Public Procurement for Responsible AI? Understanding U.S. Cities' Practices, Challenges, and Needs

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Most AI tools adopted by governments are not developed internally, but instead are acquired from third-party vendors in a process called *public procurement*. While scholars and regulatory proposals have recently turned towards procurement as a site of intervention to encourage responsible AI governance practices, little is known about the practices and needs of city employees in charge of AI procurement. In this paper, we present findings from semi-structured interviews with 18 city employees across 7 US cities. We find that AI acquired by cities often does not go through a conventional public procurement process, posing challenges to oversight and governance. We identify five key types of challenges to leveraging procurement for responsible AI that city employees face when interacting with colleagues, AI vendors, and members of the public. We conclude by discussing recommendations and implications for governments, researchers, and policymakers.

CCS Concepts: • Human-centered computing \rightarrow Empirical studies in HCI; • Social and professional topics \rightarrow Computing / technology policy.

Additional Key Words and Phrases: Public sector AI, AI procurement, AI governance, Responsible AI, Semi-structured interviews

1 INTRODUCTION

Artificial intelligence is increasingly utilized in the public sector to automate bureaucratic process and workflows, and assist critical decision-making processes that impact residents [26, 37, 52, 56, 58, 82, 102]. Often, such public-sector AI applications are not developed in-house, but are purchased from external third-party vendors through a process called "public procurement" [59, 76, 95]. In fact, in a 2023 opening statement for the full committee hearing on AI and procurement, U.S. Senator Gary Peters stated that "over half of the AI tools used by federal agencies have been purchased from commercial vendors" [74]. Experts estimate that this number is even higher at lower levels of government, such as state and local governments that are even less likely to have internal expertise to develop AI [66, 87, 88]. Thus, most public-sector AI systems used today are developed by and acquired from *private vendors*.

A growing number of academic and advocacy efforts have pointed out how AI systems procured in the public sector have predominantly targeted narrowly defined notions of efficiency and performance enhancements, resulting in adverse effects that disparately impact marginalized communities [18, 37, 46, 50, 86, 96]. While such incidents have exposed flaws in individual AI systems, they highlight deeper issues in how AI is acquired, used, and governed in the public sector. The AI procurement process encompasses decisions of which AI tools to ask for, adopt or reject, and the manner in which they are developed and deployed: decisions of critical importance for communities who may be harmed by AI. Such decisions not only influence the performance and risks posed by AI systems, but also play a significant role in shaping broader governance practices and ethical standards by which AI operates in the public sector.

Interestingly, there is a long history of governments adapting their public procurement practices to enact social change, e.g., by creating processes that prioritize minority-owned businesses [62],

enable public oversight over government surveillance [107], or incentivize other ethical behaviors, such as sustainability [61, 99]. Drawing from this tradition, several scholars point out how existing public procurement processes such as competitive solicitations (*e.g.*, RFPs), vendor selection practices, and contract negotiations pose several opportunities to encourage more responsible practices surrounding the adoption and use of AI. A shared recognition of AI procurement as a gateway to more responsible adoption and use of the technology in public sector has sparked a recent explosion of attention and action taken by governments, academics, and think-tanks to develop AI procurement guidelines and resources to be used by government employees [47, 70, 77, 83, 92]. While a handful of these resources have been empirically investigated [84], we still lack a broader understanding of if, and how, such resources align with governments' actual contexts and needs.

Our Contributions. In a time when AI procurement has become a pressing matter of policy attention, we believe that empirical research—to understand the challenges government employees face when attempting to incorporate responsible AI considerations into their procurement practices—can help inform policy development and implementation. To date, there is a dearth of empirical research focused on understanding governments' AI procurement practices. To address this gap, this work builds on the burgeoning efforts across the United States to assist governments in procuring AI and investigates how city employees are approaching the procurement of AI systems.

In this paper, we present findings from semi-structured interviews with 18 city employees across 7 cities who are responsible for AI procurement in their city. Study participants included both department leaders who made decisions and established practices on behalf of their department, and employees whose day-to-day responsibilities involved managing technology procurement. Participants were based in a variety of departments, such as IT, Innovation, and Procurement, that reflected the expertise they contributed to the procurement process. We designed our study protocol to address two key research questions:

- Characterizing existing AI procurement practices in public sector: What practices do city employees follow to acquire AI products and services?
- Understanding challenges and desires to procure AI responsibly: What challenges do city employees face through the AI procurement process, and what are their needs to address those gaps and challenges? What concrete resources can support them to overcome these obstacles?

Our analysis reveals several real-world needs of city employees that have been overlooked in past research on AI procurement. We find that while all interviewed cities have *already procured* AI technologies, cities are at highly varying levels of comfort and preparedness to anticipate and address AI harms. How third-party AI systems are governed and assessed by cities is shaped by an interlocking web of applicable procurement laws, new AI policies, and other established norms and practices. Critically, while many proposed interventions to encourage more responsible AI practices target *conventional* purchasing processes (*e.g.*, solicitations), we find that many AI products and services used by cities are not acquired this way, posing challenges to oversight and governance (Section 4.1). For example, many AI products are under cost thresholds for competitive solicitation processes, reflecting a broader trend in the availability of low- and no-cost commercial AI tools.

To understand actions that city governments have taken to promote responsible AI procurement, we analyze cities' existing procurement practices (Section 4.2). We spoke to department leaders and workers who are leading the way in adapting their cities' processes to consider new risks posed by data-driven AI systems, *e.g.*, by instituting AI-specific risk assessments. We also spoke

to many employees who did not change their procurement practices for AI, and in effect assess AI equivalently to any other software.

Next, we identify five key categories of challenges employees face in responsibly procuring AI. Cities as organizations often (1) *lack visibility* into both employees' and vendors' use of AI, a prerequisite step for oversight and governance (Section 5.1). Employees working to promote responsible AI practices within their city often encountered (2) *organizational barriers* to prioritizing this work, including severe existing constraints on their time, and conflicts with colleagues who perceived AI governance activities as a barrier to purchasing desired AI technology (Section 5.2). Employees in cities that had yet to adapt their procurement processes (3) *felt unprepared to adequately assess AI risks*, and interpret information reported by vendors, such as quantitative performance metrics (Section 5.3). We share learnings from several real-world experiences where employees (4) *lacked leverage in their relationships with AI vendors*, who invoked trade secrecy claims to avoid basic questions about system performance or training data, did not involve cities in AI design, and delegated review and oversight responsibilities away from themselves and towards cities (Section 5.4). Finally, we discuss (5) *employees' perceptions of involving impacted stakeholders* in the AI procurement process, surfacing key tensions such as fear of public scrutiny and legal secrecy obligations to promote fair competition between vendors (Section 5.5).

As one of the first qualitative investigations specifically focused on how U.S. local governments' *AI procurement practices*, we contextualize our findings by placing them in direct conversation with past scholarship on procurement (Section 7). We identify five key gaps between AI procurement as conceptualized in the literature, and the realities of how AI procurement often occurs on-the-ground. We also put forward several open directions for future research that we believe are critical to support local governments in effectively leveraging public procurement as a site of intervention for responsible AI.

2 BACKGROUND & RELATED WORK

While emerging AI technologies are new, governments must acquire *all* goods and services - including AI - using established *public procurement processes* that lay out required steps before a purchase can be made. We begin by introducing key components of this procurement process, and describe how they may be used to procure AI. Readers who are already familiar with public procurement can skip to our reviews of past scholarship on public-sector AI (Section 2.2) and procurement's potential to promote responsible AI goals (Section 2.3).

2.1 A Public Procurement Primer for Al

The term "public procurement" generally refers to the processes governments use to bring in goods and services that are developed externally [59, 76, 95], often involving paid transactions with third-party organizations. In this work, our core focus is on studying public procurement practices in the United States, particularly for *local* (city) governments. While procurement laws, organizational structures, and activities vary across different cities [59], they all specify common steps that take place in a *conventional procurement process*. These steps were designed to be applicable for *any* good or service, including pencils, school buses, and technologies, including those that have AI [29, 41, 45]. We provide a brief sketch and introduce key terminology necessary to understand

¹We note that as described by past work [76], there is no single precise agreed-upon definition for what it meant by the term "public procurement" – rather, the definition is "muddled" and varies across contexts. See Appendix A for a more detailed discussion of definitions.

²All of the cities we interviewed qualify as cities, but the procurement processes we outline here are also applicable for other types of US local government, *e.g.*, counties, municipalities, etc.

this procurement process, and direct the readers to Rubenstein [88] for a more comprehensive review.

- (1) **Planning.** The procurement process begins with *planning* when public-sector employees identify a potential need or application for procured goods or services. For AI, the planning phase might involve identifying a context or use-case where employees believe that AI might be appropriate [53, 69].
- (2) **Solicitation.** Once an employee has decided that they are interested in using an externally-developed solution for their need, they then begin a *solicitation*, a competitive process to select a vendor. One type of solicitation is a *Request For Proposal (RFP)*, a structured process where a government outlines their needs, expectations, and desired outcomes. Interested vendors then submit detailed proposals that comprehensively address these requirements [5].³ For AI, solicitations may include specific requirements and criteria desired of the procured AI solution [88]. AI vendors may also be invited to give a live demo of their product [1, 75].
- (3) **Review & Award.** In the *review and award* phase, cities evaluate vendor proposals using score sheets and other established processes. For AI, this phase might involves assessing how well the tools adhere to responsible AI standards, and deciding the level of risk that will be tolerated [84].
- (4) **Contracting.** Once a vendor is selected, the city and vendor create a *contract* that specifies legally enforceable obligations for both parties, such as the agreed price, statement of work, the vendor's support responsibilities, and an outline of how disputes will be resolved. This phase typically involves a *negotiation* involving activities such as *red-lining* (negotiating contract clauses). For AI, relevant contract terms may spell out expected AI risk management practices, such as regular performance monitoring, or procedures on how to respond to incidents where AI causes harm [9, 34, 40].
- (5) **Deployment & Use**: The deployment phase is when the procured AI solution is adopted and used by the city. For AI, this phase may involve training frontline workers and users who will consume AI outputs [54], and continued oversight and monitoring of AI risks and performance [9].

