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Artificial Intelligence in Public Procurement in Developing Countries: A Narrative Policy Review and Implications for Vietnam

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Abstract
This article provides a policy review of the application of artificial intelligence (AI) in public procurement in developing countries, using Vietnam as an illustrative context. It is designed as a narrative policy review that combines the analysis of academic literature, reports from international organizations, and current legal documents. Using the public procurement cycle as the analytical framework, the article synthesizes AI applications in procurement planning, price forecasting, supplier risk assessment, bid document processing, bid-rigging detection, and contract implementation monitoring. The synthesis shows that AI can contribute to operational efficiency, transparency, and data-driven decision-making. However, the realization of these benefits depends substantially on data quality, model explainability, algorithmic audit mechanisms, data security, and the digital capacity of the public sector. The article proposes a four-pillar policy framework consisting of data foundations, algorithm governance, legal accountability, and operational capacity. For Vietnam, the adoption of AI in public procurement should follow a cautious, risk-based trajectory, beginning with low-risk support tasks before expanding to risk warning systems and decision-support applications with high legal implications.

Keywords: Artificial Intelligence, Public Procurement, E-Procurement, AI Governance, Open Contracting Data, Developing Countries

1. Introduction

1.1 Research Background

Public procurement is an important instrument of socio-economic governance through which the State allocates a substantial share of public resources to provide public services, invest in infrastructure, and pursue development objectives. According to the OECD, public procurement expenditure in OECD countries in 2023 was equivalent to approximately 12.7% of GDP and nearly 29.9% of total government expenditure [1]. In developing countries, public procurement often has even greater significance because the public sector plays a central role in infrastructure investment, health care, education, and social welfare programs [2].

Nevertheless, public procurement is also vulnerable to inefficiency, information asymmetry, bid rigging, conflicts of interest, and corruption. These risks not only increase fiscal costs but also erode public trust in government institutions. Over the past decade, many countries have promoted e-procurement to standardize procedures, create audit trails, and expand monitoring capacity. However, many e-procurement systems still function primarily as operational data repositories, while their capacity for predictive analysis, anomaly detection, and decision support remains limited [3].

1.2 Digital transformation and the emergence of AI in public procurement

The development of machine learning, natural language processing, data mining, and generative AI opens the possibility of transforming public procurement from a process digitization model into a data-driven governance model. Instead of merely storing information on procurement packages, AI can help identify abnormal patterns in bid prices, analyze bid documents, suggest evaluation criteria, detect supplier risks, and issue early warnings of potential fraud [4, 5].

However, AI is not a solution that can automatically correct all institutional and operational weaknesses in public procurement. The effectiveness of AI depends on input data, model design, explainability, accountability rules, the capacity of procurement officials, and mechanisms for social oversight. In developing countries, where data are often fragmented and technical capacity

is uneven, AI adoption should be viewed as a coordinated reform program involving institutions, data, and technology, rather than merely as a software investment project [6, 7].

1.3 Research gap, objectives and contribution

Existing studies on AI in public governance and public procurement are largely based on the experience of countries with advanced data infrastructure, high technical capacity, and relatively mature algorithmic audit mechanisms. By contrast, in developing countries, the challenge is not limited to choosing an appropriate technology. It also involves data quality, system interoperability, legal accountability, the capacity to interpret algorithmic outputs, and the readiness of implementing agencies. This gap indicates the need for a policy-oriented analytical framework that is better aligned with the institutional, data, and operational conditions of developing countries [4, 6].

Accordingly, this article has three objectives: (i) to synthesize the main applications of AI across the public procurement cycle; (ii) to analyze the opportunities and risks of AI adoption in the context of developing countries; and (iii) to propose a policy framework for responsible AI implementation in public procurement, using Vietnam as an illustrative context. The main contribution of the article is the development of a four-pillar policy framework consisting of data foundations, algorithm governance, legal accountability, and operational capacity [19-22].

