Governing Artificial Intelligence Through Public Procurement: A Narrative Review of Adoption Conditions, Governance Risks, and Public Value

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ABSTRACT

While current Artificial Intelligence (AI) research is fragmented across technical, organizational, and governance perspectives, it has the potential to transform the public sector procurement. Public procurement differs from private procurement because AI-enabled procurement decisions have to satisfy efficiency goals along with legality, transparency, fairness, auditability, contestability, and public value accountability. This article provides a narrative review of the drivers, barriers, and governance implications of the adoption of AI in public procurement, drawing on recent academic publications to address the gap between technological capability and operations practice. To identify relevant literature, a structured literature search was carried out in the Scopus database for journal articles and conference papers written in English and published between January 2016 and December 2025, before synthesizing the literature according to eligibility criteria. The synthesis identifies four enabling factors for AI adoption: operational efficiency, improved decision-support, risk detection and strategic importance of procurement data. It also identifies four major barriers: fragmented data infrastructures, limited organizational capability, institutional and regulatory constraints, and the opacity of AI systems. Three cross-cutting gaps are developed from the literature: an implementation gap between strategic interest and low level of operational deployment, a governance-capability gap between public accountability requirements and institutional capacity to govern AI systems, and a data-value gap between procurement data availability and actionable procurement intelligence. The review suggests the interaction between AI capability, data readiness, organizational capability, procurement governance, and public value outcomes controls the responsible AI adoption in public procurement. The article contributes by reframing public procurement as a tool for institutional governance by which AI is responsibly adopted, monitored, and held accountable across the procurement lifecycle. These insights provide a research agenda for responsible adoption of AI in public procurement, considering explainability, auditability, and institutional governance.

Keywords: artificial intelligence, public procurement, AI adoption, digital governance, public value

INTRODUCTION

AI is promoted as a successful enabler for transforming public procurement because AI-enabled solutions are expected to automate and enhance public procurement activities such as supplier evaluations, spend classification, fraud detection, contract and supplier management, and decision support across the procurement lifecycle (Guida et al., 2023; Lakhal et al., 2025; Van Hoek, 2024). These developments are crucial because public procurement is considered as an administrative function as well as a governance mechanism through which governments may perform public resources allocation, supplier relationships regulation, and fairness and accountability demonstration to citizens.

In addition to the factors used to assess private sector procurement, such as achieved efficiency, cost savings, supplier performance, and competitive advantage, public sector must additionally satisfy

requirements for legality, procedural fairness, auditability, transparency, accountability, and public trust (Aboelazm & Dganni, 2025; Andersson et al., 2025; Odilla, 2024; Pesqueira et al., 2024). Therefore, same AI adoption models used for private procurement cannot be directly used in public procurement settings without considering public value and governance requirements.

Although the literature on AI adoption in public procurement has rapidly expanded, this growth has not produced a coherent body of knowledge. One difficulty is that studies examine different AI technologies, such as machine learning, predictive analytics, natural language processing (NLP), expert systems, causal machine learning, and generative AI, often without distinguishing their different data requirements and governance implications. A related difficulty is functional fragmentation where studies focus on different procurement functions, including supplier selection, tender evaluation, spend analytics, contract management, and fraud detection, without integrating these insights across the procurement lifecycle. Further, much of the evidence is cross-sectional, conceptual, technical and application-focused, with limited insights on adoption, scaling and institutionalization. The most important difficulty is that governance requirements like explainability, accountability, and transparency are usually discussed separately from enablers of adoption and organizational readiness (Guida et al., 2023).

Because the outcomes of AI adoption in public procurement depend on the interaction between technical capability, data readiness, organizational capabilities, procurement regulations, and accountability mechanisms, it is crucial to address this fragmentation (Andersson et al., 2025; Van Hoek, 2024). Without the integration of these elements, public agencies risk adopting AI systems which improve operational efficiency while limiting transparency, or public trust (Pesqueira et al., 2024). This concern is relevant for opaque AI systems, where procurement officials lack the needed technical capability to audit AI-supported decisions (Odilla, 2024).

