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Artificial Intelligence Adoption in Local Government Service Delivery: A Scoping Review of Applications, Governance Mechanisms, Benefits, and Risks

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Abstract: *Local governments are increasingly considering artificial intelligence (AI) to improve how residents obtain information, submit requests, receive benefits, navigate permits, and experience daily urban services. Yet the available evidence remains fragmented across digital government, smart-city, public administration, data governance, and responsible-AI scholarship. This targeted scoping review mapped the AI applications reported in local government service delivery and synthesized the governance mechanisms, benefits, risks, and implementation conditions associated with their use. Guided by Arksey and O'Malley's framework, Levac and colleagues' refinements, the JBI guidance for scoping reviews, and PRISMA-ScR, the review used a Population-Concept-Context approach. The population comprised local government institutions, public servants, and residents affected by local AI-enabled services; the concept covered machine learning, natural language processing, generative AI, computer vision, algorithmic decision support, and associated governance; and the context covered municipal, city, county, and local-authority service delivery. A targeted search of web-accessible peer-reviewed literature, government standards, and policy documents published from 2018 to 21 June 2026 produced 24 substantively relevant sources. Five patterns emerged: (1) citizen-facing chatbots and service navigation are common entry points; (2) operational analytics are applied to mobility, infrastructure, environment, and emergency-related tasks; (3) AI augments administrative work, document processing, anomaly detection, and civic sensemaking; (4) trustworthy deployment requires risk-tiered, lifecycle governance; and (5) benefits depend on data quality, human capability, inclusion, public trust, and a clear remedy for errors. The review advances a Responsible Local AI Service Delivery Framework that positions AI as a bounded public-service capability rather than an autonomous substitute for accountable government.*

Keywords: Artificial intelligence, Local government, Public service delivery, Digital governance, Responsible AI

1. INTRODUCTION

Local governments are the public institutions most directly encountered by citizens in everyday life. They operate service counters, licensing and permitting processes, civil registration, property-related transactions, sanitation and waste systems, local roads, public safety coordination, community programs, and increasingly digital information channels. As these functions produce high volumes of requests, documents, transactions, images, and location-based data, artificial intelligence (AI) is being explored as a way to make services more responsive, accessible, and anticipatory. The OECD (2025) observes that AI is now being used across public service design and delivery to automate processes, support resource allocation, inform decisions, improve participation, and tailor pathways for citizens. For local governments, however, the question is not simply whether AI can be adopted, but which uses create public value without weakening legality, fairness, accessibility, accountability, or residents' ability to challenge an error.

The literature portrays AI in the public sector as a family of capabilities rather than one technology. Machine learning can identify patterns and make forecasts; natural language processing can classify documents and support chat interfaces; computer vision can interpret images from inspections or citizen reports; and generative AI can summarize, draft, retrieve, and explain information. Earlier reviews describe applications in citizen interaction, public management, policy analysis, public safety, fraud detection, disaster management, and service personalization (de Sousa et al., 2019; Wirtz et al., 2019). A preliminary mapping of European public services likewise found a varied application landscape rather than a single dominant model, suggesting that AI adoption must be read in relation to the particular service, institutional mandate, data environment, and population affected (Misuraca et al., 2020).

Local government is a particularly important setting for this discussion because municipal services often combine high transaction volume with intense proximity to residents. Recent studies have examined city managers' perceptions of AI prospects, constraints, and choices; residents' perceptions of AI-enabled local services; adoption pathways in municipalities; and chatbot implementation in a city government context (Heinisuo et al., 2025; Schaefer et al., 2021; Yigitcanlar et al., 2023a, 2023b). These studies indicate that chatbots and service-navigation tools may be attractive early use cases, but they also point to limits involving capacity, data readiness, staff acceptance, public expectations, and the risk that technology is introduced because it is fashionable rather than because it solves a defined public problem.

The governance stakes are higher when AI does more than communicate information. Systems that prioritize inspections, flag fraud, classify complaints, predict demand, recommend service actions, or support eligibility-related decisions may shape how public resources and attention are distributed. The risks are not confined to technical error. They include biased or unrepresentative data, privacy and cybersecurity failures, opaque vendor systems, automation bias among staff, poor documentation, unequal access for residents with limited connectivity or digital literacy, and weak recourse when a citizen is harmed by an AI-assisted decision. Public administration research therefore frames AI adoption as a public-value and institutional-design problem, not merely an information-technology procurement exercise (Madan & Ashok, 2023; Zuiderwijk et al., 2021).

