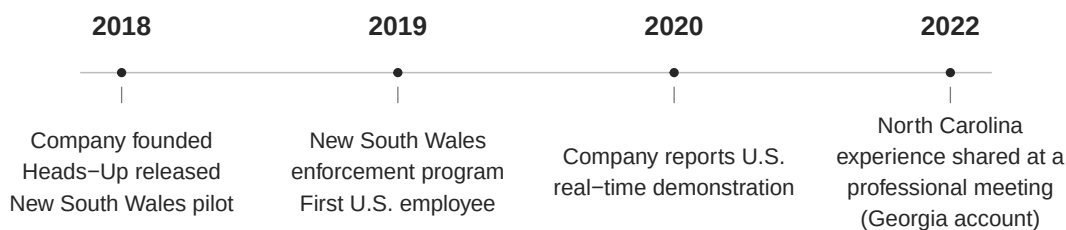
In its 2023 annual report, Acusensus traces its development from an Australian company founded in March 2018 to a supplier pursuing government customers internationally. Its timeline places the first release of Heads-Up and a New South Wales mobile phone detection pilot contract in 2018, followed by an enforcement program in 2019. The company also reports hiring its first U.S. employee in 2019 and demonstrating its real-time enforcement technology in the United States in 2020 (Acusensus Limited 2023). Its pursuit of the U.S. market therefore preceded the state procurements documented here. Figure 3 places the company milestones and professional exchange alongside the dated state requests.

Georgia’s procurement records show how experience with the technology subsequently circulated among state officials. According to its Department of Public Safety, North Carolina presented results from an Acusensus-supported distracted-driving campaign at the 2022 MCSAP Commanders Meeting in Huntsville. Georgia’s Motor Carrier Compliance Division attributed its awareness of the technology to these planning meetings and conferences (Georgia Department of Public Safety 2024). North Carolina issued its documented request for quotes on May 26, 2023, and awarded the contract on May 30 (North Carolina Department of Public Safety 2023). Acusensus describes the resulting operation, which began in mid-2023, as its first ongoing U.S. enforcement deployment (Acusensus Limited 2023). Georgia issued its own notice to lease four systems in April 2024 (Georgia Department of Public Safety 2024).

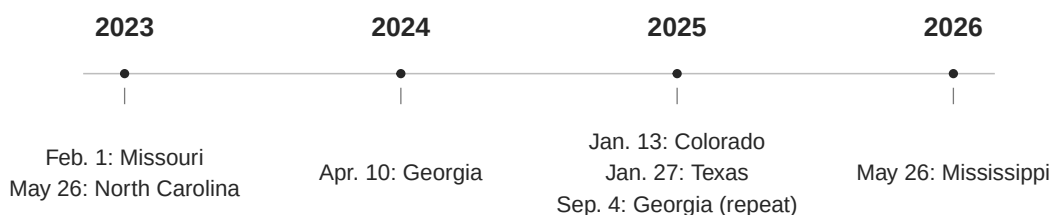
Vendor-provided information also appears in agency justifications for selecting Acusensus. A company letter to North Carolina’s State Highway Patrol described Acusensus as the only supplier combining advanced imaging, AI, and real-time enforcement (Acusensus Inc. 2023). In a March 2024 letter to Georgia, the company similarly described Heads-Up Real Time as the “only solution in existence” combining AI assessment of probable traffic offenses with live roadside enforcement (Acusensus Inc. 2024). Georgia’s notice repeated that claim and

FIGURE 3: ACUSENSUS PRODUCT ORIGINS, PROFESSIONAL EXCHANGE, AND STATE REQUESTS

Origins and professional exchange



Dated procurement initiatives



Notes: Upper row: company and agency accounts (Acusensus Limited 2023, Georgia Department of Public Safety 2024). Release dates follow Table 7.

relayed Acusensus's accounts of operating programs, pilots, and discussions with other states (Georgia Department of Public Safety 2024). The vendor was thus supplying information about both the product's capabilities and its use elsewhere.

Table 7 lists seven Acusensus-related initiatives across six states between February 2023 and May 2026. Missouri sought data on seat belt use, cell phone use, and speed, while Texas sought a 24-week assessment of traffic patterns and potential violations (Missouri Department of Transportation 2023, Texas Department of Public Safety 2025). Colorado sought a study combining data collection with officer intervention (Colorado State Patrol 2025). A May 2026 Mississippi notice sought a three-year enforcement system and support (Mississippi Information Technology Services 2026). These requests range from data collection and testing to direct enforcement support, reflecting different administrative uses of the same vendor's technology.

Georgia's later request also shows demand continuing after the initial procurement. In

TABLE 7: ACUSENSUS-RELATED PROCUREMENT INITIATIVES

Release Date	State	Requested Activity
Feb. 1, 2023	Missouri	Data collection on seat belt use, cell phone use and speed.
May 26, 2023	North Carolina	Heads-Up Real Time traffic enforcement.
Apr. 10, 2024	Georgia	Lease of four camera enforcement systems.
Jan. 13, 2025	Colorado	Mobile imaging, data collection and enforcement study.
Jan. 27, 2025	Texas	24-week Heads-Up data assessment study.
Sep. 4, 2025	Georgia	Continued lease and retrofitting of existing equipment.
May 26, 2026	Mississippi	Three-year multi-violation enforcement system and support.

Notes: Dates identify procurement releases, not awards. Source: Author’s procurement dataset.

September 2025, the Department of Public Safety reported that it had operated the program since 2024 and sought a new lease before its existing agreement expired. The request included retrofitting existing equipment with additional readers for commercial vehicle screening (Georgia Department of Public Safety 2025). This was a further decision to continue and modify an existing program, showing how procurement demand can recur after an agency first pursues a technology.