Against this background, this article provides a narrative review of AI adoption in public procurement, though we do not estimate effect sizes or map the bibliometric landscape. Instead, we synthesize conceptually diverse literature showing how adoption drivers, barriers and governance risks interact in public procurement contexts. The review is guided by the following research questions:

- RQ1: What drivers of AI adoption in public procurement are identified in literature?
- RQ2: What structural, institutional, and capability barriers constrain AI adoption in public procurement?
- RQ3: How does the literature conceptualize governance risks and public value implications of AI adoption in public procurement?
- RQ4: What research gaps remain for responsible AI adoption in public procurement?

The article contributes by showing that public procurement should not simply be understood as a setting in which AI tools are applied, but as an institutional governance mechanism through which AI is adopted, governed, monitored, and held accountable throughout the procurement lifecycle. The synthesis identifies three cross-cutting gaps, the implementation gap, the governance-capability gap, and the data-value gap, which provide a basis for future research on responsible adoption of AI in public procurement, procurement governance, and public value accountability.

METHODOLOGY

Review Design

This study adopts a narrative review approach to synthesize existing knowledge on AI adoption in public procurement. Narrative reviews are commonly used in evolving and cross-disciplinary fields where the literature is conceptually fragmented, methodologically diverse, and includes empirical, conceptual, technical, and governance-related contributions that are not easily amenable to meta-analysis or statistical aggregation (Baumeister & Leary, 1997; Green et al., 2006; Snyder, 2019). Given the emerging nature of AI applications in public procurement and the existence of institutional, ethical and regulatory aspects, a narrative review is appropriate for generating a conceptual synthesis.

Scopus, a database known for its multidisciplinary coverage of management, public administration, information systems and procurement, was chosen as the main database. To ensure transparency and replicability, the review followed a PRISMA-inspired screening procedure. Figure 1 shows the search strategy and screening flow of the study where it was conducted on 4 March 2026 and included English-language publications published between January 2016 and December 2025. The search strategy comprised three groups of terms, adoption-related terms, AI-related terms and procurement-related terms, making the following Boolean search:

("adoption" OR "implementation" OR "readiness" OR "intention" OR "acceptance" OR "diffusion" OR "integration" OR "barrier" OR "driver*") AND ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "predictive analytics" OR "intelligent system*" OR "neural network*" OR "chatbot*" OR "expert system*") AND ("procurement" OR "e-procurement" OR "purchasing" OR "sourcing" OR "tender*" OR (supplier W/1 management) OR "supplier selection" OR "vendor management" OR "contract management").*