International frameworks increasingly translate broad ethical principles into operational expectations. UNESCO (2021) foregrounds human rights, fairness, transparency, human oversight, and environmental and social well-being. The NIST Artificial Intelligence Risk Management Framework offers a lifecycle logic for governing, mapping, measuring, and managing AI risks (National Institute of Standards and Technology [NIST], 2023). The European Union's AI Act demonstrates a risk-based regulatory orientation, while Canada's Directive on Automated Decision-Making, the United Kingdom's Algorithmic Transparency Recording Standard, and comparable public-sector mechanisms illustrate practical tools such as impact assessment, public documentation, human intervention, monitoring, and recourse (European Parliament and Council, 2024; Government Digital Service, 2025; Treasury Board of Canada Secretariat, 2025).

For Philippine local government units (LGUs), this agenda also intersects with the National AI Strategy Roadmap 2.0 and the National Privacy Commission's AI guidance. The national roadmap emphasizes AI governance and ethics alongside innovation, infrastructure, and workforce development, while the NPC advisory requires transparent, accountable, privacy-conscious processing when AI systems handle personal data (Department of Trade and Industry [DTI], 2024; National Privacy Commission [NPC], 2024). These developments strengthen the need for locally appropriate evidence on how AI can be used in services while respecting the legal and ethical responsibilities of public institutions.

A scoping review is suitable because evidence on AI in local government is dispersed across public administration, information systems, smart-city research, government policy, and technology governance. Rather than estimate a pooled effectiveness effect, this review maps reported applications and identifies recurring governance, benefit, risk, and implementation patterns. It addresses the question: What AI applications are being used in local government services, and what governance, ethical, and implementation issues are reported? The review also proposes an evidence-informed framework that can guide local government leaders, public administrators, digital transformation teams, and future researchers.

2. METHODS

2.1 Design and Review Process

This study used a scoping review design. The review was conceptually anchored in Arksey and O'Malley's (2005) framework, refined by Levac et al. (2010), and aligned with the JBI guidance for scoping reviews and the PRISMA extension for scoping reviews (Peters et al., 2020; Tricco et al., 2018). A scoping review was selected because AI adoption in local government includes heterogeneous technologies, service domains, governance instruments, empirical designs, and policy documents. The purpose was therefore to map the breadth and character of the evidence, identify recurring concepts and implementation conditions, and synthesize a practical governance-oriented framework rather than determine the comparative effectiveness of any single AI system.

The review used a Population-Concept-Context (PCC) approach. The population included local government institutions, municipal employees, city managers, and citizens or residents who interact with local public services. The concept included AI and closely related systems, such as machine learning, natural language processing, generative AI, chatbots, computer vision, algorithmic decision support, predictive analytics, and automated decision systems, together with governance, ethics, data protection, public value, implementation, and accountability. The context included municipalities, cities, counties, local authorities, and comparable subnational public-service settings.

A targeted search was conducted on 21 June 2026. Search locations included Google Scholar, publisher and university repository pages, government and intergovernmental websites, standards bodies, and public digital-government portals. Search strings combined terms such as "artificial intelligence" OR "machine learning" OR "algorithmic decision making" OR "generative AI" OR chatbot with "local government" OR municipal OR municipality OR city OR "local authority" and "service delivery" OR "public service" OR governance OR implementation OR ethics. Additional searches paired local-government terms with recurring service areas, including citizen inquiry, permit, complaint, waste, traffic, infrastructure, disaster management, planning, participation, and procurement. Backward citation checking was used selectively to locate foundational and closely related studies.

Eligible sources were peer-reviewed empirical studies, conference proceedings, literature reviews with direct public-administration implications, official standards, legislation, government directives, and institutional guidance documents. Sources were included when

they described AI applications, governance mechanisms, benefits, risks, organizational readiness, or implementation issues that were directly relevant to local government or transferable to local public-service delivery. Sources focused exclusively on private-sector AI, highly technical model development without public-service implications, or national-security uses without local-service relevance were excluded. English-language sources published from 2018 to 21 June 2026 were prioritized, while foundational scoping-review methods sources published earlier were retained.