In our study, we return to these five steps to examine city employees' experiences procuring AI within a conventional purchasing process, and whether they made special adaptations for AI. Importantly, while much past work typically describes these five steps, we do not assume that all AI acquisitions are procured using this process. In doing so, we hope to characterize any differences between the conventional procurement process, versus the steps city employees actually took in specific real-world AI procurements.

2.2 Al in the Public Sector

Scholarship has documented a recent surge in public sector adoption of AI [26, 37, 52, 56, 58, 82, 102]. At times, harms caused by public-sector AI systems have further complicated government's relationship with marginalized communities. For example, past work has demonstrated how public AI algorithms trained on biased human decisions also replicate historic biases in deployment, such as disproportionately flagging Black defendants as high-risk of recidivism [15] or targeting poor families for CPS investigations [37]. In these and other high-stakes domains where AI "displaces discretion previously exercised by policymakers" [66], scholars have argued that public AI represents a fundamental shift in how public *policy* is formulated and implemented [13, 43]. Thus,

³Beyond RFPs, there are several other types of formal solicitation processes, such as a Request for Information (RFI), Request for Bid (RFB), Requests for Quotation (RFQ), and others. See [10] for a more comprehensive review.

a growing number of both technical and policy interventions have emerged to facilitate more responsible development and governance of public-sector AI [12, 42, 44, 53, 65, 82, 104], organized around principles such as fairness, transparency, accountability to the public, and democratic participation. More broadly, research has pointed to the importance of *organizational AI governance* frameworks (*e.g.*, the NIST AI Risk Management Framework [97]) to support organizations in establishing consistent standards and clear lines of accountability for AI systems [19, 68].

Our study adds to a growing body of empirical research that examines stakeholders' perspectives on public-sector AI technologies. Qualitative research on public-sector AI has surfaced how organizational complexities shape how governments envision and implement responsible AI considerations such as non-discrimination [24, 55, 109] or meaningful participation from impacted communities [23, 57, 89, 90, 96, 98]. Many such studies are grounded in specific localities and contexts, such as a child welfare agency in the Mid-western U.S. [89, 90] or criminal courts in Pennsylvania [78]. In contrast to past qualitative studies, which identify important considerations for the design, usage, and adoption of public-sector technologies, our work focuses specifically on the role of *established procurement processes* (*e.g.*, RFPs, vendor selection, or contracting) as a site of intervention to promote responsible AI goals.

To our knowledge, only two prior studies by Oluka et al. [73] and Autio et al. [17] have explicitly investigated governments' existing AI procurement practices and needs for support. Oluka et al. [73] interviewed public procurement professionals affiliated with organizations in Uganda and Kenya in 2021, and Autio et al. [17] interviewed U.S. federal employees in 2022. In contrast, our work studies the needs of U.S. *local governments*, which differ in their organizational structures, procurement practices, and capacity for AI governance [51, 59, 72, 87]. Interestingly, despite being situated in distinct organizational settings, our three studies collectively surface common challenges encountered by public sector employees across different countries and levels of government. These challenges first noted by past work include knowledge gaps in employees' understanding of AI risks, secrecy concerns when engaging with for-profit vendors, and an absence of "clearly defined standards" [17] for AI governance. In our paper, we explore how these concerns uniquely unfold for local governments, and are shaped by recent changes in AI risks, regulatory guidance, and resources to support AI procurement that have emerged since prior studies.

While not explicitly focused on procurement, a handful of related studies have shed light on challenges that governments face when interacting with third-party AI vendors. For example, in discussions with public-sector AI practitioners, Veale et al. [100] surfaced key tensions raised when governments "relied on external actors" (third-party vendors) to develop AI models. The authors shared an anecdote where an AI vendor tried to sell governments models that were "pre-trained in other jurisdictions" and may consequently underperform when deployed in previously unseen contexts. The authors also expressed concern about government employees' preparedness to assess procured AI solutions "for issues of bias and discrimination". In interviews with agency leaders to understand their decisions about whether to adopt a proposed AI technology, Kawakami et al. [52] found that government employees faced a number of challenges when procuring AI from private vendors, such as a lack of leverage in contract negotiations, a lack of awareness when new AI features are being used, and vendor secrecy. In this paper, we affirm and build on prior findings by focusing specifically on how cities' *procurement practices* influence how AI is acquired and governed.

2.3 Public Procurement for Responsible Al

In response to increasing incidents of harm caused by public AI [64], experts have called for governments to adapt their existing procurement processes to the unique challenges and risks posed

by AI [87]. Several groups have developed *practical guidance* and *readily-adoptable resources* centered around AI procurement [47, 70, 77, 83]. These resources, intended to be used by government employees, include evolving guidelines, regulation, tools, vendor repositories, and templates to guide public sector procurement practices.⁴ Many of these resources are targeted to the steps of a conventional procurement process, *e.g.*, items to add to an RFP [2, 22, 27, 35, 77, 88], guidance on how to score AI proposals [84], and AI-specific terms for procurement contracts [34, 40]. While a handful of these resources were empirically validated [84], we still lack a broader understanding of if, and how, governments have made use of these resources. Thus, we examine if existing resources address city employees' primary needs for support.

Moreover, several scholars have pointed out how the public procurement process poses opportunities to encourage better responsible AI practices. Individual cities can use their purchasing power to walk away from harmful AI systems and negotiate on behalf of residents' best interests, *e.g.*, requiring that vendors implement harm mitigation steps [27]. Furthermore, some argue that incorporating responsible AI considerations into purchasing decisions can result in broader market shifts that incentivize best practices, especially for technologies that are exclusively sold to governments, such as "smart city" (surveillance) technologies [28, 102].

More broadly, our research coincides with a landmark year of government action focused on improving AI procurement practices. The U.S. Federal government's "AI M-Memo" [6, 94] is perhaps the most comprehensive action taken by the federal government to date, and also initiated a broader conversation amongst key stakeholders about the role of procurement in responsible AI by soliciting public comments [11, 31, 108]. Several U.S. state and local governments have followed suit in adopting their first AI procurement guidelines [92]. Another key action that occurred as we were conducting interviews was the formation and announcement of the Government AI ("GovAI") Coalition [9, 36, 85], a group composed of over 1,000 members representing 350 participating U.S. governments, founded to "give local governments a voice in shaping the future of AI". Participating cities are encouraged to adopt shared AI governance practices based on resource templates created by coalition members. The coalition envisions that by working together cities can ask more of AI vendors: e.g., that they share basic information about their AI systems with cities [8]. Thus, we believe our research is of timely importance to inform evolving policy efforts and their implementation.

3 METHODS

Over a period of 6 months from December 2023 to June 2024, we leveraged semi-structured interviews to understand city employees' needs and challenges surrounding AI procurement. We interviewed 18 city employees (described in Table 1) across 7 U.S. cities that varied by region and size. Participating cities represented all four major regions (Northeast, West, Midwest, and South) defined by the U.S. Census Bureau [7]. Participating employees included both department leaders (e.g., Chief Technology Officers) tasked with providing strategic guidance and making decisions on behalf of their department, and other employees whose day-to-day responsibilities involved managing technology procurement.

Participating cities for the sample were recruited using both convenience and snowball sampling: we began by contacting city employees in our professional networks who had demonstrated a past interest in AI governance. We also cold-emailed or were introduced to employees at other cities that were referenced in our conversations with others. We intentionally selected and invited cities that represented a wide range of maturity surrounding AI (e.g., whether or not they had

⁴We refer the reader to Dotan et al. [35] for a more detailed review of existing resources.

	Department	City Size	Title
p1	Innovation	Medium	Chief Data Officer
p2	Information Technology	Large	Senior IT Manager
p3	Information Technology	Large	Privacy Program Manager
p4	Information Technology	Small	IT Business Relationship Manager
p5	Information Technology	Large	Privacy Specialist
p6	Information Technology	Small	Director of IT
p7	Information Technology	Large	Chief Privacy Officer
p8	Management & Budget	Medium	Sourcing Specialist
p9	Innovation	Medium	Innovation Specialist
p10	Information Technology	Large	Privacy & AI Analyst
p11	Information Technology	Medium	Chief Technology Officer
p12	Human Resources	Small	Talent & Culture Program Manager
p13	Information Technology	Medium	Chief Data & Analytics Officer
p14	Management & Budget	Large	Director of Procurement
p15	Information Technology	Large	Chief Technology Officer
p16	Innovation	Large	IT Policy Director
p17	Information Technology	Large	Vendor Manager
p18	Innovation	Large	Chief Information Officer

Table 1. An anonymous description of participating municipal employees. Titles were modified to preserve anonymity. Small cities have under 200,000 residents, medium cities have 200,000 - 500,000 residents, and large cities have over 500,000 residents.

privacy or AI-focused personnel or had adopted any public-facing AI policies). We invited 8 total cities, and 7 agreed to participate in the study.

To recruit participants, we used snowball sampling to ask our initial contacts at the city to introduce us to other eligible employees. Participants were eligible if their present role was involved with technology procurement or governance in their city. As shown in Table 1, the majority of interviewed employees worked in technology-focused roles in their city's IT or Innovation departments. We also were introduced to and spoke with specialists in vendor relations and procurement to provide a broad perspective on procurement processes, and one human resources representative who had conducted organizational training on AI. To maintain confidentiality and protect participant identity, all data was anonymized and presented in an aggregated form, with sensitive quotes excluded or paraphrased where necessary.