2. Materials and Methods

2.1 Type of article and research design

This article is designed as a review article in the form of a narrative policy review, rather than as a quantitative empirical study. This approach is appropriate for synthesizing evidence, analyzing risks, and proposing policy implications in an emerging topic where empirical evidence remains dispersed across several fields, including public administration, data science, technology law, and public procurement.

A narrative policy review was selected because the article does not aim to measure the quantitative impact of a specific AI system. Instead, it seeks to integrate dispersed evidence in order to identify opportunities, risks, and conditions for implementing AI in public procurement. This approach allows academic literature, policy reports, and legal documents to be combined, thereby supporting the development of policy implications suited to the context of developing countries.

2.2 Data sources and search strategy

The reviewed sources include three main groups: (i) academic articles and book chapters on AI, e-procurement, bid-rigging detection, and data governance; (ii) policy reports from international organizations such as the OECD, UNODC, the World Economic Forum, the Open Contracting Partnership, and The GovLab; and (iii) Vietnamese legal documents related to bidding, artificial intelligence, and national AI development strategies. The main keywords included “artificial intelligence”, “public procurement”, “e-procurement”, “bid rigging”, “open contracting data”, “AI governance”, “algorithmic accountability”, and “developing countries”.

The search and review of documents were conducted purposively up to June 2026. Academic sources were prioritized when they were directly related to AI in public procurement, bid-rigging detection, AI governance, or open data in the public sector. Policy and legal sources were selected when they were official, clearly documented, and able to provide evidence for the design of the policy framework. The final list consists of 22 sources that are used directly in the analysis and listed in the References section.

2.3 Inclusion and exclusion criteria

Documents were included in the review when they met at least one of the following criteria: direct relevance to AI applications in public procurement; analysis of governance, legal, or ethical risks of AI in the public sector; provision of evidence on open data, the Open Contracting Data Standard (OCDS), or fraud detection in procurement; or status as an official legal or policy document relevant to the Vietnamese context. Sources with unclear authorship, insufficient publication information, purely commercial promotional content, or no direct relevance to public procurement were excluded from the core reference list.

The screening process was conducted in two steps. The first step involved reviewing titles, abstracts, or document descriptions to determine their relevance to AI and public procurement. The second step involved reading the full text or core content to assess the contribution of each source to one of four analytical themes: AI applications, data conditions, algorithm governance, and policy implications. As a narrative policy review, this article does not claim to be a PRISMA-based systematic review. However, the inclusion and exclusion criteria are presented to enhance the transparency of the synthesis process.

2.4 Analytical framework

The documents were coded along two analytical dimensions. The first dimension is the public procurement cycle, including planning, preparation of bidding documents, receipt and evaluation of bids, contract award, and contract implementation management. The second dimension concerns the conditions for AI deployment, including data quality, algorithmic capacity, legal and ethical mechanisms, and organizational capacity. This coding approach allows the article not only to list technological applications, but also to assess the feasibility of safe implementation under the conditions of developing countries.

To deepen the analysis, the article also draws on key concepts from AI governance, including explainable AI, algorithmic accountability, human-in-the-loop, audit trail, model governance, bias testing, and post-deployment monitoring. These concepts help evaluate not only the technical performance of AI, but also the explainability, fairness, safety, and legality of AI systems when used in the public sector.

3. Results and Discussion

3.1 AI as a data-driven governance instrument in public procurement

In public procurement, AI should be approached as a tool that supports data-driven governance, not as a mechanism that fully replaces administrative judgment and human accountability. Unlike traditional operational software, AI processes large-scale data to detect patterns, forecast risks, and support decision-making under complex information conditions. When properly designed, validated, and

monitored, AI can help procurement authorities shift from ex post inspection to proactive risk governance [4, 8].

However, decision-making in public procurement is always linked to requirements of fairness, competition, transparency, and accountability. Therefore, AI-based recommendations should be treated only as supporting inputs, while decisions that have direct legal effects on suppliers or contractors should maintain a human-in-the-loop mechanism, meaning that they are reviewed, approved, and accountable through human decision-makers [4, 5].