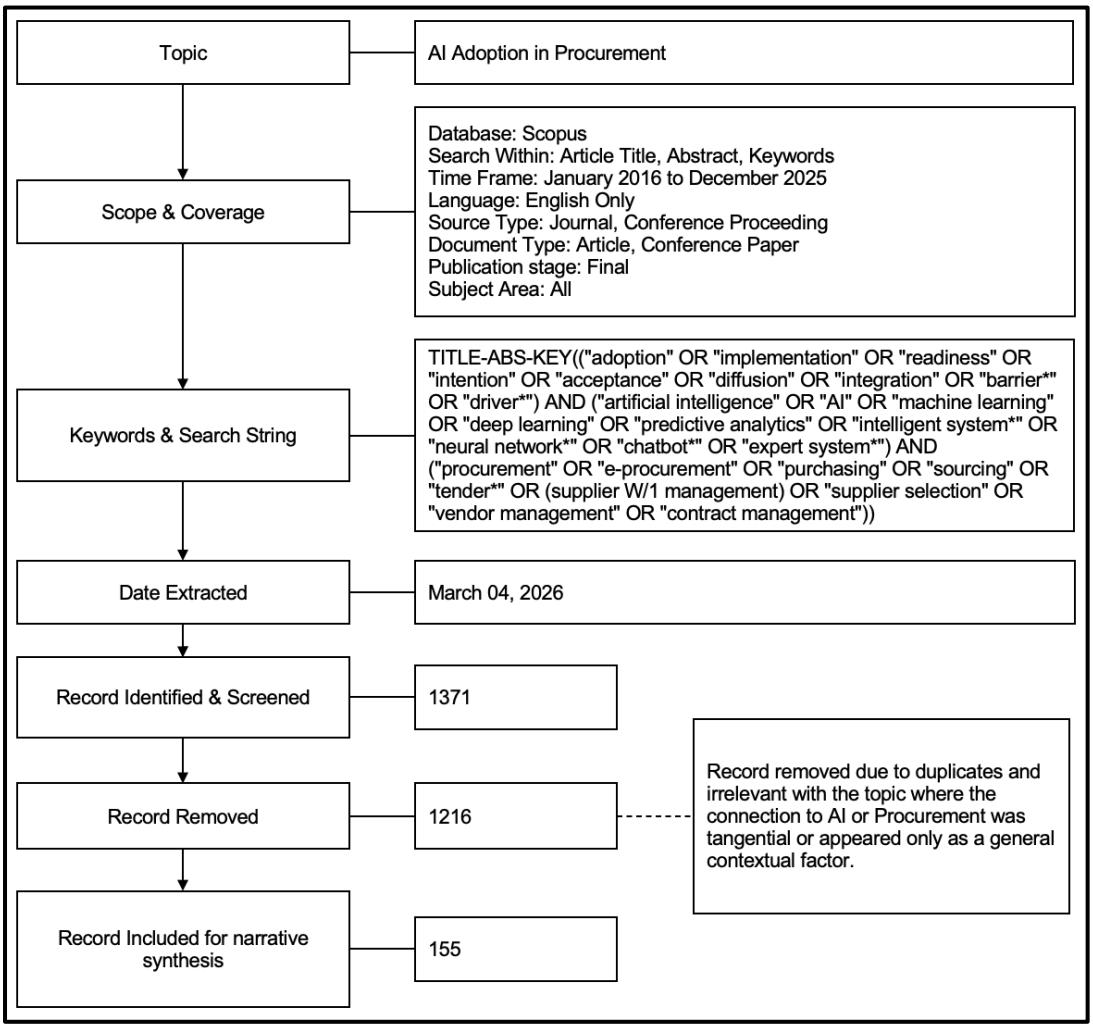

Figure 1. Search Strategy and Screening Flow

Eligibility Criteria and Screening

The initial search identified 1371 records. Of these, only publications focusing on the adoption, implementation, readiness, use, or governance of AI in procurement, purchasing, tendering, contract management, supplier management, or related public-sector procurement functions were retained. Studies were excluded if AI or procurement was mentioned only as a background context rather than being the main focus of the study. Table 1 presents summary of the inclusion and exclusion criteria, while Table 2 summarizes the screening process. After iterative screening of titles, abstracts, conclusions, and, where necessary full texts, 155 studies were retained for the narrative synthesis.

Table 1. Summary of Inclusion and Exclusion Criteria

Criterion	Included	Excluded
Topical Relevance	Studies addressing AI adoption in any part of the procurement lifecycle including tendering, supplier selection, contract management, or other procurement-related contexts.	Studies where AI or procurement appeared only as a general contextual factor.
Study Type	AI adoption in procurement in empirical, conceptual, technical, legal, review, and governance-oriented studies.	Editorials, opinion pieces, duplicate records, and studies that did not provide sufficient analytical evidence.
Publication Type	Final journal articles and conference papers indexed in Scopus.	Articles in press, unpublished materials, and sources outside the defined Scopus search scope.
Language	English-language publications.	Non-English publications.
Period	Publications from January 2016 to December 2025.	Records outside the defined time period.