Semi-Structured Interviews. We adopted a semi-structured interview approach to allow flexibility in discussions, enabling participants to express their thoughts freely and spend more time discussing phases of the procurement process that are closest to their responsibilities and expertise, while covering essential topics predetermined by the two RQs. Interviews ranged from 60 to 90 minutes, and the interview protocol included three sections. First, we asked participants about their background, such as their current role and work responsibilities relating to AI. We defined "AI" to participants as "any machine-based system that can make predictions, recommendations, or decisions"⁵, and provided examples of qualifying systems such as facial recognition,

⁵This definition is adopted directly from the OECD [39].

resume screening, and chatbot technology. Second, we asked participants to walk through how an example procurement involving AI would occur in their city, paying particular attention to any differences between a standard technology procurement. Our goal was not to impose structure on participants' descriptions of procurement, but rather allow them to describe how they personally view the procurement process. In the final section, we asked participants to reflect more deeply on their perceived challenges, needs, and desires to improve the AI procurement process. The study was approved by a university Institutional Review Board (IRB), and participants provided informed consent. We include our complete interview protocol in Appendix B.

To preserve anonymity of participating employees, we assured interviewees that their participation was voluntary, they could decline to answer interviewer questions, and their responses would be kept anonymous. For sensitive or potentially identifying interview quotes, we exclude participant IDs to preserve anonymity. When appropriate, we use the "x" character to omit exact dollar amounts to preserve confidentiality.

Qualitative Analysis. We collected 23 hours of interview audio which were transcribed and coded by four team members, including the principal investigator. We adopted a bottom-up thematic analysis approach [21] to analyze interview transcripts. Each transcript was open-coded by two authors, who met regularly to discuss each transcript and resolve any differences in interpretation [63]. The process was iterative, including regular discussions to adjust coding strategies, group codes into higher-level themes concerning employees' practices and needs, and refine the coding schema. In total, we created 305 unique codes. The first level clustered our codes into 43 themes. These were then clustered into 6 final themes to answer our two research questions, which we present in the next two sections.

4 UNDERSTANDING CITIES' EXISTING AI PROCUREMENT PRACTICES

In this section, we describe city employees' current practices and priorities when procuring public-sector AI. We found that all seven of the cities that we interviewed shared that they had already started to use procured AI technologies developed for a wide set of intended users and goals, e.g., to aid law enforcement, inform urban planning decisions, assist bureaucratic decision-making, facilitate resident communications, and increase workplace productivity. Notably, almost all of the cities we interviewed did not have the capacity to develop their own AI solutions internally, motivating their need to adopt AI developed outside of their organization, with the exception of two large cities that were experimenting with developing AI solutions internally with their own IT workforce.

In what follows, we present two key findings with implications for cities' responsible AI practices. We describe how employees often made use of alternative purchasing pathways to acquire AI. We found that three out of seven interviewed cities had changed their purchasing practices for procurements involving AI, either by making adaptations to existing procurement practices (*e.g.*, AI-specific RFP items/contract terms), or establishing an IT-led AI review process. The remaining four cities had not yet changed their practices for procurements involving AI.

4.1 Many Al acquisitions occur outside of conventional procurement processes

In Section 2, we described a classic procurement process as it is described in the literature. Our interviews, however, indicate that AI procurement often doesn't take this classic route, often skipping centralized planning, solicitation, competition, and contract negotiation phases. Participants pointed out that due broader shifts in the AI landscape, namely the availability of low- and no-cost

 $^{^6}$ In Appendix C, we describe each of these use cases in further detail and provide example real-world AI solutions mentioned by participants.

AI tools (P16), many AI acquisitions did not involve a competitive solicitation (*e.g.*, no RFP) because they were under cost thresholds that would require them to do so.⁷ Local procurement law specified that municipal employees could make purchases under a certain dollar amount at their own discretion, using a government-issued purchasing card (sometimes called a "p-card"). For example, one participant described how their department often adopted software tools by purchasing a monthly subscription on their purchasing card:

"We subscribe to a mountain of stuff on our credit cards. We don't procure [example software tool] via RFP, we pay on a monthly credit card bill. The subscription does not rise to the level of needing to legislate and budget for the line." (P1)

Types of AI tools that fell under cost thresholds included free online services (*e.g.*, chatbots), services with paid subscription models (*e.g.*, coding assistants), or AI donated through academic collaborations, foundations, or from for-profit companies.

Another alternative purchasing pathway that employees used to acquire AI was "piggybacking", *i.e.*, adopting existing contracts made by other governments with a vendor to acquire the same services at the same price. AI acquired through piggybacking does not need to go to solicitation, and existing contracts are often adopted as-is without re-negotiating. Several participants mentioned that their city often procures software using cooperative agreements with their state government. One participant described the benefits of piggybacking as:

"We're very heavily incentivised to use tools that are in state contracts. [...] The state leverages its purchasing power to buy things relatively cheaply, and they have all the compliance, so we're heavily incentivised to do that." (P18)

One participant who worked in a procurement department shared that they used cooperative contract websites to browse existing potentially relevant contracts to piggyback before going to RFP.

While participants pointed out that employees could opt in to a full solicitation process when acquiring AI, e.g., "you can go to RFP for any reason" (P3), they shared that employees preferred to use alternative purchasing pathways because they were more efficient. For example, one procurement leader (P14) shared an anecdote where they were approached by an employee that wanted to work with a vendor that they had already personally determined was the "best partner", and thus was disincentived from going to RFP, which would "take months" to complete. Similarly, employees who had already identified an AI solution that they would like to use could simply purchase it on their p-card without needing to compare offerings from multiple vendors. Interestingly, one technology department we spoke with shared that they preferred using alternative competitive purchasing methods to RFPs (e.g., RFI/RFQs or other processes to obtain multiple quotes from vendors) for all of their technology acquisitions. One participant who had been working in IT procurement for years shared that the vast majority of their software acquisitions were under RFP cost thresholds, and never went to RFP.

Finally, several participants shared how they made use of innovative acquisition processes, such a Request For Information ("RFI") or short-term contracts (discussed further in Appendix D), to purchase AI. Participants leveraged these alternative purchasing methods to innovate "within the constraints of procurement law" (P2) to better understand potential promises and risks of AI technologies by piloting or using them directly. For example, one participant (P14) shared how their city invited AI vendors to participate in "hackathon" events designated as RFIs to brainstorm public-sector use cases for AI with city employees. In contrast to a traditional procurement where governments can only begin to use a technology once it is under contract, these alternative processes

⁷These cost thresholds are specified by both state and municipal procurement law that applies for all purchases beyond technology, and varied across participating cities.

create opportunities for cities to experiment with new AI technologies before investing significant capital or committing to fixed time (*e.g.*, one-year) contracts, avoiding vendor lock-in.

4.2 Some cities, but not others, have adapted their purchasing practices for Al

We found that three out of seven cities that we spoke to had already introduced explicit changes to their existing procurement practices for AI. The remaining four cities had not changed their processes, and assessed AI similarly to "any other technology" (P6), applying broad criteria for purchasing software such as "threats to cybersecurity" (*e.g.*, data breaches), "usability", and "interoperability with [existing] enterprise systems" (P1, P4, P8, P18).⁸

In contrast, participants in the three cities that revised their processes found these broad criteria insufficient to address novel risks posed by AI technology. For example, one procurement specialist (P17) reflected on how in contrast to traditional software procurements, which were "very contained algorithms", data-driven AI posed novel risks due to risks of inaccuracy, privacy risks and "human biases encoded in [training] data", inscrutability, and changes in behavior when models are "refreshed" (re-trained). Another participant (P18) called attention to the environmental impact of training and using large language models, a consideration they did not typically consider for the average software procurement. To manage these and other risks posed by AI, some cities changed their procurement practices.

Interestingly, we found that the common step that interviewed cities took to improve their AI governance was developing new *usage policies* for how city employees should or should not interact with publicly available generative AI tools, such as ChatGPT. Common advice included not entering private city data into chatbots, using city (not personal) accounts to discuss city business, reviewing AI outputs before using them, and disclosing when AI was used to generate content. In many cities, these generative AI usage policies were the government's first (and sometimes only) action taken regarding AI. For example, one participant (P1) whose city had not yet taken action on AI shared that their city was "not initially focused on [AI] procurement", and was first trying to "wrap their arms around [how] people are already going ahead and using [generative AI] tools" by writing a usage policy. Writing a usage policy felt of urgency because the participant understood that "city employees [are already] putting private information into generative AI tools".

While all seven interviewed cities had already or intended to release generative AI usage policies, these policies were often narrowly-scoped. For example, such policies only covered *generative* AI tools, and were not applicable to other types of AI systems, such as predictive AI [101]. Similarly, such policies focused on individual employees' usage of AI tools, rather than the broader *acquisition* processes by which AI tools *came to be in use*.

We observed that cities that had changed their acquisition processes for AI could make two different types of changes: (1) adaptations to their conventional purchasing process primarily overseen by procurement specialists; and (2) independent AI reviews primarily overseen by IT specialists.

Adapting conventional purchasing processes for AI. The purchasing pathway used to acquire the AI determined whether procurement specialists and others typically involved with formal procurements got involved. Existing conventional procurement processes often established clear accompanying accountability structures: set roles, responsibilities, documentation, and lines of communication to review and oversee procured goods and services. For example, many cities had a centralized procurement department that was involved with writing and scoring every RFP. Beyond selecting a winner, several cities also had staff in vendor or technology relationship management roles who

⁸Department leaders in three out of these four cities shared that they *intended to* change their practices for procurements involving AI, but had not yet decided how to do so.

support purchasers as they work with vendors. Cities trained procurement specialists to identify and "flag" when proposed solutions involved AI, and collaborated with lawyers to write AI-specific contract terms. While procurement specialists were often not AI experts, they collaborated closely with employees based in IT to write and assess RFP items that incorporated AI vendor reporting requirements, aid in vendor selection, and provide general advice on how to evaluate AI proposals.