All in all, the Acusensus case brings professional exchange and vendor promotion into the same account of how an agency encounters an AI tool. Georgia identified North Carolina’s reported experience as a form of awareness and “learning” about the product, while its procurement justification also incorporated the company’s claims about the technology and its use elsewhere (Georgia Department of Public Safety 2024). These records do not establish how common this pathway is across the dataset. They do, however, raise a question for research on AI procurement: how much of what appears to be diffusion among governments is mediated by vendors that demonstrate products, circulate accounts of their use, and help agencies justify their selection?

The relationship may also run upstream. Firms that implement public programs have commercial interests in the policies governing those programs, particularly when new requirements create demand for additional services. Maryland’s addition of AI capabilities to

an existing Deloitte contract illustrates how demand for AI can expand through established vendor relationships (Maryland Board of Public Works 2023). Such amendments also raise questions about the scrutiny applied to changes in scope and the public visibility of decisions to introduce AI. Future research could examine whether contractors’ political contributions, lobbying, and advisory roles help shape those demands. Such an approach would connect policy diffusion to feedback processes through which implementation strengthens actors with a stake in subsequent policy choices (Moynihan & Soss 2014).

7 Discussion and Conclusion

State agencies’ pursuit of AI makes a consequential stage of policy implementation visible. Before a system is selected or deployed, officials identify a problem, specify capabilities, and decide what work they are prepared to assign to technology. Following these decisions across policy domains reveals how AI becomes relevant to different public responsibilities, from reviewing benefit documents to identifying traffic violations. Procurement records therefore provide a way to study administrative choices through which governments translate policy goals and pressures into demand for technological capabilities.

The quantitative findings provide little support for a consistent relationship between accumulated peer procurement and faster first entry. Some measures of prior activity are associated with procurement volume, but the relationships vary across peer definitions and outcomes. Repeated regional procurement also shows no clear additional association with entry or activity. These findings leave open whether the relationships that matter are organized around particular agencies, professional networks, or products rather than the broad geographic and political groupings used here. Georgia’s account of learning about Acusensus through North Carolina’s reported experience identifies one such pathway, although its prevalence remains unknown (Georgia Department of Public Safety 2024).

The Maryland project also suggests that experience can travel between states through

the firms that implement public programs. During a September 2026 public presentation, Nava engineer Laurence Goolsby explained that the firm’s earlier document-processing work in Pennsylvania informed its approach in Maryland. He described similar solutions, with the Maryland project allowing more time to reconsider implementation choices (Nava 2026*b*). This account identifies the vendor as a carrier of experience acquired in another state. An agency may therefore receive a system shaped by another government’s experience even without directly consulting that government. Such transfers would be difficult to observe through procurement timing alone, but could help explain how particular approaches spread across states served by the same firms.

Learning can also occur while states help develop a tool, before deciding whether to use it themselves. In the same presentation, Maryland DHS Chief Information Officer David Sloan reported that feedback from an APHSA-led multistate cohort helped improve the solution and make it easier for other states to use (Nava 2026*b*). This account extends the collaboration described in the project’s planning documents: prospective users could influence development while Maryland served as the initial implementation site. The first state to implement a system may consequently be one participant in a wider development process, rather than the sole source of an innovation that others later evaluate. With Nava targeting a statewide rollout in Maryland by December 2026, it remains to be seen whether other states follow suit (Nava 2026*a*).

The records capture agencies’ public pursuit of AI capabilities, with visibility shaped by what governments publish and retain. Older notices and attachments are not equally accessible across states, and some requests describe AI only within broader technical requirements. Archive searches and public records requests helped recover these materials, but uneven availability may affect comparisons across states and over time. First entry therefore refers to the earliest qualifying initiative identified in the study period. A solicitation also leaves vendor selection, implementation, and effects on public services unresolved. Although the classification procedure showed substantial agreement with researcher coding, the reference

labels came from a single researcher and were refined during development.

The analysis also uses broad geographic and political relationships to represent potential channels of influence. These comparisons may miss connections among particular agencies, professional associations, and vendors. The controls account for state size, economic composition, fiscal reserves, and political context. Appendix N shows that additional checks using baseline procurement training and staffing leave the first-entry findings substantively unchanged. These measures describe central procurement support, while agencies' technical expertise and compatibility between AI tools and existing systems remain unmeasured. Such differences could shape both agencies' ability to pursue AI and which other governments they consider useful examples. Shared pressures can also produce similar procurement patterns without interstate influence. The documentary cases help identify relationships and stated motivations that the statistical measures cannot capture, but their selection reflects the information available in their records. They do not establish how common those pathways are. Future research could link procurement histories to professional meetings, collaborative projects, and vendor relationships to examine who encountered which examples before acting.

Procurement provides a public record of how agencies turn policy responsibilities into demand for technological capabilities. Across policy domains, these choices reveal where governments see a role for AI and what work they seek to assign to it. The absence of consistent first-entry associations in this study leaves the relationships behind those choices open to further investigation. The documentary accounts point toward professional exchange, collaborative development, and experience carried by vendors as pathways worth examining more closely. Studying these relationships can connect policy diffusion to the administrative decisions through which technologies become part of government.

A Source Records and Event Construction

The replication dataset identifies each initiative by state, issuing agency, title, available procurement identifiers, date or month used in the analysis, and policy domain. It also records date precision and supporting source references, including public URLs where available. The accompanying materials provide the coding instructions and code used to construct the analytic panels and estimate the models. Downloaded documents, extracted text, generated summaries, and agency correspondence are maintained in a separate research archive that will be made public at a later date.

The initiative, rather than the individual file, is the unit counted in the analysis. A reposting, amendment, or award record was linked to the original request when it concerned the same opportunity. A distinct later request was retained separately, including a new lease or an expansion requiring another procurement. Timing follows the original release, with later records used as supporting evidence when the original notice was unavailable. The monthly analysis retains one initiative with a confirmed issuance month but no exact day. One grant application is assigned to August 2025, the final month of its documented application window; its actual submission month remains unconfirmed.