Table 2. Screening Process

Screening stage	Number of records/studies	Decision logic
Initial Scopus search	1,371 records	Records retrieved using the full search query and publication period.
Title, abstract, conclusion, and where necessary full-text screening	155 studies retained	Studies retained when they met the predefined inclusion criteria and addressed AI adoption in procurement, AI adoption drivers, barriers, or governance, or AI-enabled procurement applications.
Final studies included	155 studies	Studies included in the conceptual synthesis to identify adoption drivers, barriers, governance risks, and research gaps.

Data Extraction and Synthesis Procedure

Data extraction focused on the concepts needed to answer the review questions, with greater emphasis on conceptual integration more than frequency counting. An iterative reading process was used to examine and compare the findings reported across the 155 included studies. Relevant concepts were initially coded according to their relevance to AI adoption in public procurement. Related codes were then grouped into broader categories and compared across studies, with the categories iteratively refined to capture recurring patterns and relationships in the literature. This process resulted in four main areas of synthesis: drivers of AI adoption, barriers to implementation, governance risks and public value implications, and cross-cutting research gaps. The resulting themes were then interpreted in relation to the review questions to develop the conceptual synthesis presented in the findings.

Rigor, Transparency, and Review Boundaries

Transparent documentation of search strategy, eligibility criteria, and screening logic was maintained to ensure methodological rigor (Tranfield et al., 2003). By grounding each theme in evidence extracted from the examined studies rather than unsupported interpretation, analytical validity was maintained (Baumeister & Leary, 1997; Green et al., 2006). Therefore, it is appropriate to view the findings as a conceptual synthesis rather than as statistical estimates of the degree of AI adoption, effect size, or causal relationships (Snyder, 2019). This review synthesizes Scopus-indexed academic publications and does not claim to cover all available academic, legal, policy, or practitioner sources.

RESULTS

After reviewing the retained studies, the findings were organized into four main areas of synthesis: drivers of AI adoption, barriers to implementation, governance risks and public value implications, and cross-cutting research gaps. These areas reflect the recurring themes identified through the qualitative coding and synthesis of the reviewed literature.

Drivers of AI Adoption in Public Procurement

The first driver is operational efficiency where AI-enabled automation can reduce the efforts done by human in procurement processes. This includes tasks like invoice matching to purchase order, spending classification, and supplier analysis (Guida et al., 2025; Iders-Bankovs et al., 2025; Lakhal et al., 2025). However, in public procurement, these efficiency benefits should be treated carefully as efficiency is only valuable when decision-making processes are legally auditable and procedurally fair.

The second driver is improved decision support, as the reviewed studies shows that AI can enhance supplier selection, predictive analytics, and procurement intelligence by enabling more systematic analysis of supplier performance, risk exposure, and sustainability criteria (Abdulla & Baryannis, 2024; Khan et al., 2023; Zhu et al., 2025). These capabilities enable more consistent decisions, especially in functions like strategic sourcing and supplier evaluation.

The third driver is risk detection and transparency, where AI supports anomaly detection, fraud detection, early warning systems, and procurement records analysis (del Rey-Puech et al., 2025; Gallego et al., 2021; Soylu et al., 2022). In public procurement, these capabilities can enhance accountability by identify procurement fraud and irregular tendering behaviors before they negatively affect both public trust and institutional credibility.

The fourth driver is the strategic importance of procurement data, where the major sources for these data like Enterprise Resource Planning (ERP) systems, e-procurement platforms, and source-to-pay systems generate large amounts of transactional, tender, and contract data (Lakhal et al., 2025; Zaghdoudi et al., 2024). The reviewed studies suggest that AI can transform these data into insights that create opportunities for procurement intelligence and more informed decision-making (Balkan & Akyuz, 2025).

Barriers of AI Adoption in Public Procurement

While there is an increasing interest in AI, its operational adoption in public procurement is still limited (Andersson et al., 2025; J. M. Spreitzenbarth et al., 2024). Some of the reviewed studies suggest that actual operational deployment remains lower than strategic interest, estimating adoption levels at 9-15% only (Van Hoek, 2024). The reviewed literature links this slow AI adoption to different barriers, including data fragmentation, limited organizational capability, institutional and regulatory constraints, and the opacity of AI systems (Guida et al., 2023; Odilla, 2024).