Establishing an independent AI review. Some cities had a separate "AI review" process overseen by experts in technology, that occurred outside of conventional procurement processes (e.g., led by an IT rather than a procurement department). When an employee wanted to acquire an AI solution, they initiated an AI review by completing a form or "opening a ticket". IT employees or subcommittees trained to assess the risks of the AI then reviewed the employees' request to conduct additional reviews. AI reviews often involved AI-specific risk assessments, vendor reporting requirements, and negotiations to include additional contract terms. We describe each of these components in more detail in Appendix D. Importantly, several cities required that employees complete an AI review before procuring or using an AI system, no matter how it will be acquired – through RFP, on a purchasing card, or for free. As put by one participant (P5), "it doesn't matter [to us] if it's free or not, if we're going down the channels, it's going through assessment". Thus, the same standard of review applied to all AI acquisitions, regardless of their cost.

The three cities that made the above changes to their purchasing practices shared that they were still experimenting with their practices. For example, one participant their city as being "very early on" (P3) in their AI governance efforts. We expand on challenges that these cities faced when implementing these interventions, and also challenges faced by cities that lacked clear accountability structures for procured AI, in the next section.

5 CITIES' NEEDS AND DESIRES FOR RESPONSIBLY PROCURING AI

In this section, we describe the needs and wishes of city employees in charge of procuring AI for their city. We find that city employees face a variety of barriers to adopting and championing responsible AI best practices. In our analysis, we call attention to tensions between key groups of actors, such as other city employees (*e.g.*, purchasers of AI), AI vendors, and impacted communities. We begin by investigating an essential component of organizational AI governance: identifying the AI that a city already owns.

5.1 Cities lack visibility of and oversight over employees' and vendors' use of Al

A prerequisite step to assessing and mitigating potential harms posed by AI systems is identifying when AI is being used. Unfortunately, participants tasked with implementing responsible AI best practices within their city encountered significant obstacles in gaining awareness of both employees' and vendors' use of AI. This lack of oversight resulted in a "blind spot" (P3) for AI governance. Participants shared examples of how gaps in oversight resulted in AI harms.

5.1.1 Lack of visibility for Al acquired under cost thresholds. In many cities, Al acquisitions that occurred under cost thresholds "didn't have to go through procurement", and thus fell outside the scope of existing accountability structures for government purchasing. For example, one department leader reflected on how acquisitions under cost thresholds were particularly difficult to govern or even be aware of until after they had been purchased:

"[For purchases] below \$x0,000, there's few oversight or regulatory mechanisms to control, or even have visibility of what departments do. We can go back through our financial data to say, 'Oh, this money was spent on this procurement', but it's not routed through a centralized control mechanism." (P16)

The participant was particularly "concerned" about employees' use of free generative AI technologies after an experience where they learned that an employee started to use a free transcription tool that did not have "a consensual model for data collection". The participant reflected on the hidden costs of free AI tools:

"If you are not paying for it, you're the product. We have to be mindful about the extractive capabilities of these tools that can be free, but are at risk of us divulging resident information, possibly more secure information as well." (P16)

Cities with AI reviews required employees to complete an AI review *before* procuring or using an AI system, regardless of cost. However, in cities without AI reviews, there were often no applicable processes to oversee free or low-cost acquisitions. In effect, individual users could purchase or begin to use free and low-cost AI tools (*e.g.*, with prices under \$x00 per month) at their own discretion, without notifying others in their city.

5.1.2 "AI doesn't manifest itself as a distinct product": Identifying procurements involving AI. Even when AI systems were used as part of a formal procurement that was overseen by procurement specialists, participants found it difficult to identify when a particular procurement involved AI. Participants shared several past experiences where they acquired AI "unintentionally" or "by accident" because it was integrated into a procurement that they did not expect would involve AI, as "often AI doesn't manifest itself as a specific, distinct product, but is usually incorporated into something else" (P15).

Cities often acquired AI when vendors decided to "roll out" or enable new AI features in existing enterprise software that cities had previously purchased. One common example is that cities with existing contracts for office or word processing tools noticed that there were new generative AI productivity tools embedded into employees' software. When these new AI features were released, the city was often not notified by the vendor, and those tasked with overseeing AI governance were unaware until a user flagged the feature. One interviewee summarized the challenge of identifying these new AI features as follows:

"We have thousands of applications and platforms that we have existing governing contracts with. Now we have AI that we probably maybe don't know about at this time, because we don't have standard AI contract terms saying, 'Hey, if you do something that meets this definition, you roll out a feature, you have to tell us'. So these things are coming into our existing tech stack. They're not going through traditional procurement, because the tech is already in use. It's hard." (P3)

Another type of procurement where employees struggled to identify AI was when the AI was used as a key component of procurements that did not involve the explicit acquisition of technology – for example, when AI was used in a professional service. One such example is from a city that procured a professional service from a vendor intended to support decision-making on allocating construction funding. The participant discovered that the vendor was using a proprietary AI model to assign the grades to each street. Because this specific procurement did not involve an explicit acquisition of software – it was "just a professional service contract for street indexing" – the city was unaware that the tool even utilized AI. This example makes clear how vendors' use of AI tools to fulfill a scope-of-work can still significantly influence critical decision-making processes, even in procurements that do not explicitly involve the acquisition of technology.

5.2 Organizational dynamics shape how AI is procured

Participants' experiences and ability to prioritize responsible AI considerations were shaped by interactions with colleagues, practical constraints, and organizational priorities. In this section, we

shed light on procurement as a highly *collaborative* endeavor involving many stakeholders with varying perspectives, incentives, and expertise. Participants encountered systemic obstacles such as budgeting shortages or existing constraints on their time when trying to increase city capacity for AI governance. Conflicting incentives between reviewers and purchasers of AI technologies posed barriers to prioritizing responsible AI considerations when making purchasing decisions.

5.2.1 "We just go running around having conversations with each other": Coordination and hand-offs. Participants emphasized that procurement is a highly collaborative endeavor that requires coordination across a large number of stakeholders. While procurement processes were often overseen by specialists whose primary responsibilities were in procurement, the process often roped in many other specialists - e.g., law, technology, business, project management, and cyber-security experts - whose primary responsibilities were in not procurement, for consultation. For example, one privacy specialist described how they worked together with other specialists, such as lawyers, to assess legal risks posed by procured technologies:

"We learned quickly that [procurement] is much bigger than us. If someone checks that a procurement involves data [from the county health department], the first thing I do is go right to the business to ask for their data agreement, then go hand it to my law department [for review]. They can provide feedback, go back-and-forth. That's the kind of ad-hoc thing I was talking about – we all have our own lanes. We just go running around and having conversations with each other." (P3)

The participant continued to reflect on the opportunities of leveraging their colleagues' "many lenses and considerations" to "assess [AI] risks more comprehensively". However, the participant found coordinating multi-department reviews to be challenging due to a lack of procedural guidance and structure for collaborative risk assessments.

5.2.2 "So little funding, so little capacity": Cities are under-resourced for AI governance. A common theme expressed by participants across cities of all sizes was that cities were under-resourced and under-staffed in roles they perceived as critical to AI governance. Some participants shared that a culture of austerity had posed difficulties to purchasing technologies, anticipating that they might encounter obstacles when trying to purchase any AI. One participant described their frustration with the city's budgeting process:

"Because there are so many technology needs, and so little funding, and so little capacity on behalf of our IT department to support every need, it's not likely that a request will get approved, funded, and executed. So we end up with this backlog of a lot of departments that are frustrated." (P2)

Beyond the monetary resources required to purchase AI, participants in many of the interviewed cities expressed concern over their *staffing* capacity to review and govern procured AI. Participants who were based in municipal IT or Innovation departments repeatedly expressed their desire to hire more personnel, or felt their organization was understaffed more broadly. While many participants expressed an interest in up-skilling to learn more about AI risks, they often shared that they could only do so within severe existing constraints on their time as learning about AI was not explicitly part of their existing job responsibilities. Several participants called attention to the fact that they were repeatedly told that their city didn't have enough resources to hire individuals with expertise in managing AI risks, such as Privacy or AI professionals. One IT leader explained,

"I think the number of cities with Chief Privacy Officers can fit on my hand. It's cool when we talk to them, but that's different than how far we'll go with this stuff, when we're the other cities looking at them." (P1)

When we spoke to cities that *did* have these roles, participants still shared similar concerns about their capacity. Participating privacy employees emphasized the relatively small size of their organizations, *e.g.*, most cities employed 2-5 total privacy employees tasked with reviewing all of the city's technology purchases. Notably, several cities tasked their existing *privacy* staffers as also being responsible for overseeing their city's AI reviews and governance. As one privacy specialist reflected on the challenges posted by this expansion of responsibilities:

"Now we have basically a new function that we're responsible for, [but] we don't have any additional resources or capacity." (P3)

This sentiment of learning how to best make do with existing staffing shortages when faced with systemic obstacles (*e.g.*, budgeting shortages) that kept them from hiring additional staff was shared across interviewed cities.

5.2.3 "Review is an obstacle and they just want to use the technology": Conflicting incentives between AI reviewers and customers. Participants responsible for identifying and mitigating risks posed by AI systems perceived tensions between their own goals and those of customers wanting to purchase AI. For example, one department leader who led a team "responsible for thinking about" potential negative societal impacts of AI noticed that in their experience, other teams were motivated by different incentives:

"The promise of efficiency of [AI], as our departments are making their own decisions, outweighs the opportunities of inaccuracy. Most departments are like, 'I want to buy the cool thing. I want to enhance my operations. I want to get promoted.' But they're not thinking through some of the ethics and accountability stuff." (P2)

These conflicting incentives often became visible in cities that had mandatory reviews before customers could purchase and begin using new technologies. As described by one IT leader, while some departments "are more than willing to be partners" throughout reviews, "others get angry, because they feel like [the review] is an obstacle and they just want to use the technology" (P6). IT leaders across cities shared similar experiences of being perceived by customers as "a bureaucratic hurdle".