I used conversational AI research assistants with the recorded model labels 5.6 Sol, 6 Sol, 6.1 Sol, and 6 Astra to support collection. Their work included search planning, portal navigation, document recovery, source linkage, duplicate and date screening, and preparation of records inquiries and review materials. I directed the scope of collection and made the recorded eligibility and episode decisions. Model assignments to individual collection actions, exact backend versions, and request settings were not consistently recorded. Collection is therefore documented through source references, retained files, acquisition records, and researcher decisions.

B Policy-Domain Coding

Policy-domain coding follows the public program served by the requested AI capability. The purchasing office, technology format, and vendor name do not determine the assignment. Maryland’s proposed assistant for SNAP and Medicaid, for example, belongs to health and human services because it supports those programs. The same rule keeps program-specific fraud detection in health and human services, while cross-government financial oversight belongs to tax, finance, and revenue. Specialized training can retain the domain of the service it supports; education and workforce includes programs whose purpose is to develop educational or workforce capabilities. Table A1 lists the final analytic categories and their counts.

TABLE A1: POLICY-DOMAIN CODING GUIDE

Policy domain	Scope	Initiatives
Health and human services	Health, Medicaid, welfare, and social services, including program-specific eligibility and integrity.	53
General government / enterprise	Government-wide administration, employee services, enterprise operations, and cybersecurity without a more specific service domain.	44
Education and workforce	Education, workforce preparation, labor-market services, and public workforce capability building.	36
Transportation and infrastructure	Transportation, mobility, DMV services, and transport infrastructure.	35
Legal, judicial, or regulatory	Courts, legal services, records of legal rights, licensing, and regulatory supervision.	28
Public safety, law enforcement, or corrections	Public safety, law enforcement, border security, and correctional services.	22
Tax, finance, and revenue	Tax collection, revenue, financial administration, and cross-government payment or financial-integrity oversight.	18
Environment, energy, or natural resources	Environmental management, energy, natural resources, parks, and related public services.	15
Other	Requests outside the listed domains or with insufficient information for a defensible assignment.	18
Total		269

Note: Each initiative receives one analytic domain.

C Summary Generation and Classification

Summarization and classification were conducted as separate stages. The summarizer received the retained source text for each initiative, organized into identified passages with links to the original documents. Exact repeated paragraphs shared a text entry while retaining their source locations. Instructions required four narratives covering agency context, the AI component’s function, the buyer’s stated rationale, and the policy setting. The model was told to distinguish required from optional capabilities, buyer requirements from vendor claims, and proposed activities from implementation. It also recorded missing or ambiguous information and linked substantive claims to passage identifiers. Mechanical checks verified the output structure and citation links; they did not independently establish that every summary was complete or accurate.

Production summaries used GPT-6.1 Sol with low reasoning effort, a maximum output allowance of 12,000 tokens, and automatic input truncation disabled. The classification stage used GPT-6 Luna through the Decisions API, receiving the complete summary and domain instructions without the original source passages or researcher labels. It selected a domain and returned probabilities across the available choices. These probabilities were retained as model scores, without assuming that they represented calibrated chances of correctness. The replication materials preserve the full summary instructions, output schema, classifier instructions, category definitions, and request settings separately from the final analytic assignments.

D Researcher Reference and Classification Agreement

The reference set comprised 80 initiatives coded by a single researcher from the available source documents. Sixty cases supported development of the summary procedure and coding instructions. Twenty additional cases were drawn randomly from initiatives outside that set. After coding began, one selected case was replaced because its substantive solicitation was

unavailable. A replacement was drawn randomly from the remaining pool and checked for usable source material, without using researcher labels or model predictions to choose it. The resulting evaluation therefore depends partly on document availability.

Table A2 reports exact agreement between the classifier and the researcher’s policy-domain labels at three stages. The development comparison and subsequent evaluation used the instructions and reference labels available at those stages. Source review and clarification of coding rules preceded the final comparison across all 80 cases. Because these cases also informed development, the final agreement provides no independent estimate of performance on new initiatives. The study retains the earlier results alongside the final comparison to make that distinction visible.

The agreement rates in Table A2 were calculated against the domain choices offered in the corresponding classification requests. Those requests provided eight substantive domains and an insufficient-evidence option. The final analytic categories in Table A1 incorporate researcher-reviewed assignments and distinguish an Other category for poorly fitting, sparsely represented, or insufficiently documented cases. The reported agreement should not be read as an independent validation of every final analytic assignment. Model predictions, researcher labels, reviewed assignments, and the analytic mapping were retained separately.

TABLE A2: POLICY-DOMAIN CLASSIFICATION AGREEMENT

Comparison	Matches	Agreement
Development cases	57/60	95%
Additional evaluation cases	16/20	80%
Final comparison after refinement	76/80	95%

Note: The final comparison reuses both earlier sets.

E Peer Exposure and Recurring Procurement

Peer exposure is the weighted average of other states’ cumulative initiatives from earlier months. Let C_{jdt} denote the number of initiatives issued by state j in policy domain d before month t , and let w_{ijt} denote the weight assigned to that state when measuring exposure for

state i . Exposure is calculated as

$$E_{idt} = \sum_{j \neq i} w_{ijt} C_{jdt}, \quad \sum_{j \neq i} w_{ijt} = 1. \quad (1)$$

The weights follow the geographic or political relationship being examined, and each state receives zero weight in its own exposure measure. Statewide models count initiatives across all domains. An initiative released during a given month first contributes to peer exposure in the following month.