3.2 Applications of AI across the public procurement cycle

At the planning stage, AI can support demand forecasting, analysis of historical price data, identification of market fluctuations, and estimation of procurement package values. Forecasting models, if trained on clean data, can reduce subjective bias in cost estimation and support more realistic budget planning [12, 13].

At the preparation and bid submission stage, natural language processing can assist in reviewing tender conditions, detecting inconsistent clauses, extracting technical criteria, checking the completeness of documents, and comparing information across documents. The ALICE case in Brazil shows that tools for analyzing procurement notices and documents can generate early warnings for auditors, thereby shifting the focus from detecting violations after the fact to preventing problems before contracts are implemented [8, 9].

At the supplier evaluation and fraud detection stage, machine learning can identify abnormal indicators such as unusually low variance in bid prices, rotating winning patterns, similar submission times, or hidden networks among bidders. Studies on bid-rigging detection in infrastructure procurement suggest that AI can help construct reference scenarios and issue risk alerts. However, model outputs need to be validated by competition experts and procurement specialists before they are used as a basis for legal enforcement [10, 11].

At the contract management stage, AI can combine disbursement data, progress records, acceptance data, field images, and complaint data to develop early warning systems. This application is particularly important for construction and infrastructure procurement, where risks often emerge after contract award, including delays, cost overruns, changes in quantities, or non-compliance with quality requirements [3, 15].

Table 1 summarizes selected evidence and cases used in the article. These cases indicate that AI in public procurement should first be understood as a tool for detection, prioritization, and inspection support, rather than as an automated decision-making mechanism replacing public authorities.

Table 1: Selected evidence and cases of AI/data-driven adoption in public procurement

Case/evidence	Main application	Lesson for developing countries	Source
ALICE, Brazil	Analysis of procurement notices and documents to generate early warnings for auditors.	AI creates the clearest value when embedded in audit procedures, structured data, and expert review of outputs.	[8, 9]
Studies on bid-rigging detection in infrastructure projects	Construction of reference scenarios and identification of abnormal patterns in bidding data.	AI is suitable for risk warning; outputs should not be used as an independent basis for sanctions.	[10, 11]
AI Procurement in a Box	Guidance framework for procuring and implementing AI in the public sector.	Clear requirements are needed for human-in-the-loop, auditing, security, and supplier responsibility.	[5]
OCDS and open contracting data	Standardization of procurement data to support analysis and social oversight.	Structured, machine-readable, and interoperable data are foundational before investing in complex AI models.	[17, 18]

3.3 Opportunities for developing countries

The first opportunity is improved operational efficiency. AI can shorten document review time, automate repetitive tasks, and prioritize high-risk procurement packages so that oversight bodies can concentrate limited resources. This is particularly valuable in developing countries, where the number of specialized officials and data analytics capacity are often limited [3, 8].

The second opportunity is enhanced transparency and integrity. When combined with open data and open contracting data standards, AI can help civil society, the media, auditors, and anti-corruption agencies analyze procurement data at scale. However, transparency does not arise automatically from AI deployment; it depends on whether data are disclosed fully, in a structured format, in a timely manner, and in machine-readable form [6, 7].

The third opportunity is improved decision quality. AI enables procurement authorities to identify data patterns that are difficult to detect through manual inspection, thereby supporting planning, market assessment, and risk management. In the long term, the adoption of higher digital standards in public procurement may also encourage the private sector to upgrade its data capacity and ability to participate in public markets [14, 18].

3.4 Risks and implementation constraints

The most fundamental risk concerns data quality. If procurement data are missing, inaccurate, inconsistent, or stored in unstructured formats, AI models may generate high false alert rates or miss real risks. In such circumstances, AI may fail to improve governance quality and may even increase the inspection burden and reduce the confidence of implementing officials [6, 7].

The second risk is algorithmic bias. Because machine learning models are trained on historical data, they may reproduce or amplify existing biases, such as favoring large contractors, familiar suppliers, or firms with more complete historical data. This may disadvantage small and medium-sized enterprises, new contractors, or local firms with limited digital capacity [5, 16].