While employees that valued reducing negative societal impacts of AI could use mandatory review processes as a "leverage point", they often lacked the authority to make final purchasing decisions. For example, one privacy specialist (P3) who conducted AI reviews described that they "[were] not in a position to necessarily mandate people walk away from things, despite risks". Instead, their department "tried to approach [the review] as partners", with a shared understanding that "at the end of the day, there are other pressures that exist and factors to weigh when it comes to what ends up moving forward or not".

5.3 Preparing for and assessing AI risks

All of the cities we interviewed already utilized a risk management approach [97] to anticipate and mitigate risks posed by procured *technologies*. In this section, we investigate challenges participants faced when assessing risks posed by procurements specifically involving *AI*. We find that participants who had not yet adopted their policies for AI assessed AI similarly to other software, and desired focused training on AI-specific risks. Participants also wished for guidance on determining their risk tolerance, and choosing their customized risk management approach.

5.3.1 "Is that hallucination thing for real?": Participants desire focused training on Al risks. Participants located in cities that had yet to develop AI-specific components of their procurement process expressed anxiety and a lack of confidence in their ability to assess AI solutions.

One participant who had worked for 15+ years as an IT project leader in their city expressed their concern:

"There's a risk to how we work with AI. If I don't really know what those risks are, and I can't protect us from those risks comfortably, then I'm not doing my job" (P4).

When discussing what they perceived to be significant risks posed by AI systems, many participants shared concerns about data security, data ownership and retention, and data privacy - risks that are also considered during a typical software procurement. However, a much smaller number of participants mentioned risks posed by (in)accuracy [79], (un)fairness [20], adversarial robustness [38], lack of transparency or explainability [14], contestability and recourse [67], or broader societal impacts, *e.g.*, to labor or the environment [60, 93]. For example, one participant mentioned that their team did not consider risks posed by "hallucinations" in a recent procurement of an AI chatbot service, and that risks due to inaccuracies were "not part of the conversations" they had with the vendor.

While most AI procurements went through a centralized IT review, participants emphasized the importance of all types of reviewers involved with an AI purchase having "some basic-level understanding of AI [...], especially folks in procurement, because they're the ones who are going to be identifying these systems" (P10) and "adding functional requirements [to a solicitation]" (P8). Another participant shared that because their organization "struggle[d] to define [AI-specific] contract terms and legal contracts" because they did not have procurement or legal staff who were knowledgeable about AI (P2).

Beyond developing AI expertise for employees tasked with reviewing AI systems, participants also emphasized the importance of cultivating a baseline level of AI literacy for all municipal employees, as all employees are prospective customers who might someday participate in or be impacted by an AI procurement. To this end, some cities designed and ran workplace-wide AI trainings, *e.g.*, to educate their workforce on the potential benefits and harms of popular generative AI tools (P10, P12, P16). Participants involved with organizing broader educational initiatives noted dramatic differences across their workforce in employees' existing awareness of and enthusiasm for AI, and technology literacy more broadly, as described by one department leader:

"The vast majority of our staff are not that technically forward. It took me [5 months] to help all the directors and chiefs even know what generative AI is. [They're] like, 'I pick up the trash, I save people in ambulances, I measure that the building is the correct height. My job does not require me to know anything about this geeky stuff'." (P11)

Overall, participants across cities consistently expressed a desire for more education and training about the potential risks and benefits posed by AI. Cities that perceived they were behind their peers expressed a need for further guidance about the unique risks introduced by data-driven AI solutions, so that AI reviewers could make more informed decisions.

5.3.2 "What is acceptable here?": Determining organizational AI risk profile & risk tolerance. Due to their varying levels of AI preparedness, expertise, and capacity, cities wanted to pick and choose the specific steps they would take to conduct their own risk assessment. Although several cities were members of the Government AI Coalition, and thus were aware of ready-to-adopt resources (e.g., lists of questions to ask AI vendors during a review), none of the cities we interviewed adopted them as-is. Instead, they adopted revised versions of existing resources that they felt were adapted to their city's needs and priorities. For example, one participant who was concerned that the original list of questions was too long decided to incorporate modified versions of the 10 "most important questions" (P1).

Participants across cities also repeatedly expressed uncertainty and confusion about determining their organization's *risk tolerance*, *i.e.*, how much risk they were willing to accept. Some cities established hard ceilings on certain types of risks by instituting minimum "red line" requirements [81] of procured AI systems. But sometimes, participants struggled to find AI that met their requirements. For example, one department leader recently instituted "language in [their] city policy that city officials had to make a reasonable effort to ensure [AI] use was not violating existing intellectual property laws". In response, a generative AI vendor told the city that this requirement disqualified them from consideration. While the requirement worked as intended to protect the city from potentially using illegal software, the participant wondered it would disqualify most eligible vendors:

"We had a number of conversations about that – in particular, are our standards too high? Or is the technology simply too risky or problematic for us to use effectively?" (P15)

In contrast to red line requirements, participants also had to make ad-hoc judgment calls after collecting relevant information from vendors, such as performance metrics. Some participants struggled to determine what values of the metric were good enough, or "set the line" (P9). One participant discussed how their department had trouble interpreting the values of the metrics reported by vendors when making decisions about whether to move forward with a purchase:

"We ask some sort of question: 'What's your R-squared value'? And how do we know if [what is reported] is good? Someone needs to be able to say, is that good or not good? Like, have that kind of technical acumen to say what is acceptable here in terms of accuracy, error rates, thresholds, or whatever." (P3)

Other participants also expressed enthusiasm for clear guidance and thresholds when interpreting measures of AI risk, noting that such guidance might be most impactful for "small jurisdictions that just don't have the capacity [to conduct AI reviews]" (P7). The participant conceptualized this guidance as a consistent "stamp of quality" for AI that could institute a minimal set of requirements, *e.g.*, for performance and non-discrimination.

5.4 Cities lack leverage in their relationships with vendors

While participants tried to leverage their city's purchasing power to ask more from vendors, *e.g.*, to provide basic information about their AI system or amend their contracting terms, many participants found that vendors were unwilling to amend their position. With some exceptions, participants repeatedly felt that they lacked leverage in advocating on behalf of their city. As put by one participant: "companies are willing to walk away from a contract, because they know they can sell that product to another city really easily" (P2). Below, we identify specific challenges participants faced when trying to uphold AI vendors to responsible AI best practices and standards.

5.4.1 "Information is typically black-boxed": Vendor secrecy & obfuscation. Vendors frequently refused to disclose information that reviewers requested, claiming that the information was proprietary (i.e., protected as the vendor's intellectual property). One participant explained how vendors' refusal to grant cities access or provide basic information about their system limited the participant's ability to make informed purchasing decisions:

"What we need to perform a risk assessment is intimately tied to the [data] models that power AI systems, which most vendors treat as proprietary. So, having access to the model, which is the engine of how the AI tool is working, knowing the sources of training data that are being used, having information on the accuracy of the AI [...] this information is typically black-boxed." (P2)

Participants described other tactics beyond invoking IP that vendors used to avoid answering their questions, such as "ghosting" (not responding to e-mails) (P5), "deflecting" (P10), or simply stating that they cannot answer (P5, P10, P13). Other denied requests for information included questions about the presence of copyrighted content in a model's training corpus (P3, P5), whether data collected from employees' interactions with the AI would be used to train the vendor's models (P1, P17), and disaggregated performance measures of the model's accuracy, *e.g.*, across different demographic groups (P2, P7, P10).

5.4.2 "Few companies are willing to do boutique AI models": Lack of customization. Several participants valued the ability to customize the AI services that they procured to the unique context and needs of their locality. However, participants shared that they often were not consulted or involved with the design or development of procured AI solutions. Instead, the majority of procured AI systems were designed to be deployed off-the-shelf, without being customized to (e.g., trained or fine-tuned using data from) each city. One participant used the term "turn-key" to describe this type of vendor business model:

"[Vendors] are like, 'We just want to scale our business model and get out of the game'. To do that, it has to be this turn-key thing. Very few companies are willing to do 'boutique' AI models where they're taking your specific dataset and training their model off of that." (P2)

Participants also wished that vendors modify their AI models to apply technical mitigations to reduce potential societal harms. As one example, a participant whose background was in data privacy discussed a positive experience where the participant worked with a vendor who developed AI models to count the number of people using city facilities:

"We were like: 'Whoa, why are we just watching people?' So we worked with the vendor to ask: Do we actually need this video on, or can you blur it, or make it a heat map? What functionality can you give the city so we don't have to literally watch humans walk in, when all we need is a count number?" (P3)

In this procurement, the vendor applied the city's requested mitigations and trained an AI model to detect people entering a building using alternative data sources, instead of a live video feed. This example illustrates the importance of implementing technical mitigation steps (*e.g.*, changing the form of the data given as input to a predictive model) to manage and reduce risks.

5.4.3 "What responsibility can we put on the vendor?": Delegating responsibilities between parties. Review and oversight of procured AI technologies requires labor and expertise, e.g., to conduct evaluations, train users, and enforce compliance. However, several participants shared that vendors failed to complete these steps, claiming that they were instead the city's responsibility. For example, when one participant asked for a vendor's assistance in assessing whether city employees were entering sensitive information into a procured AI tool, the vendor used "indemnification language" to state that such reviews were the city (not the vendor)'s responsibility (P5).

Vendors often did not conduct evaluations, leading several participants to evaluate models "on their own" (P10). For example, one participant wanted to monitor the performance of a procured gunshot detection AI service to verify if it "was continuing to be effective and meet the needs of the city". However, the vendor did not provide the city with performance evaluations, nor provide the city with guidance on how to evaluate system performance. In response, the city had to "develop their own metrics" and monitor service performance themselves.