The first barrier is data fragmentation, where public procurement data are often fragmented across multiple legacy systems and incomplete contract repositories (Flores et al., 2025; Soylu et al., 2022). The ability to make use of advanced analytics of AI models is reduced because of this issue, making it difficult for agencies to generate meaningful insights for better procurement decisions (Guida et al., 2025; Lakhal et al., 2025).

The second barrier is limited organizational capability, as many public agencies lack the skills needed to assess and audit complex AI systems (Guida et al., 2023), this makes them often adopt black-box AI solutions that limit transparency (Andersson et al., 2025; Cernăzanu-Glăvan & Bulzan, 2025; Meyer & Henke, 2023). The capability gaps include technical expertise, procurement design, contract management, ethical assessment, and post-award monitoring (Ashal & Morshed, 2024; Pesqueira et al., 2024).

The third barrier is institutional and regulatory constraints, as public procurement is subject to strict legal

and administrative regulations which were built to guarantee fairness, transparency, and competition (Andersson et al., 2025). Despite the importance of these requirements, they can complicate the integration of AI into procurement processes (Aboelazm & Dganni, 2025; Andersson et al., 2025). Therefore, public sector agencies find it difficult to balance AI advancement capabilities with regulatory compliance (Pesqueira et al., 2024).

The fourth barrier is opacity of AI systems, especially systems built on complex machine learning algorithms, which makes it challenging for procurement officials or other stakeholders to interpret the output generated by AI (Cernăzanu-Glăvan & Bulzan, 2025; Odilla, 2024). Such uncertainty reduces trust in AI-enabled procurement processes and may prevent organizations from adopting AI in procurement activities (Abdulla & Baryannis, 2024; Gupta et al., 2025).

Governance Risks and Public Value Implications

The literature indicates that the degree of accepting AI adoption in public procurement depends on governance implications of such adoption (Pesqueira et al., 2024). In order to guarantee public value, decisions made in public procurement must be auditable, explainable, and accountable (Cernăzanu-Glăvan & Bulzan, 2025), otherwise AI adoption may improve efficiency without preserving the creditability expected for public sector decisions (Andersson et al., 2025).

The first governance risk considered in this review is regulatory hallucination, which was originally introduced by Sanchez-Graells (2024) in the context of procuring AI systems that is applied here to understand governance risks associated with AI adoption in public procurement. It refers to the wrong assumption that complex AI systems may be governed by standard contractual clauses (Sanchez-Graells, 2024). This assumption ignores that many public agencies have insufficient technical expertise to evaluate vendor claims or ensure effective accountability (Andersson et al., 2025).

The second governance risk is algorithmic unfairness, where algorithms used by public agencies to evaluate suppliers or assess tenders may unintentionally introduce historical biases into procurement decisions (Odilla, 2024). This may advantage suppliers with extensive historical data while disadvantaging smaller suppliers with less organized data (Odilla, 2024), resulting in unfair procurement outcomes and reduced public trust (Pesqueira et al., 2024).

The third governance risk is the opacity of some AI systems, where limited explainability reduces transparency and accountability in AI-enabled public procurement (Odilla, 2024). To ensure legal compliance and public trust, public procurement relies on transparent and accountable decision-making (Andersson et al., 2025). When AI-supported decisions cannot be sufficiently explained, public agencies may fail to demonstrate that procurement outcomes are fair, objective, and consistent with regulatory requirements (Cernăzanu-Glăvan & Bulzan, 2025; Pesqueira et al., 2024).

The fourth governance risk is vendor dependence, where public agencies rely heavily on external technology providers to implement and maintain AI-supported procurement systems. When public agencies lack the technical capability to assess or adapt AI systems, they may have limited understanding of how these systems operate (Andersson et al., 2025; Guida et al., 2023; Odilla, 2024; Soylu et al., 2022). As a result, public agencies may have less control on AI governance and greater difficulty ensuring that these AI systems continue to meet regulatory and organizational requirements.