For the regional decomposition, cumulative exposure is separated into participation and additional procurement. Participation, B_{idt} , is the weighted share of peers with at least one prior initiative. Additional procurement, R_{idt} , counts each peer’s initiatives beyond its first, using the same weights:

$$B_{idt} = \sum_{j \neq i} w_{ijt} \mathbf{1}(C_{jdt} > 0), \quad R_{idt} = \sum_{j \neq i} w_{ijt} \max(C_{jdt} - 1, 0). \quad (2)$$

Before standardization, these components sum exactly to total exposure: $E_{idt} = B_{idt} + R_{idt}$. A peer with four prior initiatives therefore contributes one to participation and three to additional procurement before its weight is applied. This distinguishes a larger number of states entering procurement from further requests among states that have already entered.

E.1 Comparison Groups and Reporting Scales

Table A3 summarizes the comparison groups used to construct exposure. Regional and ideological analyses include all 50 states, while analyses involving neighboring states use the 48 contiguous states. Party-based comparisons also use those 48 states and begin in 2018 because the measure requires a previous-year partisan snapshot. Alaska and Hawaii can still contribute initiatives as regional, ideological, or partisan peers where the relevant weights permit. The party measure applies each year’s lagged partisan alignment to peers’ entire prior initiative histories.

TABLE A3: PEER DEFINITIONS AND PRIMARY ANALYSIS SAMPLES

Peer definition	Weights assigned to other states	States and period	
Census region	Equal weights within the same Census region.	50; Jan.	2017–May 2026
Neighbors	Equal weights among adjacent states, including point contact at Four Corners.	48; Jan.	2017–May 2026
Citizen ideology	One minus the absolute difference in 2016 ideology scores rescaled to $[0, 1]$, then normalized to sum to one.	50; Jan.	2017–May 2026
Governor party	Equal weights among states with the same major-party governor in the previous calendar year.	48; Jan.	2018–May 2026

Note: All weights exclude the focal state.

Exposure was centered and divided by a fixed standard deviation, calculated separately for statewide and pooled policy-domain panels. Regional and ideological scales use the complete 50-state monthly panels for 2017–2026; neighboring-state scales use the corresponding 48-state panels. Party scales use the 48-state panels beginning in 2018. These scales were calculated before restricting first-entry risk sets or removing observations during estimation, and were retained across separate and combined exposure models. A one-standard-deviation increase therefore represents a different number of prior initiatives for each peer definition.

F Control Variables and Measurement Timing

Table A4 documents the adjustment variables and their timing. The political peer-exposure measures in Table A3 enter separately as predictors of procurement entry and activity. Continuous controls were centered and divided by their standard deviations across the complete 50-state monthly control panel. Population was logged before standardization, while the technology share and fiscal-reserve ratio entered in levels. Partisan indicators retain their zero-or-one coding, and the South is the reference category for Census region.

The citizen-ideology control uses the 2016 wave through 2021 and the 2020 wave from 2022 onward, with scores first standardized within each wave. This updating differs from

TABLE A4: ADJUSTMENT VARIABLES, SOURCES, AND MEASUREMENT TIMING

Control	Construction	Source and timing
Population	Natural logarithm of state population.	U.S. Census Bureau; preceding calendar year.
Technology-related economy	Information industries, computer systems design, and miscellaneous professional, scientific, and technical services as a share of state GDP.	Bureau of Economic Analysis; preceding year, with 2024 data retained for 2026.
Citizen ideology	State citizen-ideology estimates standardized within survey wave.	American Ideology Project; 2016 wave through 2021, 2020 wave thereafter.
Fiscal reserves	Rainy-day fund balance relative to general-fund spending; negative values set to zero.	National Association of State Budget Officers; preceding fiscal year.
Partisan control	Separate indicators for a Republican governor, Republican legislative control, and divided legislative control.	National Conference of State Legislatures; annual snapshots.
Census region	Midwest, Northeast, and West indicators; South is the reference category.	U.S. Census Bureau; fixed state classification.

Note: Annual measurements are held constant within each year.

the fixed 2016 ideology scores used to define peer weights. Annual partisan snapshots are held constant within each year, including the March 2017 snapshot used for that year. They therefore approximate the political context without identifying the exact month of transitions in office or legislative control.

G Model Specifications

The domain-entry analysis uses a Cox model with a separate baseline hazard for each policy domain:

$$h_{id}(t) = h_{0d}(t) \exp(\beta' \mathbf{Z}_{idt} + \gamma' \mathbf{X}_{it}). \quad (3)$$

Here, $h_{id}(t)$ is the entry rate for state i in domain d while it remains at risk, and $h_{0d}(t)$ allows that rate to vary over calendar time separately by domain. The vector $\mathbf{Z}_{idt}$ contains the standardized peer-exposure measures, and $\mathbf{X}_{it}$ contains the adjustment variables defined in

Table A4. Their coefficients, β and γ , are shared across domains. The general first-entry model omits the domain index and uses a single baseline hazard. Tied entry months are handled using Efron’s approximation.

The activity models estimate the expected number of initiatives, μ_{idt} , using Poisson pseudo-maximum likelihood:

$$\mu_{idt} = \exp(\alpha_{id} + \delta_{dt} + \beta' \mathbf{Z}_{idt} + \gamma' \mathbf{X}_{it}). \quad (4)$$

The state-domain effects α_{id} account for stable differences between states within domains, and domain-month effects δ_{dt} account for monthly changes shared across states in each domain. Statewide models instead use state and calendar-month effects. The fixed effects also absorb time-invariant controls such as Census region. The post-entry models begin in the month after domain entry. Fixed-effect groups containing only zeros or one observation are removed during estimation. Additional checks test whether combinations of predictors perfectly separate zero counts from positive counts. In the post-entry models, separated observations are removed before re-estimation; partisan controls that are then redundant with the fixed effects receive no separate coefficients. Both model families use standard errors clustered by state, with 95 percent confidence intervals calculated from each coefficient plus or minus 1.96 standard errors. Main tables exponentiate those bounds to report ratios; Appendix O retains the full activity coefficients on the log scale. Political activity contrasts use the conditional exposure scales described in Appendix K.