The third risk is limited model explainability. In public administration, a decision to reject a bid, issue a risk alert, or refer a case for inspection requires a clear legal basis. If an AI system provides only a risk score without identifying the

variables or logic influencing the result, public agencies may find it difficult to defend their decisions when complaints or disputes arise [4, 5].

The fourth risk is data security and vendor dependency. AI systems in public procurement may process sensitive information on prices, business profiles, bidding strategies, and contracts. Outsourcing AI solutions without requirements on security, auditing, data portability, and data sovereignty may create long-term technological dependency [5, 18].

Table 2 presents an analytical framework for AI adoption risks in public procurement. The framework emphasizes that risks arise not only from algorithmic models, but also from data quality, legal accountability, and organizational capacity.

Table 2: Analytical framework for AI adoption risks in public procurement

Pillar	Main issue	Risk if uncontrolled	Treatment direction
Data	Fragmented data, lack of standards, and absence of unified identifiers.	False alerts, missed fraud, and unstable models.	Standardize data according to OCDS, enable API-based interoperability, establish data dictionaries, and apply data quality checks.
Algorithms	Black-box models, limited explainability, and dependence on historical data.	Bias against SMEs or new contractors; difficulty using outputs as a legal basis.	Prioritize explainable AI, conduct model audits, evaluate errors, monitor model drift, and disclose risk logic at an appropriate level.
Legal and ethical mechanisms	Unclear responsibility for incorrect AI recommendations and lack of complaint mechanisms.	Disputes, avoidance of responsibility, and erosion of contractor trust.	Maintain human-in-the-loop processes, classify risk levels, establish feedback and complaint procedures, and maintain audit trails and decision logs.
Organizational capacity	Lack of data personnel and limited skills in interpreting AI outputs.	Vendor dependency, symbolic AI use, and failure to extract value from data.	Train procurement officials, establish interdisciplinary data-legal-procurement teams, use controlled PPPs, and implement post-deployment monitoring.

Table 3: Policy framework for responsible AI adoption in public procurement

S. No	Policy pillar	Objective	Implementation tools	Monitoring indicators
1	Data foundation	Ensure that input data are clean, complete, and analyzable.	OCDS standards; machine-readable data; APIs; unified identifiers for contractors and procurement packages; data lineage controls.	Share of mandatory data fields completed; share of data disclosed on time; number of interoperable systems; rate of detected and corrected data errors.
2	Algorithm governance	Ensure that AI models are accurate, explainable, fair, and stable over time.	Technical model documentation; algorithm audits; bias/fairness assessment; periodic validation; model drift monitoring.	Alert accuracy; false alert rate; model audit reports; version change logs; results of bias testing.
3	Legal accountability	Protect contractor rights and ensure accountability of public agencies.	Human-in-the-loop; complaint mechanisms; audit trails; decision logs; AI system risk classification.	Share of decisions with explanations; number of complaints processed; complaint response time; number of cases adjusted after review.
4	Operational capacity	Ensure that procurement agencies use AI substantively, safely, and sustainably.	Training for officials; interdisciplinary teams; standards for selecting AI vendors; controlled sandboxes; post-deployment evaluation.	Number of trained officials; number of pilot projects; degree of vendor dependency; results of post-deployment evaluation.

3.5 Policy framework for responsible AI in public procurement

Based on the synthesis, the article proposes a four-pillar policy framework. The first pillar is the data foundation: before investing in complex AI models, governments need to standardize procurement data, disclose machine-readable data, and establish interoperability with budget, business registration, tax, social insurance, and contract history databases. The second pillar is algorithm governance: any AI system that affects the rights and interests of suppliers or contractors should be subject to requirements on explainability, independent auditing, error assessment, bias testing, and post-deployment monitoring. The third pillar is legal accountability: the system must clearly define the boundary between automated recommendations and administrative decisions, while providing mechanisms for complaints, correction, and traceability. The fourth pillar is operational capacity: procurement officials do not need advanced programming skills, but they should have the ability to understand data, interpret model outputs, and critically question algorithmic recommendations.