The fifth governance risk is automation bias, where procurement officials may over trust AI-generated recommendations and reduce their independent judgment (Burger et al., 2023). Overreliance on AI outputs may result in procurement decisions being accepted without sufficient review, even when recommendations are inappropriate or unjustified (Pesqueira et al., 2024). Instead of replacing human decisions, the reviewed studies emphasize that AI should support human decision-making through appropriate human oversight (Lakhal et al., 2025).

Cross-Cutting Research Gaps

There are three recurring gaps in the reviewed studies that restrict both theoretical development and practical implementation (J. M. Spreitzenbarth et al., 2024). These gaps are related to the limited ability to translate AI from strategic interest to operational practice, the mismatch between governance requirements and organizational capability, and inadequate procurement data readiness to support value creation.

First, the literature indicates a gap between strategic interest and operational implementation of AI (Van Hoek, 2024). Despite public agencies' growing recognition of AI's potential to improve procurement processes, fear of taking risks, complex procurement regulations, fragmented data, technical uncertainty, and insufficient organizational capability continue to constrain its actual implementation (Andersson et al., 2025).

Second, a gap exists between governance requirements and institutional capability. Public procurement requires AI systems to guarantee transparency, accountability, and fairness. However, many public agencies lack the technical expertise, governance structures, or contractual mechanisms needed to effectively ensure that these requirements are consistently addressed (Andersson et al., 2025; Guida et al., 2023).

Third, the literature identifies a gap between procurement data availability and value creation. Although public agencies often have large volumes of procurement data, these data usually are in poor quality, fragmented information, and inconsistent documentation, restricting their ability to generate reliable insights for AI-supported decision-making (Flores et al., 2025; Soylu et al., 2022).

These research gaps show that responsible AI adoption in public procurement requires greater integration between technological capability, organizational readiness, procurement governance, and data management.

CONCEPTUAL FRAMEWORK

Figure 2 presents an integrative governance framework for responsible AI adoption in public procurement. The framework shows that AI adoption is shaped by the interaction between three core adoption conditions: AI capability, data readiness, and organizational capability. AI capability includes technical capabilities such as automation, analytics, natural language processing (NLP), prediction and classification. Data readiness includes the quality, interoperability, accessibility, and semantic usability of procurement data. Organizational capability combines the skills, routines, leadership, procurement maturity, vendor-management competence and institutional learning necessary to evaluate and use AI responsibly.

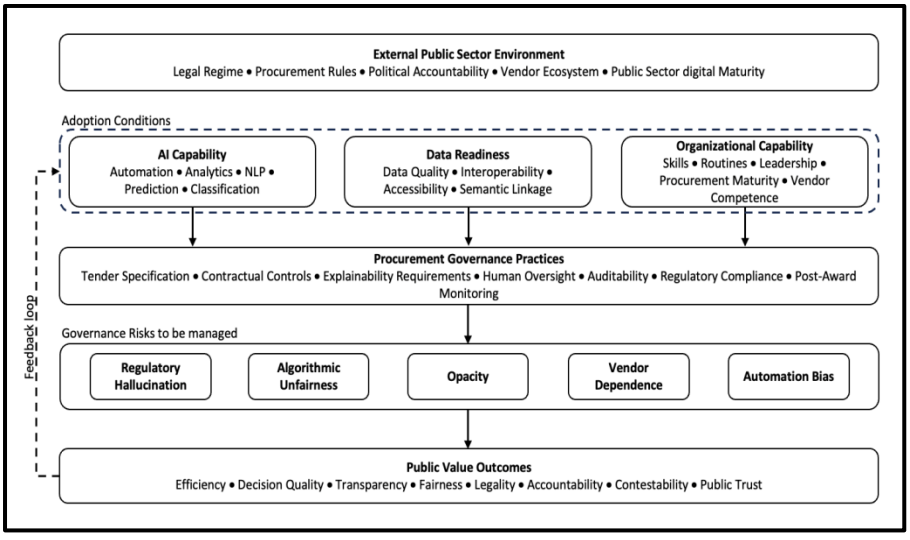

Figure 2. An integrative governance framework for responsible AI adoption in public procurement