H General First Entry: Alternative Adjustment Sets

Table A5 compares the general first-entry models under reduced and full adjustment. The reduced models include population, the technology-related share of state GDP, citizen ideology, and Census region. The full models add governor party, legislative control, and fiscal reserves. Each comparison uses the same states and monthly observations, so changes in the estimates

reflect the additional adjustment rather than a different estimation sample.

TABLE A5: FIRST AI INITIATIVE: REDUCED AND FULL CONTROLS

	Regional exposure		Adjacent-state exposure	
	(1) Reduced	(2) Full	(3) Reduced	(4) Full
Prior AI initiatives: regional peers	0.44 (0.06, 3.19)	0.45 (0.06, 3.56)		
Prior AI initiatives: neighboring states			0.83 (0.41, 1.68)	0.80 (0.38, 1.65)
State population (logged)	1.06 (0.67, 1.67)	1.06 (0.63, 1.78)	1.12 (0.74, 1.70)	1.13 (0.70, 1.82)
Technology-related share of state GDP	1.81** (1.22, 2.69)	1.81** (1.19, 2.74)	1.72* (1.06, 2.80)	1.75* (1.06, 2.87)
Citizen ideology (state score)	1.21 (0.85, 1.73)	1.55 (0.80, 2.97)	1.24 (0.74, 2.09)	1.70 (0.77, 3.77)
Midwest (vs. South)	0.59 (0.19, 1.83)	0.58 (0.18, 1.85)	0.69 (0.24, 1.99)	0.66 (0.22, 1.96)
Northeast (vs. South)	2.58 (0.42, 15.74)	2.67 (0.40, 18.01)	1.94 (0.44, 8.56)	2.13 (0.45, 10.05)
West (vs. South)	2.27* (1.09, 4.71)	2.05 (0.91, 4.61)	1.92 (0.88, 4.21)	1.61 (0.66, 3.94)
Republican governor		0.99 (0.49, 1.99)		0.96 (0.48, 1.92)
Republican-controlled legislature		0.59 (0.15, 2.33)		0.51 (0.12, 2.18)
Divided legislative control		0.84 (0.18, 3.86)		0.79 (0.17, 3.58)
Rainy-day reserves / general-fund spending		0.94 (0.76, 1.18)		0.94 (0.73, 1.21)
States	50	50	48	48
First AI entries	50	50	48	48
Monthly observations	2,990	2,990	2,829	2,829
Partial log likelihood	-139.9	-139.5	-132.7	-132.1
AIC	293.9	301.0	279.4	286.2

Notes: Cox hazard ratios with state-clustered 95% intervals; continuous predictors are standardized. * $p < .05$, ** $p < .01$, *** $p < .001$.

Adding the political and fiscal controls changes the peer-exposure estimates little. Regional and adjacent-state estimates remain below one, but their confidence intervals allow both lower and higher entry rates. These comparisons provide no clear evidence that greater

geographic peer activity predicts earlier first AI procurement. The regional models also fail the global proportional-hazards check under both adjustment sets, suggesting that at least one association may change over time. Their estimates consequently require caution as summaries of associations across the study period.

I Study Window and Classification Uncertainty

Table A6 examines whether the domain-entry findings depend on the observation window or uncertain classifications. Starting in January 2018 excludes state-domain pairs that had already entered, while retaining earlier initiatives in peer histories. Ending in December 2025 removes the final five months of observation. Neither change produces a clear positive association between regional peer activity and domain entry.

The classification check uses 19 initiatives flagged for low or closely divided model scores, insufficient evidence, or disagreement with researcher coding. These flags identify uncertainty rather than confirmed errors. The check excludes flagged initiatives from peer histories and stops observing each affected state across its remaining domains before its first flagged initiative. This restriction affects 13 states and reduces observed entries from 162 to 116. The estimated association remains close to the main estimate, although its wider interval reflects greater uncertainty about the entry-rate difference.

TABLE A6: DOMAIN ENTRY: STUDY WINDOW AND CLASSIFICATION UNCERTAINTY

Specification	Hazard ratio	95% CI	First entries
Main specification	0.94	(0.79, 1.11)	162
Start in January 2018	0.94	(0.80, 1.12)	158
End in December 2025	1.01	(0.83, 1.24)	142
End follow-up before uncertain cases	0.93	(0.73, 1.19)	116

Notes: Regional exposure per SD, full controls, 50 states and state-clustered 95% intervals. * $p < .05$, ** $p < .01$, *** $p < .001$.

J Entry-Model Time Diagnostics

Table A7 reports checks of whether the regional entry models’ associations remain constant over time. This assumption concerns the size of the associations, while the baseline entry rate can already change over the study period. The global test considers the model as a whole, and the peer-specific test considers regional exposure separately. The main general first-entry model shows a global concern ($p = 0.026$), while neither test flags a comparable concern in the main domain-entry model.

Alternative specifications allow the associations for population, technology share, citizen ideology, and Census region to change with logged study time. The domain model also allows the governor-party association to change. Each selected control is interacted with $\log(m + 1)$, where $m = 1$ in January 2017. The domain-entry estimate remains nearly unchanged, while the general first-entry estimate becomes highly imprecise. Although the general model’s global test no longer rejects the assumption, its peer-specific test does ($p = 0.031$). These alternatives therefore leave a timing concern for general first entry, alongside substantial uncertainty about the magnitude and direction of its peer association.