After relevance screening, 24 substantive sources were charted: 14 peer-reviewed articles or conference papers, seven official policy, standards, or regulatory documents, and three strategic or implementation-oriented institutional sources. Data were extracted on source type, jurisdiction or setting, local service area, AI application, purpose, reported benefit, governance or implementation mechanism, and reported risk. The charted evidence was analyzed through an inductive-deductive thematic synthesis. Initial codes captured uses such as chatbots, document processing, prediction, computer vision, anomaly detection, and consultation analysis, as well as governance mechanisms such as risk assessment, human oversight, transparency, data governance, procurement safeguards, monitoring, public engagement, and appeal. Codes were then organized into themes that address the review question.

2.2 PCC Framework and Eligibility Criteria

Table 1. Population-Concept-Context framework and eligibility criteria

Element	Description
Population	Municipal institutions, officials, staff, and residents affected by local public services.
Concept	AI systems (machine learning, NLP, generative AI, chatbots, computer vision, and predictive or algorithmic decision support) and their governance, ethics, privacy, transparency, and accountability.
Context	Municipal, city, county, and comparable subnational public-service settings.
Included sources	Empirical studies, proceedings, reviews, standards, laws, directives, and institutional guidance with public-service relevance.
Excluded sources	Private-sector-only studies; model development without public-service relevance; national-security uses; sources without an AI, governance, or service-delivery contribution.
Time coverage	2018–21 June 2026; earlier scoping-review methods retained when necessary.
Language	English.

3. RESULTS AND DICUSSIONS

The synthesis shows that local government AI adoption is not concentrated in one type of service. Instead, AI is appearing as a portfolio of capabilities that can assist citizens, support staff, interpret data, and coordinate operations. The level of risk depends less on whether a system is called AI and more on what it does, which data it uses, and what consequences follow from its outputs. Table 2 summarizes the recurring application clusters identified across the charted evidence.

Table 2. Recurring AI Application Clusters in Local Government Service Delivery

Application cluster	Illustrative local service uses	Primary public-service value	Main risks or conditions
Citizen-facing assistance	Chatbots, virtual assistants, multilingual service navigation, frequently asked questions, appointment and status guidance, complaint intake.	24/7 access, reduced routine inquiries, clearer pathways, staff time for complex cases.	Inaccurate answers, unequal access, weak handoff to staff, privacy exposure in conversations.
Administrative workflow support	Document classification, search and retrieval, transcription, summarization, form checking, case triage, record management.	Faster processing, improved consistency, lower administrative burden.	Automation bias, erroneous classification, confidentiality, poor audit trails, vendor dependence.
Operational and urban analytics	Traffic and mobility management, waste routing, infrastructure inspection, water and environmental monitoring, emergency and disaster support.	Proactive maintenance, better allocation, faster incident detection, resilience.	Data gaps, surveillance creep, unsafe recommendations, lack of local validation.
Predictive and decision support	Demand forecasting, inspection prioritization, fraud or anomaly flags, resource allocation, risk alerts.	Earlier action, focused field work, more informed planning.	Bias, false positives, opaque criteria, harmful gatekeeping when outputs influence rights or benefits.
Civic participation and sensemaking	Clustering consultation inputs, topic detection, sentiment analysis, accessible explanation of policy options, planning visualization.	Ability to process large volumes of resident input and improve participation support.	Misclassification of viewpoints, representational bias, manipulation, unclear influence on final decisions.

Theme 1: Citizen-Facing Assistance

A The most immediately visible local-government use of AI is the citizen-facing interface. Chatbots and virtual assistants can guide residents through common procedures, explain service requirements, route questions, provide operating hours, assist with appointment preparation, and direct users to relevant forms or staff. This type of use is attractive because it addresses routine, high-volume inquiries without necessarily changing the legal authority for a public decision. In the City of Oulu case, the chatbot was designed to operate across devices and to draw on municipal information sources, chat histories, and databases, illustrating how local AI can become an interface between residents and dispersed municipal knowledge (Heinisuo et al., 2025). Research on AI-based self-service technology also indicates that user experience is affected by citizens' confidence in government and their perceptions of the service, not merely by technical functionality (Chen et al., 2021).