While some participants with AI expertise enjoyed designing and conducting independent evaluations (P7, P10, P18), one participant expressed reservations about their organizations' capacity to do so:

"I'm not a technical person. I'm not gonna be evaluating these systems that we're bringing in for bias, right? But we can ask questions. What responsibility can we put on the vendor?" (P3)

5.4.4 Federal regulation can establish consistent minimum standards for Al vendors. While participants tried their best to hold vendors accountable to their city's established ethical AI standards, they pointed out that in the current U.S. regulatory regime, vendors had no obligations to comply. One privacy specialist reflected on their past experiences where AI vendors "made no effort" to address the citys' privacy concerns:

"If we were to see [federal] laws around privacy and AI governance, I do think it would shift responsibility. In the US, vendors can do a lot. They have a lot of leeway." (P5)

This participant, and several others, expressed a wish for regulation from higher levels of government, e.g., from federal legislation or regulatory agencies, to institute "consumer protections" and "known [behavioral] expectations" for AI vendors. Federal regulation that established consistent minimum standards could "lessen the burden [on local governments]" in negotiating on behalf of city employees and residents (P3). For example, several participants specifically flagged "baseline data privacy regulation" as an important step that could allow individuals to opt out of their data being used for AI training (P1, P3, P5, P16).

5.5 Cities perceive obstacles to meaningful public engagement

Meaningful transparency and public engagement can give communities and stakeholders who might be affected by an AI procurement a say in where and if its use is acceptable. For example, cities can notify residents of upcoming or under-contract AI by creating a *public AI registry* of relevant procurements. Beyond posting public notice of procured AI, cities could also directly elicit input from residents. One interviewed city shared that they made use of existing neighborhood association meetings to elicit residents' feedback on what they believed were appropriate uses of potentially high-risk AI technologies, such as license plate readers used by police. However, most participants interviewed shared that their city *does not* engage members of the public throughout their AI procurement processes due to several perceived barriers.

5.5.1 "Transparency is a double-edged sword": Fear of public scrutiny. While several interviewees liked the idea of creating a public AI registry, they shared concerns that creating a registry would make them vulnerable to public scrutiny for past purchasing decisions, or for "not doing enough" to provide information about procured technologies. One participant observed that other cities that had "ventured forth to put AI registries get a lot of criticism from experts and the public at large", which they perceived as a "deterrent to be transparent" as their city "really [struggles] to get over the hurdle of getting information from vendors" (P2). Another privacy specialist who was interested in creating a public registry for their organization shared concerns that doing so might "be a liability to the city [as an organization]":

"[Transparency] is a double-edged sword. I feel as though there could be an additional level of scrutiny that's placed on the organization with the publication of a registry of like, 'Why are you using this tool?'. Or [if] the company later on gets in trouble. There's an aspect of scrutiny that could go along, that could be not as advantageous as you had hoped or intended." (P3)

5.5.2 "It almost wastes money if that is public": Which AI to prioritize for engagement? Several participants shared uncertainties about which procurements they should prioritize informing and eliciting feedback from the public about, given that they felt they "do not have the capacity or authority to require all of our departments to do [their own] community engagement for [just] any AI tool" (P2). In their existing practices, participants pointed out, they did not do public engagement for other technology procurements – so why make an exception for AI? One participant felt that many technology procurements would not be of interest to the public, and struggled to think of a past procurement where they felt engagement would be appropriate:

"If someone is using Microsoft Word, there's no need for [engagement]. It almost wastes money if that is public." (P5)

The city that did do public engagement addressed this challenge by prioritizing "AI tools tied to high-risk use cases" for public engagement, as they are "most likely to impact people in a really substantial way". However, some participants did not believe that public engagement should be necessary for all such procurements. For example, one department leader (P6) shared that they strategically did not make information about all of their procured AI public, due to "public safety aspects" and the possibility of manipulation or evasion by adversarial actors.

5.5.3 "We can't give out budget information": Procurement law prohibits certain types of transparency. In our discussions with procurement specialists, we found that some cities had legal obligations to keep specific information secret during certain phases of the procurement process to promote broader objectives of government procurement, such enabling a fair competition between vendors. One procurement specialist (P8) described how they legally could not involve members of the public in selecting a vendor. Basic information about both the solicitation process and final contract was required to be kept secret.

Thus, initiatives to encourage transparency and participation throughout the AI procurement process must take existing legal constraints and customary procurement objectives (e.g., encouraging competitive bidding), which vary across cities, into account. Importantly, such laws often target solicitation and vendor selection processes, but do not prohibit public engagement in earlier planning phases of the procurement.

6 LIMITATIONS

We acknowledge several methodological limitations of our study, many of which pose directions for future work. We leveraged our personal networks and snowball sampling to recruit participating cities and employees for our study. As such, our sample was skewed towards large cities who had leaders that were already interested in and knowledgeable about artificial intelligence. Similarly, our recruitment criteria may have led us to recruit participants who stood at the "forefront" of their citys' emerging AI practices, a methodological limitation shared by related empirical studies on topics related to responsible AI [33, 48, 80]. To address these limitations, we intentionally tried to recruit smaller cities and participant roles that were under-represented in our sample. While our focus on U.S. cities enabled us to draw productive comparisons across jurisdictions, we believe that understanding generalizability and distinctions across governments in other countries is an important direction for future work. Finally, we acknowledge that our decision to focus on city employees as a key stakeholder group in public-sector AI governance neglects the perspectives of other important actors, such as AI vendors, civil society and other members of the public, and impacted communities.

7 DISCUSSION

Procurement is a promising site of intervention to assist local governments in harnessing AI to the benefit of their residents. A growing body of literature identifies this opportunity and attempts to act on it by providing theories and resources that could help practitioners procure AI responsibly [47, 66, 70, 77, 83, 88]. Our paper supports these efforts by offering an empirical study of AI procurement in public administration. Understanding on-the-ground realities of AI procurement is crucial for creating theories and tools to utilize procurement as a lever of change.

In this section, we compare the landscape of scholarship and resources described in the related work section, to the challenges and needs of practitioners described in the findings sections. We discuss five key practical and procedural tensions between how procurement is addressed in the current literature, and how procurement actually occurs in the field. Under each, we share implications for scholars, resource creators, and policymakers, and highlight directions for future research. We view these directions as critical opportunities to understand how local governments can effectively incorporate responsible AI considerations into their procurement practices.

Support cities in governing AI acquired outside of conventional procurement processes. The literature on AI procurement typically highlights a linear process with stages such as problem definition, solicitation (writing an RFP), evaluating vendors, and contracting. However, our findings show that city employees mostly utilize procurement pathways such as p-card purchases and piggyback contracts that skip steps of the conventional procurement process. Most notably, these pathways do not include a competitive solicitation (e.g., an RFP process), which is the most prominent procurement component that the existing resource landscape addresses [2, 22, 27, 35, 77, 88]. The result is a dearth of resources to support the procurement processes practitioners encounter. To address this gap:

- Governments can define clear governance structures to establish who is accountable for a procured AI system, even in situations where the system does not go through a formal procurement. While conventional procurement practices use cost-based thresholds that conceptualize cost as a proxy for risk, our findings and several real-world examples (e.g., [50, 105]) illustrate that low-cost AI systems can still pose critical risks to residents' privacy, civil liberties, human rights, and wellbeing. As such, we encourage governments to "establish clear accountability structures so that appropriate teams are responsible and trained" [97] for understanding and addressing risks posed by these systems. One approach that worked for several interviewed cities was requiring employees to complete a form before adopting a new AI system, which was then reviewed by trained IT specialists. More research is needed to understand possible organizational governance structures to support the many ways (e.g., through research collaborations, free services, or donations) in which AI is acquired.
- Governments can establish processes to identify incoming AI in existing procurements, e.g., new AI features in existing enterprise software. This could involve including additional contracting clauses that require vendors to notify cities of new AI features, and opt out of such features being enabled.
- Researchers should prioritize creating resources tailored to encourage responsible AI practices
 in procurement pathways beyond RFPs in which AI acquisitions frequently occur, i.e., piggyback contracts and purchasing cards. For example, resource developers can explore how to
 incorporate responsible AI considerations into existing piggyback contract databases, or
 help purchasers in acquisitions that do not involve contract negotiation to understand AI
 vendors' terms-of-use.

Develop interventions that acknowledge existing organizational dynamics within cities.

Most literature on AI procurement in public administration is silent on the organizational complexities of local government. For example, when specifying questions to ask in the solicitation processes, resources often focus on the questions and evaluative processes alone without recognizing challenges related to carrying out the processes in an organizational setting or suggesting strategies for overcoming them [2, 4, 83]. Our findings highlight that, typically, there isn't a clear line of action for procurements, with one primary actor guiding the process smoothly through to completion. Instead, procurement involves coordination across many actors: a finding affirmed by past empirical research with federal employees Autio et al. [17]. Departments and employees involved in the procurement process sometimes have inconsistent incentives and unclear roles and responsibilities. To address this gap:

- Governments can work to create an organizational culture that values responsible AI, and prioritizes addressing AI harms. Cultural change can be initiated top-down by city leadership. For example, city leadership should ensure employees have the capacity, time, and resources to discharge the responsibilities given to them. Department leaders can work to ensure employees have adequate preparation and training on the unique and emerging risks posed by AI technologies. To support employees in AI review roles, cities can also consider new policies e.g., to require that all incoming AI procurements meet minimum ethical standards. We believe that more empirical research is needed to understand how such policies should be designed and implemented. Future work may benefit on drawing scholarship in organizational psychology [30, 91] and referencing related efforts to shift organizational cultures in related fields, such as privacy [49].
- Researchers can develop AI-specific resources and training tailored to the many distinct roles
 and areas of expertise that are already involved in purchasing. Our findings indicate that
 local governments strongly desire role-specific training tailored to different actors' existing responsibilities, such as procurement specialists, lawyers who review and negotiate AI
 contracts, public records departments who manage data ownership rights for AI procurements, cybersecurity experts who assess emerging security threats posed by AI systems,
 and project managers who conduct regular vendor and business need reviews. Such resources should also support collaboration between and effective hand-offs across actors.