TABLE A7: ENTRY MODELS: TIME DIAGNOSTICS AND ALTERNATIVE SPECIFICATIONS

Model	Hazard ratio	95% CI	Overall PH p	Peer PH p
General: main	0.45	(0.06, 3.56)	0.026	0.129
General: time interactions	1.96	(0.09, 41.36)	0.211	0.029
Domain: main	0.94	(0.79, 1.11)	0.315	0.926
Domain: time interactions	0.94	(0.79, 1.12)	0.310	0.591

Notes: Regional exposure, full controls and state-clustered 95% intervals; PH tests assess constant associations over time. $*p < .05$, $**p < .01$, $***p < .001$.

K Political Exposure and Conditional Variation

Table A8 reports the political activity estimates over smaller contrasts that reflect the variation remaining after adjustment. For each fitted sample, I removed the variation in political exposure accounted for by the other predictors and fixed effects, weighting observations by

their fitted expected counts. The standard deviation of the remaining exposure defines the reporting contrast. In the domain-level ideological model, this contrast is only 0.083 of the original whole-panel standard deviation, showing why a full-unit contrast produces unusually large reported differences.

Over one conditional standard deviation, ideological peer activity is associated with about 68 percent more expected monthly initiatives within a domain (95 percent confidence interval: 44–95 percent more). The corresponding partisan contrast is associated with about 17 percent more initiatives (95 percent confidence interval: 4–33 percent more). These calculations rescale the existing coefficients and state-clustered intervals, treating the estimated reporting scale as fixed. They describe the fitted associations over smaller exposure differences. Shared priorities, common pressures, and the small post-entry samples continue to limit interpretation.

TABLE A8: POLITICAL PEER ACTIVITY: CONTRASTS BASED ON CONDITIONAL EXPOSURE VARIATION

Peer measure	Outcome	Conditional SD	Count ratio	95% CI
Ideology	Statewide	0.062	1.21 ^{**}	(1.06, 1.37)
Ideology	Within domain	0.083	1.68 ^{***}	(1.44, 1.95)
Ideology	After domain entry	0.058	1.63 ^{***}	(1.30, 2.05)
Governor party	Statewide	0.156	1.07	(0.93, 1.22)
Governor party	Within domain	0.299	1.17 [*]	(1.04, 1.33)
Governor party	After domain entry	0.183	1.07	(0.88, 1.31)

Notes: Conditional SD uses original reporting units; state-clustered 95% intervals hold the scale fixed. ^{*} $p < .05$, ^{**} $p < .01$, ^{***} $p < .001$.

L Activity-Model Estimation Samples

Table A9 distinguishes the constructed activity panels from the observations retained for estimation. The Poisson estimator removes fixed-effect groups containing only zero counts and groups containing a single observation. These removals repeat because dropping one group can leave another with no usable comparison. In the regional domain-level model,

4,032 of the 50,850 constructed observations remain, while all 269 initiatives are retained. Much of the reduction therefore reflects the sparse distribution of initiatives across states, domains, and months.

The post-entry models have considerably less support. The regional post-entry panel contains 106 initiatives. Removing zero-only and singleton groups initially retains 99 initiatives, but further separation checks identify combinations of predictors that perfectly predict some zero counts. Repeating separation and group-removal checks leaves 97 initiatives in 444 observations across 30 states for the regional and ideological models, and 90 initiatives in 396 observations across 28 states for the partisan model. The three partisan controls are then redundant with the fixed effects and cannot be estimated separately. The peer coefficients change negligibly, but other controls remain imprecise. These corrected post-entry estimates are treated as exploratory associations, with their fitted sample sizes reported in Appendix O.

TABLE A9: ACTIVITY MODELS: CONSTRUCTED AND FITTED SAMPLES

Outcome	Panel rows	Fitted rows	States	Initiatives
<i>Regional and ideological peers: 50 states</i>				
Statewide	5,650	4,000	50	269
Within domain	50,850	4,032	50	269
<i>Adjacent-state peers: 48 states</i>				
Statewide	5,424	3,792	48	257
Within domain	48,816	3,750	48	257
<i>Governor-party peers: 48 states</i>				
Statewide	4,848	3,648	48	253
Within domain	43,632	3,621	48	253

Notes: Single-network models. States and initiatives refer to fitted samples.

M Documentary Sources and Timing

For Acusensus, Georgia’s notice supplies the agency’s account of how it encountered the technology, while company letters and annual reports supply vendor representations (Georgia Department of Public Safety 2024, Acusensus Inc. 2024, Acusensus Limited 2023). The

chronology preserves those sources' different roles: Georgia describes a presentation at a 2022 professional meeting, whereas the documented North Carolina request and award occurred in May 2023 (Georgia Department of Public Safety 2024, North Carolina Department of Public Safety 2023). The meeting account therefore concerns experience preceding that documented procurement. The records do not establish the date or design of a particular demonstration.

The qualitative material also includes sources published after the quantitative observation window. Idaho's August 2026 request illustrates an agency linking its pursuit of AI to federal scrutiny, but falls outside the initiative counts ending in May 2026 (Idaho Department of Health and Welfare 2026). The September 2026 Nava presentation provides a later account of the Maryland project and its collaborative development, rather than a separate acquisition initiative (Nava 2026*b*). Statements targeting a statewide rollout by December 2026 describe a planned milestone, leaving subsequent implementation and uptake by other states unresolved (Nava 2026*a*).

