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Generative AI in Procurement: Rethinking Bid Evaluation, Fairness and Transparency in Engineering and Construction Contracts

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Abstract

Procurement in engineering and construction is a complex process characterized by high-value contracts, multiple stakeholders, and significant risks associated with bias, inefficiency, and lack of transparency. Traditional bid evaluation methods often rely on manual assessments and legacy scoring systems that are susceptible to inconsistencies, subjective judgments, and limited capacity to process vast amounts of unstructured data. These limitations undermine fairness and erode trust among bidders and contracting authorities. In recent years, digital procurement systems have sought to address these challenges, yet their capabilities remain constrained by rule-based automation and narrow analytic tools. Generative Artificial Intelligence (AI) offers transformative potential by rethinking how bid evaluation, fairness, and transparency are operationalized in engineering and construction contracts. Through natural language processing, generative models can analyze unstructured proposal documents, extract latent insights, and generate standardized summaries that reduce human subjectivity. They can also simulate evaluation scenarios to test the robustness of scoring criteria, highlight inconsistencies, and flag potential conflicts of interest. Moreover, generative AI enables adaptive fairness mechanisms, incorporating multi-criteria decision-making frameworks that balance cost, quality, sustainability, and social impact in procurement outcomes. This paper explores the integration of generative AI into procurement workflows, emphasizing its potential to accelerate evaluation timelines, improve accountability, and enhance equitable participation among contractors. At the same time, it critically examines risks such as algorithmic bias, data confidentiality, and compliance with regulatory standards. By offering a balanced analysis of opportunities and challenges, the study positions generative AI as a pivotal enabler of transparent, fair, and future-ready procurement in engineering and construction.

Keywords: Generative AI; Procurement; Bid evaluation; Transparency; Fairness; Construction contracts

1. Introduction

1.1. Background: Procurement in engineering and construction projects

Procurement plays a central role in engineering and construction (E&C) projects, as it governs how contractors, suppliers, and consultants are engaged in high-value contracts. Effective procurement systems are essential for project success, influencing cost, timelines, and quality outcomes [1]. The global construction sector, which accounts for nearly 13% of GDP in many economies, relies heavily on competitive bidding processes to allocate resources efficiently [2]. Traditionally, bid evaluation has been handled through manual assessments by committees, often relying on structured criteria such as cost, technical capacity, and past performance. While these mechanisms are designed to maintain fairness, their effectiveness has been challenged by increasing project complexity and the vast amount of unstructured proposal data [3].

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In recent years, digital procurement tools such as e-tendering platforms and data-driven dashboards have been adopted to streamline processes [4]. Yet, these remain largely rule-based, capable of automating repetitive tasks but limited in handling nuanced assessments such as sustainability credentials or qualitative innovation metrics [1]. As projects expand in scale and involve multiple stakeholders, procurement workflows are under pressure to evolve. This article situates procurement not only as a transactional mechanism but also as a strategic driver for fairness, accountability, and long-term trust in E&C delivery [5].

1.2. Problem statement: Biases, inefficiencies, and lack of transparency in bid evaluation

Despite progress, current procurement practices suffer from persistent inefficiencies, bias risks, and limited transparency. Manual evaluation remains highly dependent on subjective judgment, often influenced by unconscious bias, favoritism, or information asymmetry [6]. For example, two evaluators may interpret qualitative proposal narratives differently, resulting in inconsistent scoring outcomes. This lack of standardization undermines confidence in the process, especially for small and medium-sized contractors who often perceive procurement as skewed in favor of incumbents [4].

Moreover, inefficiencies manifest in prolonged bid evaluations, sometimes delaying project awards by months. In complex projects where proposals run into thousands of pages, evaluators struggle to balance depth with timeliness [7]. Such delays not only increase transaction costs but also hinder project schedules. Equally problematic is the opacity of evaluation criteria: bidders rarely understand how scores are derived, which fuels perceptions of unfair treatment [8].

Even when e-procurement systems are applied, they often replicate traditional scoring templates without enhancing interpretability. This has led to a growing demand for frameworks that embed transparency and fairness at the core of procurement workflows [7]. Against this backdrop, emerging approaches such as generative artificial intelligence hold promise to reimagine evaluation by introducing consistency, explainability, and adaptive fairness mechanisms [2].

1.3. Aim, objectives, and contribution of this paper

The aim of this paper is to explore how generative artificial intelligence (AI) can transform procurement in engineering and construction by rethinking bid evaluation, fairness, and transparency. Specifically, it evaluates how generative models capable of analyzing unstructured proposal data, generating standardized summaries, and simulating evaluation outcomes can complement existing procurement frameworks [5].