The public-service value of these systems lies in service accessibility and staff augmentation. They can extend information provision beyond office hours, support multilingual communication, reduce repeated visits to an office, and allow frontline staff to focus on cases requiring judgment, empathy, or cross-agency coordination. Yet a conversational system can become harmful when residents rely on incorrect or incomplete advice about deadlines, eligibility, fees, or legal requirements. The safest design is therefore not a chatbot that appears authoritative in all circumstances, but one that is grounded in verified local content, identifies its limitations, cites or links to official instructions, logs quality issues, and offers a clear path to a human employee when the question is complex, sensitive, or consequential.

Local governments should also treat accessibility as a substantive governance requirement. Digital-only assistance may disadvantage residents with limited devices, connectivity, language access, disability accommodation, or confidence in online transactions. The existence of a chatbot should expand service channels, not silently replace physical, telephone, or assisted channels. This principle reflects the broader public-value concern that the same tool can improve convenience for one group while deepening exclusion for another. Public acceptance research in Australia and Hong Kong suggests that perceptions of usefulness and ease of use are shaped by context, reinforcing the need for local testing with diverse resident groups rather than relying on general claims about AI acceptance (Yigitcanlar et al., 2023b).

Theme 2: Operational Intelligence Brings AI Closest to the Physical City

A second cluster concerns operational and place-based services. The literature describes applications of AI and advanced analytics in mobility, road and infrastructure management, environmental monitoring, waste systems, disaster-related information, and the coordination of public assets. These uses often involve data that are spatial, temporal, sensor-based, or image-based. Computer vision may assist in detecting reported defects or analyzing inspection images; predictive models may estimate demand or identify patterns that merit attention; and optimization tools may support routing or scheduling. The public value is not automation for its own sake, but improved capacity to identify issues earlier, allocate scarce field resources more effectively, and support preventive maintenance or emergency preparedness (de Sousa et al., 2019; Wirtz et al., 2019).

These uses are often described as less controversial than eligibility or enforcement systems because they can be designed as operational support. However, their social effects can still be significant. Uneven sensor coverage may result in better service visibility in central or affluent areas than in peripheral communities. Image-based systems may capture identifiable people or vehicles. Predictive outputs may concentrate inspections in the same neighborhoods if historical reporting patterns are treated as neutral evidence of need. For this reason, data quality, representativeness, privacy, and periodic evaluation are necessary even when the system does not directly make a decision about an individual.

Vogl et al. (2020) describe the emergence of algorithmic bureaucracy in UK local authorities, underscoring that local AI adoption changes not only a technical workflow but also the informational basis of administrative action. The implementation question is therefore whether a model meaningfully improves an existing service process and whether staff can understand, validate, and act appropriately on its output. Local governments should begin with narrowly defined operational problems, establish baseline service measures, and test whether the tool improves timeliness, error rates, cost, equity, or safety before scaling it.

Theme 3: AI is increasingly used to augment administrative judgment and civic sensemaking, but final authority should remain contestable and accountable.

The third pattern is the use of AI to assist public servants with information-intensive work. This includes document search and classification, summarization, routing, anomaly detection, demand forecasting, and the analysis of large volumes of text from complaints, consultations, or feedback channels. According to the OECD's analysis of 200 government AI use cases, 57% supported automating, streamlining, or tailoring services; 45% supported decision-making, sensemaking, or forecasting; and 30% supported accountability or anomaly detection (OECD, 2025). These findings indicate that AI in government is often used for analytical or support tasks, not only for simple routine automation.

For local governments, this can be particularly useful when administrative staff need to interpret a large volume of resident input or coordinate information across multiple service units. AI-assisted clustering and topic detection may help staff identify common concerns in public consultations, while document and data tools may reduce the time required to retrieve regulations, summarize case materials, or prepare routine reports. The OECD (2025) documents a municipal participation example in which an AI-powered sensemaking tool was used to cluster and prioritize citizen input for a local design-code process. Such tools may make participation more manageable, but they do not replace the democratic responsibility to explain how resident contributions were considered and how final decisions were made.