Essentially, procurement governance is framed as the mechanism through which these conditions are translated into public value. It is implemented through a set of governance practices embedded throughout

the procurement lifecycle, including tender specification, contractual controls, explainability requirements, human oversight, auditability, regulatory compliance, and post-award monitoring. Together, these practices help ensure that AI systems are implemented, monitored, and governed in a transparent, accountable, and legally compliant manner.

The framework recognizes five governance risks that may constrain responsible AI adoption: regulatory hallucination, algorithmic unfairness, opacity, vendor dependence, and automation bias. Collectively, these risks may prevent AI capability from producing public value even when technical capabilities are at the cutting edge. Public value outcomes include efficiency, decision quality, transparency, fairness, legality, accountability, contestability and public trust. The framework is not linear as public value outcomes feed into organizational learning, data availability, procurement capabilities, and the future AI adoption conditions, which in turn feed into public value outcomes.

DISCUSSION

Theoretical Contribution

This review contributes to the literature on AI adoption and procurement by framing public procurement as an institutional governance mechanism for responsible AI adoption. The framework identifies six elements that need to be aligned for responsible AI adoption: AI capability, data readiness, organizational capability, procurement governance, governance risks and public value outcomes. This advances adoption-oriented perspectives by shifting the focus from how agencies adopt AI to how they govern the broader institutional transformation associated with AI adoption (Meyer & Henke, 2023; Van Hoek, 2024).

The framework shows that while AI capabilities, such as automation, analytics, prediction, classification, and NLP can boost procurement processes, they must be supported by reliable data, adequate organizational capability, and procurement governance practices integrated across the procurement lifecycle in order to generate public value. This integration is especially important in the public sector, as AI-supported decisions must be legally compliant, transparent, auditable, and fair (Andersson et al., 2025).

Public Procurement as an Institutional Foundation for AI Governance

Public procurement should not be viewed simply as the process through which AI is adopted, but as the institutional foundation that determines whether AI is governed responsibly throughout the procurement lifecycle. This is especially important for AI-supported procurement activities such as supplier screening, tender evaluation, fraud detection, and compliance assessment (Lakhal et al., 2025; J. M. Spreitzenbarth et al., 2024).

The proposed framework emphasizes that governance should be proactive rather than reactive by ensuring that governance practices guide AI adoption throughout the procurement lifecycle instead of being introduced as a separate activity introduced after AI implementation. This proactive approach helps to ensure that legal, ethical, and accountability requirements are integrated into procurement decisions from the beginning of AI adoption (Pesqueira et al., 2024).

The framework highlights that governance risks are not isolated technical issues but they are interconnected constraints on responsible AI adoption in public procurement. It synthesizes five governance risks identified across the reviewed literature, regulatory hallucination, algorithmic unfairness, opacity, vendor dependence, and automation bias, into a unified governance perspective.

Together, these risks interact to constrain the ability of public agencies to govern AI effectively, reducing transparency, accountability, and public trust, and helping explain why AI systems with strong technical capabilities may still fail to deliver meaningful public value.

Boundary Conditions

Because AI adoption is impacted by variations in the external public sector environment, the applicability of the proposed framework may vary in different public-sector contexts. The legal regime, procurement rules, political accountability, vendor ecosystem, and public sector digital maturity are factors that may shape governance risks, procurement governance practices, and the responsible adoption of AI (Andersson et al., 2025; Van Hoek, 2024). For example, AI used for spend classification implies different risks from AI used for supplier evaluation, tender scoring, fraud detection, or contract monitoring (Guida et al., 2023; J. Spreitzenbarth et al., 2021). Agencies with mature e-procurement systems and strong data governance may also face different barriers from agencies dependent on fragmented legacy systems and scanned records (Flores et al., 2025; Soylu et al., 2022).