4. Vietnam as an illustrative policy context

4.1 Legal and institutional foundation

Vietnam is a notable illustrative context because it is simultaneously promoting e-procurement, public sector digital transformation, and the development of a legal framework for AI. This context is to some extent representative of many developing countries: an e-procurement system has been established and has generated a large volume of operational data, while requirements relating to data standardization, system interoperability, analytical capacity, and algorithmic control are still being improved. The Law on Bidding No. 22/2023/QH15, effective from 1 January 2024, provides a new legal foundation for the management of bidding activities, including the strengthening of state management, process transparency, and the responsibilities of participating actors [19].

The Law on Artificial Intelligence No. 134/2025/QH15, effective from 1 March 2026, and Decree No. 142/2026/ND-CP, effective from 1 May 2026, establish a legal basis for managing AI systems according to risk levels,

promoting transparency, and controlling the deployment of AI in the public sector [20, 21]. In addition, the National Strategy on Research, Development and Application of Artificial Intelligence to 2030, issued under Decision No. 127/QD-TTg, identifies AI as a foundational technology for digital transformation and socio-economic development [22].

4.2 Proposed implementation roadmap for Vietnam

Considering Vietnam's current institutional, data, and operational capacity conditions, the roadmap for AI adoption in public procurement should follow a cautious, phased, and risk-based approach. During 2026-2027, priority should be given to data standardization, the development of a structured procurement data repository, the review of missing data fields, and the deployment of AI in low-risk support tasks such as search, classification, document summarization, and regulatory lookup support.

During 2027-2030, AI adoption may be expanded to risk warning systems, detection of bid-rigging indicators, identification of abnormal clauses in bidding documents, and monitoring of contract delays. At this stage, every AI model should be accompanied by validation reports, clear warning thresholds, expert review procedures, and complaint mechanisms for contractors.

After 2030, when data and organizational capacity have become more mature, Vietnam may consider the use of generative AI and advanced decision-support systems in drafting contract clauses, simulating negotiation scenarios, analyzing project risks, and monitoring contract implementation in real time. However, applications that directly affect bid rejection, contractor scoring, or recommendations for sanctions should always maintain human control and accountability by the competent authority.

5. Recommendations

First, data standardization should be regarded as a mandatory step before investment in complex AI models. Without clean data, AI will primarily create additional inspection costs and risks of error. Second, a minimum set of technical requirements for AI in public procurement should be issued, covering explainability, auditing, information security, traceability, model lifecycle governance, and post-deployment monitoring. Third, sandbox pilots should be used for risk warning functions, while automated decision-making systems should not yet be deployed for decisions with direct legal effects. Fourth, procurement officials should be trained in data literacy, algorithm oversight, and the capacity to manage technology vendors. Fifth, a controlled data disclosure mechanism should be established so that civil society, audit bodies, competition authorities, and the research community can participate in oversight.

6. Conclusion

AI has the potential to support greater efficiency, transparency, and risk governance capacity in public procurement. Applications such as price forecasting, document processing, risk scoring, bid-rigging detection, and contract monitoring show that AI can help the public sector move from reactive management to proactive data-driven governance. However, AI does not by itself create integrity or governance efficiency if it is deployed on weak data foundations, opaque processes, and unclear legal accountability.

For developing countries, the core challenge lies not only in choosing algorithms, but also in data governance capacity, model audit capacity, and organizational capacity to use AI responsibly. This article proposes a four-pillar policy framework consisting of data foundations, algorithm governance, legal accountability, and operational capacity. For Vietnam, the Law on Bidding 2023, the Law on Artificial Intelligence 2025, Decree No. 142/2026/ND-CP, and the National AI Strategy provide an initial basis for developing a roadmap for AI adoption in public procurement. The success of this roadmap depends on phased implementation, beginning with low-risk support tasks before expanding to risk warning and decision support under controlled conditions.

This study has limitations because it is based on a policy review and secondary sources and has not empirically tested the readiness or impact of AI in a specific procurement system. Future studies may analyze data from e-procurement systems, interview procurement officials and contractors, or develop a readiness assessment model for AI adoption in public procurement in Vietnam.

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