A critical distinction is between augmentation and substitution. AI is relatively defensible when it helps staff notice patterns, retrieve information, or organize work, provided that trained officials review the output. It becomes more problematic when it effectively determines an individual's access to a service, imposes an enforcement consequence, or creates a risk score that cannot be inspected or challenged. The literature on public governance repeatedly emphasizes transparency, explainability, human responsibility, and meaningful contestability as conditions for legitimate use (Madan & Ashok, 2023; Zuiderwijk et al., 2021). Accordingly, local-government systems should be designed so that human decision makers can override inappropriate outputs, residents can seek an explanation and correction, and the organization can identify who is accountable for the system's use.

Theme 4: Trustworthy Municipal AI Requires Lifecycle Governance Rather

Across the evidence, governance was most credible when framed as a set of recurring controls applied from problem definition through procurement, deployment, monitoring, and retirement. Broad ethical principles are important, but they do not by themselves tell a local government whether a proposed service chatbot is sufficiently accurate, whether an inspection-priority model is biased,

whether a vendor can retain resident data, or whether an AI-assisted recommendation needs human review. Lifecycle governance addresses these questions by connecting values to specific decisions, records, roles, and procedures.

The major governance mechanisms that recur across standards and public-sector guidance are summarized in Table 3. Together, they move AI governance from an abstract aspiration to a practical administrative function. Risk proportionality is especially important. A system that answers routine questions from a public website should not face the same control burden as a system that influences housing, social assistance, enforcement, or emergency response. However, both should have a named owner, accurate source content, privacy and security review where personal data are involved, staff guidance, monitoring, and a mechanism to identify and correct errors.

The NIST framework, the EU AI Act, Canada's Directive on Automated Decision-Making, and the United Kingdom's transparency standard differ in legal force and institutional setting, but they converge on several expectations: define the purpose and impact of the system; evaluate risk; document data, methods, and intended use; provide suitable human oversight; manage privacy and security; monitor system performance; and ensure transparency appropriate to the context (European Parliament and Council, 2024; Government Digital Service, 2025; NIST, 2023; Treasury Board of Canada Secretariat, 2025). These are adaptable foundations for local governments that may not have a large AI governance office.

Table 3. Practical Governance Mechanisms for Local Government AI

Governance mechanism	Practical local-government application	Risk addressed
Mandate, accountable owner, and risk assessment	Document the public problem, legal basis, service objective, responsible officer, scope, and impact on rights, benefits, safety, privacy, and public trust; apply stronger review to higher-consequence uses.	Technology-first adoption, unclear responsibility, and unexamined high-stakes harms.
Data, privacy, and security by design	Record data sources, quality checks, access, retention, minimization, lawful basis, security controls, and privacy-impact assessment where required.	Privacy violations, data leakage, poor-quality or biased inputs.
Procurement, documentation, and vendor controls	Require audit rights, system and data documentation, performance obligations, exit provisions, security commitments, and limits on secondary data use.	Vendor lock-in, opaque systems, and weak accountability for outsourced services.
Transparency, human oversight, and redress	Publish plain-language purpose and role; maintain human review points, override authority, decision logs, correction routes, and a complaint or appeal channel.	Opacity, automation bias, harmful errors, and lack of contestability.
Monitoring, audit, inclusion, and public engagement	Track accuracy, equity, drift, service quality, complaints, and incidents; test with affected groups and retain accessible assisted channels.	Performance failure, discrimination, digital exclusion, and weak legitimacy.

Theme 5: Benefits Materialize Only When Local Governments Build Capability, Sustain Public Trust, And Protect Inclusion

The literature does not support a simple claim that AI automatically creates better local services. Reported benefits include faster response, improved information access, stronger analytical capacity, more efficient routing of work, earlier detection of operational issues, and a better ability to process high volumes of resident input. Yet these benefits are conditional. City-manager research identifies constraints involving finance, limited expertise, insufficient data infrastructure, organizational resistance, and uncertainty about appropriate use (Yigitcanlar et al., 2023a). Municipal adoption studies similarly stress that transition requires more than technology acquisition; it involves staff learning, managerial sponsorship, cross-functional collaboration, and a service environment where employees understand how AI changes their work (Heinisuo et al., 2025; Schaefer et al., 2021).