N Baseline Procurement Capacity

The 2016 NASPO Survey of State Procurement Practices records central procurement practices as of August 2016, before the study period (National Association of State Procurement Officials 2016). Among the 46 states with responses, 29 reported that the central procurement office provided contract-management training to state agencies and 17 reported that it did not. Table A10 compares the first-entry models with and without this measure on identical samples, using the full control set. Peer histories and exposure scales remain unchanged, including contributions from states without survey responses. Models of states that share a border cover 44 states because Alaska and Hawaii have no such neighbors. Separate staffing checks use logged central-office headcounts while retaining the population control. These cover 45 states after excluding Texas's separate IT and non-IT office counts, with a further check restricted to the 40 states that gave numeric responses. The five additional responses

provide an explicit overall count alongside a description of staff roles or an approximation. All coding decisions and original wording are retained in the replication records.

Adding training leaves the policy-domain results nearly unchanged. Regional peer activity is associated with an approximately 8 percent lower entry rate, with an interval ranging from 23 percent lower to 11 percent higher. Neighbor activity is associated with an approximately 3 percent higher rate, with an interval ranging from 10 percent lower to 19 percent higher. The staffing checks, both separately and alongside training, also provide no consistent positive first-entry association. General first-entry estimates remain imprecise, and the regional model continues to show a concern about changes in associations over time, as discussed in Appendix J. These checks account for general procurement support, while agency-specific AI expertise and compatibility with existing systems remain unmeasured. Because baseline staffing and training are constant within each state, they are absorbed by the state or state-domain fixed effects in the activity models.

TABLE A10: FIRST-ENTRY ESTIMATES WITH BASELINE PROCUREMENT TRAINING

Outcome	Peers	Adjustment	States	First entries	Hazard ratio	95% CI
General	Regional	Full controls	46	46	0.28	(0.04, 2.00)
General	Regional	+ Procurement training	46	46	0.21	(0.03, 1.76)
General	Neighbor	Full controls	44	44	0.71	(0.34, 1.49)
General	Neighbor	+ Procurement training	44	44	0.67	(0.31, 1.45)
Domain	Regional	Full controls	46	155	0.93	(0.77, 1.11)
Domain	Regional	+ Procurement training	46	155	0.92	(0.77, 1.11)
Domain	Neighbor	Full controls	44	149	1.03	(0.90, 1.19)
Domain	Neighbor	+ Procurement training	44	149	1.03	(0.90, 1.19)

Notes: Matched samples, full controls and state-clustered 95% intervals. * $p < .05$, ** $p < .01$, *** $p < .001$.

O Full Activity-Model Coefficients

The main activity tables emphasize peer measures while retaining population, economic composition, citizen ideology, political control, and fiscal reserves in the fitted models. Tables A11 and A12 report all coefficients from those models. Table A13 provides the full participation and repeated-procurement specifications, and Table A14 reports the exploratory post-entry models.

These tables use log coefficients, with zero indicating no association. The first two columns of Table A13 report log hazard coefficients; the remaining models report log count coefficients. Population, technology-related GDP share, citizen ideology, and fiscal reserves were already standardized before estimation. Large coefficients and wide intervals therefore indicate limited support for some adjusted comparisons; standardizing again would not resolve that uncertainty. State effects absorb stable differences, leaving the activity models to distinguish the remaining changes over time. Sparse post-entry samples provide particularly limited information for that task. After separation checks, the three partisan controls are absorbed by the fixed effects in these models, so they have no reported coefficients. Coefficients and intervals are retained without exponentiation to avoid presenting extremely large or small count ratios as substantively interpretable findings.

TABLE A11: GEOGRAPHIC ACTIVITY MODELS: FULL COEFFICIENTS

	Statewide activity		Activity within domain	
	Region	Neighbors	Region	Neighbors
Prior AI initiatives: regional peers	0.39 (-0.54, 1.31)		0.24 (-0.06, 0.54)	
Prior AI initiatives: neighboring states		0.41** (0.11, 0.70)		0.18 (-0.12, 0.48)
State population (logged)	-1.44 (-13.80, 10.92)	2.51 (-9.06, 14.08)	-5.04 (-18.71, 8.63)	-0.75 (-14.23, 12.74)
Technology-related share of state GDP	-0.05 (-1.52, 1.42)	0.20 (-1.07, 1.47)	0.34 (-1.00, 1.67)	0.54 (-0.76, 1.85)
Citizen ideology (state score)	-0.20 (-2.50, 2.10)	-0.04 (-2.55, 2.46)	0.31 (-1.85, 2.46)	0.58 (-1.71, 2.87)
Republican governor	-0.27 (-1.03, 0.49)	-0.27 (-1.05, 0.51)	-0.17 (-0.89, 0.56)	-0.20 (-0.93, 0.54)
Republican-controlled legislature	0.36 (-1.02, 1.74)	0.25 (-1.14, 1.63)	0.41 (-1.06, 1.89)	0.24 (-1.21, 1.68)
Divided legislative control	0.32 (-0.45, 1.10)	0.35 (-0.45, 1.15)	0.42 (-0.54, 1.38)	0.43 (-0.49, 1.36)
Rainy-day reserves / general-fund spending	-0.04 (-0.54, 0.45)	-0.11 (-0.82, 0.61)	0.11 (-0.53, 0.75)	0.02 (-0.85, 0.89)
States	50	48	50	48
AI initiatives	269	257	269	257
Monthly observations	4,000	3,792	4,032	3,750
Fixed effects	State Month	State Month	State-domain Domain-month	State-domain Domain-month
Log likelihood	-848.8	-804.0	-912.3	-865.5
AIC	1,971.6	1,876.0	2,566.7	2,447.0

Notes: Log coefficients with state-clustered 95% intervals; peer measures use whole-panel SDs. * $p < .05$, ** $p < .01$, *** $p < .001$.