Create concrete models of and infrastructure for meaningful public participation during procurement. Scholars, advocates, and civil society have called for governments to meaningfully involve impacted communities in critical decision-making processes about public AI systems [65, 66, 82, 106], particularly in high-stakes scenarios. However, in our interviews we found that with the exception of one city, most cities do not engage with impacted communities before purchasing decisions are made. Like past HCI research exploring the possibility of participatory AI in the public sector [52], we found that interviewed employees expressed strong hesitation regarding the value such participation or even basic transparency could provide. Our findings explicitly surface how cities' existing procurement practices, e.g., norms around transparency shaped by procurement laws that govern what type of information can be made public, influence employees' attitudes around participation. To address this gap:

• Researchers can create concrete models for how cities can structure participatory engagements with affected groups, with an eye towards practical implementation guidance for cities, as recommended by Kawakami et al. [52]. In particular, because some cities have procurement laws that limit transparency once a purchase goes to soliciation, we recommend that such engagements take place in the planning phase. For example, cities could benefit from

concrete guidance on how to determine which AI systems to prioritize for public engagement, and think through who should be invited to the engagement. One promising direction identified in interviews is relationship-building with existing neighborhood and civil rights organizations.

Researchers can also support cities in developing necessary *infrastructure* [106] to support continued engagements with residents. When imagining possible implementations, researchers can look to how cities with surveillance ordinances structure mandatory engagements with the public [107]. Engagements should keep in mind extractive histories between governments and marginalized groups, and move beyond consulting and towards empowering stakeholders to make key decisions about procured AI [32, 52, 96].

Re-thinking AI risk assessment for local governments. Conducting risk assessments for AI is one of the strongest recommendations in the literature, typically recommended when identifying a need or evaluating vendors [9, 83, 87, 97]. Such reviews are important because they could anticipate and prevent AI systems from perpetuating public harm. However, we found that many cities are unprepared to conduct adequate risk assessments. Employees struggle to know what to ask of vendors, and make decisions using the information they are provided. We propose several directions for future work, with particular attention to ideas raised by participants:

- Resource developers can develop risk assessment instruments better-adapted to the average
 municipal employee making purchasing decisions. While participants with more training
 on AI-specific risks could easily navigate the existing landscape of risk assessment instruments, many participants who were less comfortable felt that existing risk assessments
 asked too many questions. Furthermore, participants expressed a strong wish for actionable guidance on how to interpret the information provided (e.g., values of accuracy metrics
 or open-form responses about processes used to train models).
- Researchers can support cities by exploring standardized ways to assess vendors, such as "stamps of quality" or communities of practice. Today, individual cities are responsible for conducting their own AI risk assessments. While a few interviewed large cities had risen to this challenge, several smaller cities are unable to successfully implement adequate risk assessments. Several interviewees expressed a wish for a standardized body (e.g., a professional agency or certification regime) that could assist in evaluating AI vendors. Future research can further examine what types of responsible and ethical considerations should be included in such certifications, who conducts them, and limitations of such approaches.
- Researchers can support cities by creating measurement methodologies and evaluation in-frastructure for public-sector AI, e.g., both standardized benchmarks and field testing guidance. For example, one participant shared that they collaborated with a university to translate policy objectives into quantifiable "measures of success" for a generative AI project. Academic researchers can similarly design empirically-informed resources and tooling to support evaluation and measurement. Researchers can aid cities in creating standardized benchmarks to enable consistent comparison of performance across vendor offerings, e.g., by helping them build trusts to share data for common public-sector use cases [3, 9]. Researchers can also draw from the field of program evaluation [103] to help cities understand the extent to which already-procured AI, achieves its proposed goals (e.g., of increasing worker productivity, making government services more accessible to residents, preventing car accidents, or other goals).
- Higher levels of government can support cities by establishing minimum standards for publicsector AI tools. Participants across cities expressed a clear desire for stronger regulations to establish minimum standards of AI vendors, e.g., to protect consumers' likeness and data

from being used against their will. Executive agencies can exercise their rule-making power to establish enforceable standards for commercial AI systems, *e.g.*, so that they comply with existing civil rights and other consumer protection law [25]. While local government employees lack the legal jurisdiction to influence vendors' behavior, they pointed out how federal regulation (*e.g.*, the establishment of standard-setting and review agencies such as the FDA) sparked safe innovation in other technology markets, such as automobiles.

Navigating the larger AI marketplace. Finally, the focus on the conventional procurement process leaves out the complexities of navigating the broader AI marketplace, one of the main challenges our participants tried to navigate. A key challenge was the lack of cooperation from vendors on responsible AI issues, from refusing to answer questions to refusing to customize products. Cities felt they lacked leverage when working with vendors, resulting in a power imbalance. This challenge points to a crucial opportunity for growth in the AI procurement literature:

- Researchers can create resources and infrastructure to support cities given the realities of these vendor relationships. For example, we found that cities oftentimes have to conduct their own independent evaluations of procured AI what guidance or tools may support them? Cities often need assistance negotiating contracts in their best interest what items are typically struck down, and how can they be supported? Finally, cities are oftentimes sold "turn-key" models what procedural mitigations can they introduce on top of them to mitigate potential harms?
- Researchers can focus on understanding the perspectives and concerns of AI vendors. Future literature should address the vendors, understand them, and build resources that serve them as well as the cities, complementing the current literature, which focuses mostly on city governments as buyers. Our paper is limited in this respect as well, as we also focused on the perspectives of the cities alone. However, our findings helped us see the extent to which incorporating the vendors' perspective is essential for leveraging procurement to promote responsible AI practices. Future work can imagine resources that could bring vendors and government buyers together, as opportunities to sell to governments can create revenue streams for businesses, especially smaller ones which may be looking to cultivate a competitive advantage.

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A DEFINING "PROCUREMENT"

Despite the differences, all the definitions of "public procurement" encountered share fundamental similarities: they all concern the process of bringing in goods and services that are developed externally, to achieve the goals of a public sector entity. They differ, however, in specific components of the process. For example, while the United States' federal definition emphasizes a "competitive" purchasing process, denoting the exchange of money as part of procurement, some local governments, like New York City, have definitions that are broader, encompassing all functions related to obtaining goods and services whether or not money changes hands [16, 71].

In this paper we do not adopt a single definition of public procurement as methodologically we chose to leave such distinctions to our interviewees who were encouraged to discuss whatever processes and components they personally and professionally associated with public procurement. Given the broader diversity of the term, as would be expected, we observed differences across municipalities in what types of acquisitions and activities participants deemed as falling under the umbrella of "procurement". For example, procurement departments often did not oversee governments' acquisition and use of free technologies, which we discuss further in Section 5.1.

B INTERVIEW PROTOCOL

We began the interview by reminding the participant of our informed consent protocol (approved by our institution's IRB board), and asking for their consent to record.

Introduction. The goal of this interview is to learn more about existing procurement practices specifically for artificial intelligence, or AI, technologies in your city. We adopt a wide definition of AI as "any machine-based system that can make predictions, recommendations, or decisions". This would include technologies such as facial recognition, gunshot recognition technology, resume screening technology, ChatGPT, etc.

Our goal is not to assess your practices, but rather to identify needs and opportunities for researchers as partners to support US cities.

Q1.1: Can you tell me a bit about your current role, and any past work experiences or responsibilities relating to artificial intelligence?

Q1.2: Have you ever been involved in a past procurement of an artificial intelligence technology?

- If YES: How were you involved?
- If NO: Has your [agency] ever considered or talked about procuring AI?

Walk-through. The goal is to understand how a "typical" AI procurement occurs in the city. Our goal is not to impose structure on the participant's description, but rather allow them to describe how they personally view/understand the procurement process.

If it doesn't come up naturally, we can prompt them to reflect on specific parts of procurement, such as (1) Planning, (2) RFP writing, (3) Evaluating Vendors, (4) Contracting, (5) Designing/Building/Evaluating the AI, and (6) Deployment, and (7) Post-deployment.

Q2.1., Walkthrough. Can you briefly walk us through how a typical procurement involving an artificial intelligence technology would occur in your city? We're specifically interested in understanding any difference between a standard technology procurement, vs. a procurement involving AI.

• If never procured AI: *e.g.*, imagine your city is considering procuring an enterprise-level generative AI product, like a chatbot to screen 311 questions.

Drill-down prompts on specific parts of the procurement process: Planning (Problem Formulation):

- (1) What does your city do to plan for the procurement before the RFP (request for proposal) writing stage?
- (2) (if not covered) Pre-RFP, how does the agency identify that an AI tool might be a part of the solution (rather than a tool that does not use AI)?
- (3) (if not covered) Do you have a process for evaluating the risks of a proposed AI technology before RFP writing?
 - If YES: What about potential mitigation processes for these risks?

RFPs:

- (1) Is there anything different in the content of the RFP for AI procurements, compared to standard technology procurements that do not involve AI?
- (2) (if not covered) In the RFP, do you ask vendors questions about potential risks and mitigation strategies?

Evaluating Proposals:

- (1) How does your city evaluate proposed AI solutions? We are especially interested in differences between evaluating standard technology vs. AI proposals.
- (2) (if not covered) What information do you ask vendors to report in their proposal? Do you ever encounter "trade secrecy" claims?
- (3) (if not covered) What measures do you expect them to report? Do they validate that the technology works as claimed using data from your city?

Contracting:

- (1) Are there any differences in the contracting process for AI vs. non-AI (standard technology) technologies?
- (2) Are there specific terms and conditions that you include in AI contracts?
- (3) Can you share a past contract for an AI technology with us?

AI Design, Development, and Evaluation:

- (1) How are people from your city involved with the design, development and evaluation of AI technologies under contract?
 - If YES: How were you involved? What type of feedback did you give?
- (2) How often do vendors make changes to their technologies (like updating or improving it using data from your city) before they are deployed?
- (3) How do vendors evaluate the AI solution they have designed and developed to make sure it fits your use case?
 - Do they use data from your municipality for evaluation?
 - What kind of measures do they look at and report to you?

AI Deployment:

- (1) How often do vendors (or the city) provide training or onboarding for people who will be using the AI?
- (2) How are agency workers involved in deciding the way the AI is used in their everyday practice?