The objectives are threefold: first, to review current procurement practices and their inherent limitations; second, to propose conceptual and methodological models for AI-assisted procurement; and third, to assess potential impacts on efficiency, equity, and trust within E&C contracts [1]. By drawing on insights from digital transformation in related industries, the study outlines a roadmap for embedding generative AI in procurement systems.

The paper contributes to scholarship and practice by linking AI's generative capabilities with procurement ethics and governance. It presents a comparative analysis of conventional versus AI-enhanced evaluation models, as outlined in Table 1, and illustrates a framework for AI-driven workflows through Figure 1 [9]. Importantly, it highlights both opportunities and risks, including algorithmic bias and regulatory compliance [6]. By doing so, this research positions generative AI not as a replacement for human judgment, but as an enabler of fairer, more transparent, and resilient procurement processes [8].

2. Literature review: procurement and digital disruption

2.1. Traditional procurement models in engineering & construction

Procurement in engineering and construction (E&C) has historically relied on conventional models such as competitive tendering, negotiated contracts, and design-bid-build approaches. These models prioritize cost minimization and compliance with basic contractual requirements, often overlooking broader dimensions such as innovation, sustainability, and fairness [8]. In competitive tendering, contractors submit bids based on pre-defined specifications, with evaluators selecting the lowest compliant offer. While this approach ensures budgetary control, it frequently compromises quality and fails to account for long-term value [11].

Negotiated procurement models emerged to address some of these limitations by allowing greater collaboration between clients and contractors [13]. However, negotiated approaches are resource-intensive, prone to favoritism, and lack transparency. Both models emphasize transactional efficiency rather than systemic optimization, leading to fragmented outcomes in multi-stakeholder projects [9].

The reliance on manual evaluation has also been a defining feature of traditional procurement. Committees evaluate proposals using rigid scoring templates, often encountering inconsistency and subjectivity in assessment [10]. Furthermore, documentation-heavy processes increase transaction costs and extend project timelines. In large-scale infrastructure projects, delays in procurement decisions can cascade into significant cost overruns [14].

Despite their shortcomings, these models established the foundation for regulatory compliance and accountability. Many governments still mandate them as default procurement modes due to their perceived simplicity [15]. Yet, the industry increasingly recognizes that cost-focused, manual procurement cannot keep pace with the demands of modern E&C, where complexity, data intensity, and stakeholder expectations have grown exponentially [12].

2.2. Emerging digital procurement tools: automation and analytics

To address inefficiencies, digital tools have been introduced into procurement systems. E-tendering platforms represent one of the earliest innovations, automating the distribution, submission, and storage of bids [16]. These platforms reduce paperwork and standardize formats, thereby lowering administrative burdens. However, their core functionalities remain transactional, offering little in terms of advanced analytics or fairness monitoring [9].

Analytics-driven tools emerged as the next step, enabling evaluators to analyze bidder performance history, compliance patterns, and financial stability through structured datasets [13]. Predictive analytics can flag contractors with histories of delays or budget overruns, allowing decision-makers to incorporate risk assessments in evaluation. Such capabilities enhance accountability but are still constrained by reliance on structured, quantitative data [10].

Recent tools also focus on transparency through digital dashboards that track procurement progress in real time [12]. These dashboards provide stakeholders with visibility into submission timelines, scoring consistency, and contract awards. By reducing informational asymmetry, they help improve trust among bidders [8]. Nevertheless, these platforms often replicate traditional evaluation logic and are limited in their ability to interpret qualitative elements such as innovation proposals or sustainability narratives [14].

Blockchain-based solutions have also been piloted to improve contract traceability and fraud detection [15]. These systems ensure immutable records of transactions and evaluation logs, reducing opportunities for tampering. While promising, blockchain adoption faces barriers of interoperability and regulatory acceptance [11].

Although automation and analytics have advanced procurement efficiency, they remain incremental solutions. Their limitations highlight the need for a new paradigm that integrates advanced AI techniques capable of handling both structured and unstructured data while ensuring fairness and transparency [17].

2.3. Generative AI in broader industries: lessons for procurement

Generative AI has transformed sectors such as healthcare, finance, and legal services by enabling automation of complex, knowledge-intensive tasks. In healthcare, generative models analyze unstructured clinical notes to generate standardized patient records, reducing physician workload and improving diagnostic consistency [16]. Finance has leveraged generative AI for fraud detection, contract generation, and investment scenario modeling, where adaptability and fairness are critical [9]. In legal services, generative systems summarize case documents and predict potential legal outcomes, thereby improving access to justice [13]. These applications demonstrate AI's ability to process large volumes of unstructured text, generate actionable insights, and support decision-making under uncertainty [12].