TABLE A12: POLITICAL ACTIVITY MODELS: FULL COEFFICIENTS

	Statewide activity		Activity within domain	
	Ideology	Same-party	Ideology	Same-party
Prior AI initiatives: ideological peers	3.03** (0.96, 5.11)		6.23*** (4.39, 8.08)	
Prior AI initiatives: same-party governors		0.41 (-0.45, 1.27)		0.54* (0.12, 0.95)
State population (logged)	4.49 (-8.19, 17.16)	4.87 (-10.34, 20.09)	-3.27 (-17.75, 11.21)	-0.50 (-15.92, 14.92)
Technology-related share of state GDP	-0.55 (-1.93, 0.83)	0.14 (-1.16, 1.43)	-0.52 (-1.94, 0.91)	0.23 (-1.07, 1.53)
Citizen ideology (state score)	-0.51 (-2.78, 1.76)	0.57 (-1.58, 2.72)	-0.40 (-3.46, 2.66)	0.79 (-1.40, 2.98)
Republican governor	-0.00 (-0.82, 0.82)	-0.16 (-0.98, 0.66)	0.30 (-0.77, 1.38)	-0.05 (-0.98, 0.88)
Republican-controlled legislature	0.42 (-0.99, 1.82)	0.15 (-1.26, 1.56)	0.89 (-1.20, 2.98)	0.36 (-1.23, 1.95)
Divided legislative control	0.33 (-0.41, 1.08)	0.33 (-0.42, 1.08)	0.53 (-0.44, 1.50)	0.44 (-0.51, 1.39)
Rainy-day reserves / general-fund spending	0.00 (-0.52, 0.53)	-0.09 (-0.92, 0.74)	0.08 (-0.68, 0.85)	-0.05 (-0.98, 0.87)
States	50	48	50	48
AI initiatives	269	253	269	253
Monthly observations	4,000	3,648	4,032	3,621
Fixed effects	State Month	State Month	State-domain Domain-month	State-domain Domain-month
Log likelihood	-844.6	-790.3	-867.3	-843.1
AIC	1,963.1	1,842.5	2,476.6	2,386.3

Notes: Log coefficients with state-clustered 95% intervals; peer measures use whole-panel SDs. * $p < .05$, ** $p < .01$, *** $p < .001$.

TABLE A13: REGIONAL PARTICIPATION AND REPEATED PROCUREMENT: FULL COEFFICIENTS

	First AI initiative	First in domain	Domain activity
Regional peers with prior AI activity (share)	-1.74 [*] (-3.22, -0.25)	-0.20 (-0.45, 0.05)	0.31 [*] (0.01, 0.60)
Repeat AI initiatives among regional peers	-0.50 (-2.11, 1.11)	0.05 (-0.11, 0.20)	0.02 (-0.24, 0.27)
State population (logged)	0.11 (-0.38, 0.61)	0.39 ^{***} (0.16, 0.61)	-4.13 (-18.21, 9.96)
Technology-related share of state GDP	0.60 ^{**} (0.18, 1.01)	0.15 (-0.12, 0.42)	0.38 (-0.97, 1.73)
Citizen ideology (state score)	0.51 (-0.15, 1.17)	0.01 (-0.43, 0.45)	0.26 (-1.94, 2.46)
Midwest (vs. South)	-0.38 (-1.52, 0.76)	0.04 (-0.47, 0.55)	
Northeast (vs. South)	2.54 [*] (0.21, 4.87)	0.92 [*] (0.17, 1.67)	
West (vs. South)	1.63 ^{**} (0.58, 2.67)	0.46 (-0.12, 1.03)	
Republican governor	-0.01 (-0.68, 0.67)	0.23 (-0.15, 0.61)	-0.17 (-0.91, 0.56)
Republican-controlled legislature	-0.55 (-1.87, 0.77)	0.21 (-0.39, 0.81)	0.36 (-1.08, 1.79)
Divided legislative control	-0.21 (-1.79, 1.37)	0.59 (-0.04, 1.21)	0.37 (-0.57, 1.32)
Rainy-day reserves / general-fund spending	-0.04 (-0.25, 0.17)	-0.03 (-0.24, 0.18)	0.10 (-0.52, 0.72)
States	50	50	50
First AI entries	50	162	
AI initiatives			269
Monthly observations	2,990	45,337	4,032
Fixed effects			State-domain Domain-month
Log likelihood	-137.3	-573.3	-911.4
AIC	298.5	1,170.6	2,566.9

Notes: Log coefficients with state-clustered 95% intervals; peer measures use whole-panel SDs. ^{*} $p < .05$, ^{**} $p < .01$, ^{***} $p < .001$.

TABLE A14: AI PROCUREMENT ACTIVITY AFTER DOMAIN ENTRY

	(1) Region	(2) Ideology	(3) Same-party
Prior AI initiatives: regional peers	0.23 (-0.75, 1.22)		
Prior AI initiatives: ideological peers		8.47*** (4.53, 12.42)	
Prior AI initiatives: same-party governors			0.37 (-0.72, 1.46)
State population (logged)	42.11 (-12.66, 96.88)	74.64 (-1.12, 150.40)	55.31 (-12.52, 123.14)
Technology-related share of state GDP	-1.10 (-3.67, 1.46)	-4.66 (-9.36, 0.04)	-1.91 (-4.50, 0.68)
Citizen ideology (state score)	1.38 (-4.99, 7.75)	0.85 (-7.74, 9.45)	1.98 (-4.99, 8.95)
Rainy-day reserves / general-fund spending	0.97 (-0.36, 2.30)	0.96 (-0.75, 2.68)	0.70 (-0.69, 2.10)
States	30	30	28
AI initiatives	97	97	90
Monthly observations	444	444	396
Fixed effects	State-domain Domain-month	State-domain Domain-month	State-domain Domain-month
Log likelihood	-219.9	-205.1	-199.9
AIC	709.9	680.3	651.8

Notes: Log count coefficients with state-clustered 95% intervals; peer measures use whole-panel SDs. * $p < .05$, ** $p < .01$, *** $p < .001$.

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