Post-deployment:

- (1) How do you oversee and monitor deployed AI technologies?
 - What is the vendors' responsibility?
 - What if something goes wrong? (liability)

Q2.3 (if unclear) Can you remind me of who in your city is involved or oversees each phase of this procurement process?

- Q2.4 (if unclear): Do you believe the process that we just went through together is representative of most AI procurements in your city (if relevant: beyond that specific example)?
- Q2.5: Are there any existing policies in place that target the procurement of AI technologies specifically?
 - If YES:
 - Can you share your city's policies/guidelines with us?
 - How long have these policies been in place?
 - If NO:
 - Is this something you anticipate being developed in the near future, or something that has been discussed?
- Q2.6: Can you direct us to your city's general procurement policies that may be applicable to AI technologies? e.g., such as data privacy policies?
- Q2.7: Are there any AI technologies that come to be used through processes outside of the traditional procurement process? (e.g., research partnerships, foundations, donations, or free tools?)
 - Do these technologies undergo a similar "vetting" process to procured technologies?
 - Do similar people evaluate these proposals?
 - Do similar people oversee or monitor their deployment?
- Q2.8: Does your city consider opportunities to engage with residents who may be affected by an AI tool during the procurement process?

Challenges & Desires. The goal is to understand the participant's needs and desires to improve the procurement process.

For the last part of our interview, we'd like to understand your opinions and wishes for improving AI procurement.

- Q3.1: What do you believe are the main challenges or "pain points" for AI procurement in your city?
 - Do you have any suggestions as to how cities could improve their procurement of AI?
 - (if relevant) Do you have any examples where [this challenge] happened in the past?
 - Q3.2: Can you imagine any new resources that could help you address these challenges?
 - What resource format would be most helpful? ex: Checklists? Templates? Trainings?

C CITIES' AI USE CASES

Table 2 groups examples of AI adopted by municipalities into five categories based on their intended usage. In our discussions, employees in each city shared at least one example that they were aware of belonging to one of these five categories.

Interestingly, not all of the employees that we interviewed were aware that other employees in their city had already procured or adopted AI technologies: for example, one city employee stated that to their knowledge, their city "has never purchased anything AI related", whereas their colleagues stated that the city in fact has.

Type of AI technology	Examples	
Facilitating resident communication	Translation services, chatbots, 311 assistance, public meeting summaries	
Law enforcement	License plate readers, gunshot detection, object detection	
Smart cities/urban planning	Sensors to track service utilization, accident tracking, snow plow routing	
Assisting bureaucratic decision-making	Funding allocation, service allocation, school bus routing	
Workplace productivity tools	Chatbots, image generation, voice generation, coding assistants	

Table 2. We grouped the AI systems that municipal employees discussed procuring or adopting in interviews, into 5 categories based on their intended usage. We provide anonymized examples of types of AI systems that were mentioned in each category. Employees in each city shared at least one example that they were aware of belonging to one of these five categories.

D EXTENDED DESCRIPTIONS OF CITIES' AI PROCUREMENT REVIEW PROCESSES

Several cities that we spoke with had already introduced specific changes to their existing procurement practices for AI, beginning in 2021 onwards. Notably, many participants felt that it was "early days" in revising their AI review processes: for example, participants were in the midst of overseeing their first formal AI procurement, conducting their first AI risk assessments, and revising their processes more broadly. With this rapidly evolving landscape in mind, we group changes cities had made so far to their practices into 5 categories, based on their goals. We discuss each of the interventions in detail below, providing examples when appropriate.

Vendor reporting requirements. Several cities instituted additional reporting requirements to ask vendors for important information about AI systems. Cities could mandate that vendors complete the reporting requirements by adding them as required items on an RFP or solicitation, or asking a vendor to provide them separately for purchases without a solicitation. Participants believed that learning additional information about an AI system could help cities with making more informed purchasing decisions, risk assessments, and contract negotiations.

When deciding what to ask of vendors, several participants shared that their city started with the list of questions from Government AI Coalition's "AI FactSheet" [9], a resource designed to support local governments in understanding third-party AI systems. The factsheet asks vendors to report "essential technical details" such as on what data the AI was trained, under what conditions the system was tested, the values of relevant performance metrics, and measures taken to promote values of fairness, robustness, and explainability.

AI risk or impact assessments. Participants conducted additional risk or impact assessments to better understand the possible positive or negative impacts of procured AI systems. While some cities conducted such assessments in an informal or ad-hoc way, others had started to standardize assessment processes by creating assessment templates with lists of questions and considerations. Different cities also conducted risk or impact assessments at different phases of the procurement process: some assessment instruments could be completed based on a "purpose statement" for AI, before a specific vendor or AI system is identified. In contrast, other risk assessments can only be completed once a concrete system has been identified, e.g., they require knowledge of the system's performance.

The role and purpose of these assessments varied across interviewed cities. In many cities, the risk assessment had no immediate outcome, but employees were encouraged to take action to manage and if possible, mitigate potential risks identified in the process. Beyond informing mitigation steps, some participants also used risk assessments to triage AI solutions into "high" or "low" risk categories, which then determined subsequent requirements for review and oversight. For example, one city required high-risk AI to have additional reporting requirements, further risk assessment, usage protocols, and regular post-deployment monitoring. Participants viewed risk triaging as a way to reduce reviewing burden and better allocate their limited technical expertise. One participant who conducted AI risk assessments explained:

"[When triaging risk], we're just trying to get a sense of how thorough a review we need to do, because we're working with very limited capacity and resources. So we've got to decide: is this a low-risk system that we can just do a really quick look at? Or is this going to be something really sensitive and safety-impacting, rights-impacting, that we need to dedicate a lot of our time to?" (P10)

Participants also noted how risk triaging was also time-saving for their colleagues on the other end trying to purchase the AI, as put by one employee: "If it's low risk, I'll approve it, and you'll be on your way tomorrow!"

Independent evaluations. While less common, some participants conducted their own independent evaluations (or "audits") of third-party AI systems. Participants were motivated to conduct their own evaluations for a variety of reasons, such as wanting to measure constructs that vendors had not reported, or calculate these measures using their own data. For example, one participant described an experience where they wanted to understand how a translation model's accuracy rates differed across languages, but the vendor didn't give the city "any meaningful information" about the system's performance. When the employee realized they had API access to the model, they decided to "go into the platform [themselves]" to calculate performance metrics.

Another participant was motivated to design and conduct their own independent evaluations because they believed demos to "show them [the AI] works" were insufficient to evaluating AI, "because [vendors] give a demo of the one thing that works". The participant appreciated their city's ability to define what measures were most important for them:

"Early on, doing early experimentation very cheaply and fastly helps weed out a lot of things. [...] The people that will best know what might be helpful, are the employees of the city. It's not like some CIO in the clouds coming like: 'Oh, I have determined that this would be helpful'." (P18)

AI contracting terms. Procurement contracts specify legally enforceable obligations for both cities and vendors, such as the agreed price, statement of work, the vendor's support responsibilities, and an outline of how disputes will be resolved. Participants across cities pointed to the importance of including clear expectations of vendors in the contract, as put by one participant (P17): "The problem with holding a vendor accountable, was you got to make sure you actually have somewhere where it's documented what we're going to hold them accountable to".

To hold AI vendors accountable, some cities created contract language templates that spelled out expected risk mitigation practices for procurements involving AI. Example contract terms included requirements for vendors to regularly monitor system performance, train city users on how to operate the AI, respond in a timely manner to incidents where AI causes harm, and comply with data privacy legislation. Participants who were members of the Government AI Coalition shared their intentions to adopt terms from the GovAI's Vendor Agreement contract template, believing that cities could ask for more from vendors when they "stand together" and adopt similar terms.

Prototype deployments. Typical procurement contracts require significant commitment from a city, both financially and legally through a binding contract. As an alternative, several participants instead preferred to "try out" emerging AI technologies via fixed-length contracts. One department leader who ran a prototyping program explained how they "work within the constraints of state procurement law" by "paying for short-term, small-scale prototypes on the order of weeks to months, that are under requirements for payment thresholds". Successful prototypes can then go through a formal solicitation after the short-term contract has ended.

Beyond helping understand if an AI technology is financially worthwhile, the participant believed that prototype contracts can help surface potential risks posed by procured AI. The participant described an example of how they deployed a prototype of an AI chatbot that "started hallucinating and interacting with people in really unexpected ways", which "sparked an interesting conversation in our community about the risks of AI tools". When reflecting on the experience, the participant was grateful that they had procured the service using a short-term contract:

"This is exactly why we need a program like ours, to create a safe space to test these things out and explore their capabilities, and understand what it would actually mean in practice. You learn so much more just deploying [AI] than by trying to plan out every detail in advance." (P2)

D.1 Practice vs. policy?

In many cities, employees made one or more of the above changes to their procurement practices simply by adjusting their existing practices, *e.g.*, by electing to include vendor reporting requirements in an AI RFP. Some cities decided to make these changes in their practices more formal or mandatory for vendors or city employees, by adopting policies or passing laws that required them. For example, one department leader walked through how their city's formal AI policy spelled out mandatory steps, such as a risk assessment, that city employees must complete for any AI procurement. The participant viewed the policy, which was passed by their city council, as an "accountability trigger" to incentivise compliance for both colleagues and vendors:

"Council adopted the policy. So you can't just say no. I'm going to have some leverage to say, we can't just say we're not going to do this. [...] [The policy] is really meant to be a way to say the city is going to be taking this on, these are our values." (P13)

Participants in another city shared that while ideally someday they would like to institutionalize their practices via a formal policy, at the time of interviewing, they did not yet have one:

"We very intentionally have not put out a [formal] AI policy yet, because we wanted more [community and government] input on it. And the space, especially in 2023, was very new for us. So we wanted to get a better understanding before asking our leadership to pass a policy." (P7)

This city has since adopted a formal AI policy following engagement with the community, experts, and agency staff.