Public trust is a central implementation condition. Residents are more likely to accept AI-enabled services when they understand the purpose, perceive a clear benefit, retain access to a human channel, and believe that government remains accountable for the result. Conversely, trust can decline when AI use appears secretive, discriminatory, or unreviewable. The critical public-administration question is therefore not only whether a model performs well on a technical benchmark but whether the service remains lawful, understandable, accessible, and correctable in lived experience.

The Philippine context provides two practical anchors for LGU adoption. First, the National AI Strategy Roadmap 2.0 positions governance and ethics alongside digitization, infrastructure, and workforce development (DTI, 2024). Second, NPC Advisory No.

2024-04 requires organizations processing personal data through AI systems to uphold transparency, accountability, data minimization, privacy-by-design, continuous monitoring, and mechanisms that support data-subject rights (NPC, 2024). For LGUs, these expectations suggest a cautious sequence: strengthen digital records and data governance, select bounded service problems, pilot low-to-moderate-risk tools, train personnel, publish clear public information, monitor service and equity outcomes, and expand only when benefits are demonstrated.

Emergent Framework

The synthesis suggests a Responsible Local AI Service Delivery Framework in which AI adoption begins with a defined local service need rather than a technology procurement decision. On one side of the framework are local service needs: access to information, processing delays, urban operations, resilience, participation, and accountability. On the other side are readiness conditions: data quality, interoperability, leadership, staff skills, finance, procurement capacity, inclusion, and public trust. These conditions determine whether an AI use case is likely to be useful, feasible, and legitimate.

At the center is an AI service application portfolio that includes citizen-facing assistance, administrative workflow support, operational analytics, predictive and decision support, and civic sensemaking. These applications may create value through automation, augmentation, prediction, classification, personalization, and pattern recognition. They should lead to outcomes such as faster and more accessible services, better resource stewardship, proactive operations, more informed participation, and stronger institutional trust. However, these outcomes are expected only when governance guardrails operate throughout the lifecycle: a clear legal mandate, risk classification, data governance, procurement control, transparency, human oversight, monitoring, redress, and inclusion.

The framework treats AI as a support capability whose acceptable level of autonomy decreases as the potential consequences to a person's rights, access to benefits, safety, livelihood, or dignity increase. Low-risk uses may be piloted through controlled experimentation. Higher-risk systems require more rigorous impact assessment, human review, documentation, public explanation, and meaningful appeal. The framework thus frames responsible local AI not as a barrier to innovation but as the administrative infrastructure that makes public-value innovation possible.