For procurement agencies, the findings imply that requirements for explainability, auditability, data quality, human oversight, risk mitigation, and post-award monitoring could be incorporated early in the design of the tender. For regulators, the findings highlight the need for AI governance standards that translate high-level principles into operational requirements that can be specified, evaluated, monitored, and enforced throughout AI adoption in public procurement. For vendors, the findings suggest that, in addition to achieving technical performance, they need to show explainability, bias mitigation, compliance, data governance and audit readiness. For auditors, the findings suggest that audit practices should expand to include algorithmic accountability and data governance, in addition to financial and procedural compliance.

Future research should avoid blanket statements about the potential of AI. Instead, researchers should investigate best practices for responsibly adopting, implementing, governing and evaluating AI through the procurement lifecycle. Overcoming the challenge of scaling small-scale pilots into AI-enabled procurement practices across the enterprise should be investigated, as should the ways in which procurement governance can be operationalized through tender documents, evaluation criteria, contractual provisions, and post-award monitoring. In addition, further research should investigate data readiness, knowledge graphs, retrieval-augmented systems, public value metrics, and the ways in which procurement outcomes contribute to institutional learning.

LIMITATIONS

This review is limited to literature indexed in Scopus to provide a comprehensive overview of the academic publications on AI governance and public procurement. This excludes literature published in legal scholarship, reports by legal practitioners, policy documents, and guidelines by public sector organizations, which are particularly important in the rapidly changing field of AI governance and public procurement. Moreover, selecting English-language publications may leave out the unique procurement systems and governance practices adopted in non-English-speaking jurisdictions.

Because this study adopts a narrative review approach rather than a systematic review or meta-analysis, the framework proposed in this study should not be seen as an empirically tested causal model but rather as a conceptual and analytical framework. The review includes conceptual, empirical, technical, and legal studies, which makes it challenging to directly compare findings across studies. With this in mind, themes also vary in strength of evidence.

The framework accounts for external conditions, governance mechanisms, risk controls, public value outcomes, and feedback loops, but these theoretical relationships should still be examined within the context of public procurement and across other AI technologies.

CONCLUSION

This review shows that responsible AI adoption in public procurement depends on more than the availability of advanced AI tools. It requires the alignment of AI capability, data readiness, organizational capability, procurement governance practices, governance risks, and public value outcomes. The proposed framework supports the focus of this article that public procurement should not be viewed simply as the organizational

setting in which AI is adopted, but rather as an institutional governance mechanism for adopting, evaluating, contracting, monitoring, contesting and holding AI systems accountable.

The synthesis also identifies three gaps, translating strategic AI interest into operational practice, aligning institutional capability with governance requirements, and transforming procurement data into meaningful AI-enabled insights. Addressing these gaps is essential for supporting responsible AI adoption and mitigating governance risks identified in the proposed framework, including regulatory hallucination, algorithmic unfairness, opacity, vendor dependence, and automation bias.

Public procurement agencies should direct the adoption and governance of AI across the procurement lifecycle rather than accepting it passively. AI may improve public procurement processes, strengthen risk assessment, and enhance decision-making when it is supported by procurement governance practices that promote public values of fairness, transparency and accountability. In addition to examining whether AI enhances procurement performance, future studies should concentrate on how public agencies can control AI adoption to promote public value and boost institutional learning in public procurement.

AI USE DISCLOSURE STATEMENT

Generative AI tools were used only to improve language, readability, and overall presentation of the manuscript. They were not used to identify or evaluate the literature, analyze the evidence, verify references, or generate the findings or conclusions. All academic decisions, including the selection of sources, interpretation of the evidence, and development of the manuscript, were made by the authors, who take full responsibility for the accuracy and integrity of the work.

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