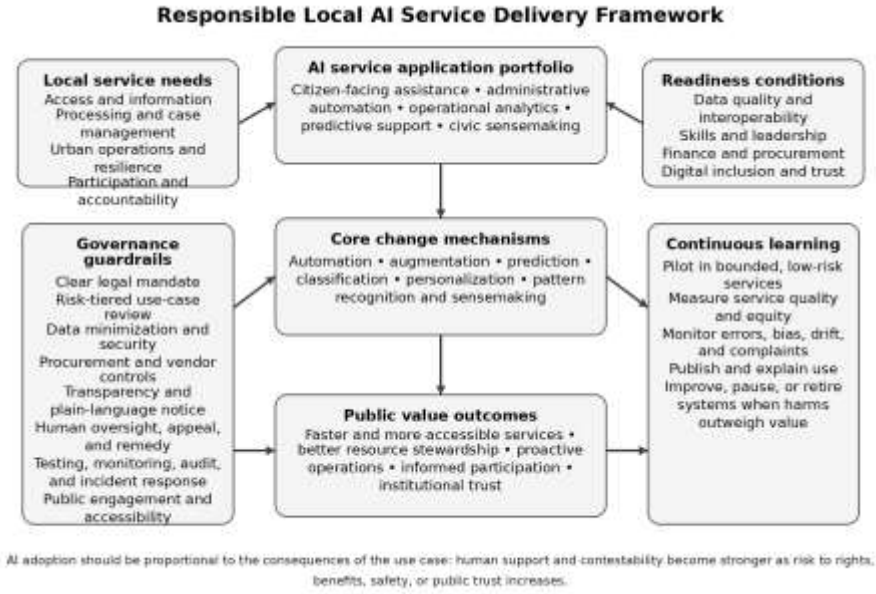

Figure 1. *Responsible Local AI Service Delivery Framework*

This review has limitations. First, it used a targeted, web-accessible search rather than a full database export with duplicate management and reproducible indexing across Scopus, Web of Science, or other subscription databases. Second, English-language sources were prioritized, potentially excluding relevant experience from non-English-speaking jurisdictions. Third, the evidence base is uneven: much of the accessible literature describes public-sector AI broadly or examines promising pilots, while fewer studies provide long-term evaluations of local-government outcomes, costs, equity impacts, or residents' ability to obtain redress. Fourth, no formal quality appraisal was undertaken because the objective was to map the evidence and governance landscape rather than rank

effect sizes or causal certainty. Findings should therefore be read as an evidence-informed conceptual map and practice guide, not as a claim that any particular AI application is universally appropriate or effective.

4. CONCLUSION

This scoping review shows that AI adoption in local government service delivery is best understood as a portfolio of bounded applications rather than a single digital transformation. Citizen-facing chatbots and service-navigation tools are common and relatively accessible entry points when they are accurate, inclusive, and connected to human assistance. Operational analytics can support infrastructure, mobility, environmental, waste, and resilience functions, while administrative tools can help staff retrieve, classify, summarize, and interpret information. AI can also support civic sensemaking when local governments need to process large volumes of resident input. The most important finding is that technical capability is not enough. The legitimacy of local-government AI depends on proportionate governance: a clear public-service purpose, defined accountability, risk assessment, privacy and data controls, vendor safeguards, public transparency, human oversight, continuous monitoring, and meaningful redress. As the consequences of a use case become more serious, the need for human responsibility and contestability must become stronger. Local government should not delegate final public accountability to a model or vendor.

The proposed Responsible Local AI Service Delivery Framework therefore positions AI as an augmentative public-service capability. It encourages local governments to begin with real service problems, choose low-to-moderate-risk pilots, validate outputs using local data and user feedback, protect nondigital access channels, and scale only after demonstrating public value. This approach supports innovation while preserving the democratic, legal, and ethical responsibilities that distinguish public service from ordinary commercial automation.

5. RECOMMENDATION

Local governments may establish a small cross-functional AI governance mechanism that includes the service owner, information technology personnel, data protection officer or privacy lead, legal or records representative, procurement officer, frontline employee representative, and, where appropriate, community or sectoral stakeholders. Its first task should be to maintain an inventory of AI-enabled systems and proposed use cases, classify them by risk, and identify the accountable officer for each system. LGUs may prioritize pilots that solve clearly bounded, low-to-moderate-risk problems, such as verified service-information assistance, internal document retrieval, complaint categorization with staff review, maintenance prioritization, or accessible summarization of consultation inputs. Each pilot should specify a baseline problem, expected benefit, affected groups, quality measures, equity measures, privacy controls, human escalation process, and criteria for continuation, modification, suspension, or retirement.

Procurement documents should require local governments to retain institutional control. Contracts may include data ownership and retention terms, security requirements, restrictions on secondary use of resident data, documentation of system purpose and limitations, testing access, audit rights, incident notification, support and exit arrangements, and an obligation to assist the government in meeting transparency and redress requirements. These safeguards are particularly important when an AI service is supplied as a cloud-based or generative-AI product. For Philippine LGUs, implementation should be aligned with the National AI Strategy Roadmap 2.0, the Data Privacy Act of 2012, and the NPC's AI guidance. Capacity-building should cover data governance, privacy impact assessment, prompt and output evaluation for generative AI, information security, accessibility, procurement, risk communication, and public-service ethics. Future research may examine actual LGU pilots in the Philippines, compare urban and rural readiness, develop local AI-risk assessment tools, assess residents' acceptance across marginalized groups, and evaluate whether AI-supported services improve both efficiency and equity over time.

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