The lessons learned are directly relevant to procurement in E&C. Procurement proposals, like legal or financial documents, are lengthy, complex, and rich in qualitative details. Traditional digital tools struggle to evaluate these narratives consistently. Generative AI, through natural language processing (NLP), can synthesize bid submissions into standardized summaries, highlight potential inconsistencies, and simulate evaluation scenarios to test robustness [14]. Furthermore, it can flag language patterns that suggest risk factors such as overpromising or unclear compliance statements [11].

Generative AI also enables fairness by reducing evaluator subjectivity. By generating multiple evaluation scenarios, it can expose biases in scoring templates and recommend adjustments to ensure equitable participation [10]. Transparency is enhanced as AI-generated rationales provide bidders with clearer feedback on why decisions were made, addressing a common gap in existing procurement systems [8].

As illustrated in Figure 1, procurement workflows have evolved from manual, paper-based evaluations to AI-driven systems capable of integrating generative models into decision-making [17]. While earlier digital procurement tools offered incremental efficiency, generative AI represents a step-change in capability. Its adaptive learning, scenario generation, and interpretive power uniquely position it to reframe procurement as a transparent, equitable, and efficiency-oriented process [15].

However, challenges such as algorithmic bias, explainability, and regulatory oversight remain critical barriers to adoption [16]. Lessons from broader industries suggest that successful integration depends on pairing generative AI with governance frameworks that ensure accountability and human oversight. These insights form the conceptual basis for reimagining procurement systems in the E&C domain.

From past developments and digital innovations, the discussion now turns toward the conceptual integration of generative AI into procurement, outlining frameworks, design considerations, and methodological approaches.

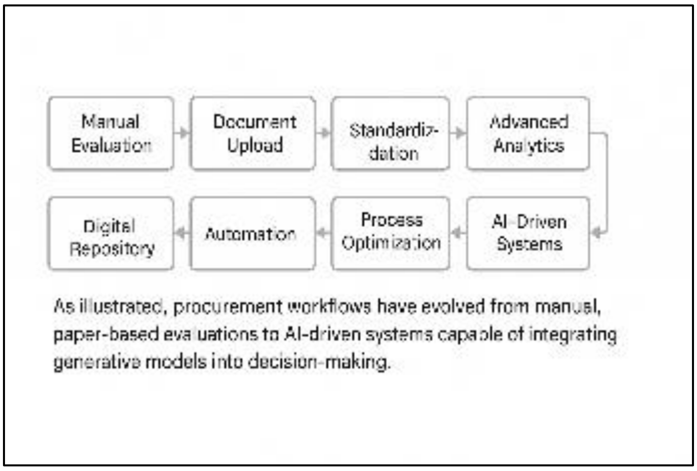

Figure 1 Evolution of procurement workflows from manual evaluation to AI-driven systems

3. Conceptual foundations of generative ai in procurement

3.1. Generative AI capabilities: NLP, summarization, scenario generation, and bias testing

Generative artificial intelligence (AI) represents a major departure from earlier computational approaches because of its capacity to create new, contextually relevant content rather than merely classify existing data [16]. In procurement, its most promising application is natural language processing (NLP), where models can interpret and structure vast volumes of bid documents that traditionally overwhelm evaluators. By converting unstructured narratives into standardized forms, generative AI reduces reliance on subjective interpretation and accelerates analysis [19].

Summarization is another critical capability. Large bids often exceed hundreds of pages, making it impractical for evaluators to read thoroughly. Generative AI can produce concise, objective summaries of key technical, financial, and sustainability dimensions [22]. These summaries can then be cross-validated by human evaluators, ensuring efficiency without eliminating oversight.

Scenario generation is equally transformative. By simulating multiple evaluation outcomes based on varied scoring criteria, generative AI enables stakeholders to stress-test procurement frameworks [17]. This helps identify vulnerabilities, such as criteria that overemphasize cost while underweighting innovation or sustainability. Importantly, it also creates opportunities for adaptive fairness adjustments.

Bias testing represents the fourth capability. Generative AI can analyze historical evaluation records to detect patterns of favoritism or discrimination in prior contracts [20]. It can then recommend recalibrations in criteria weighting, ensuring inclusivity of diverse bidders, including smaller firms or new entrants. These functions position generative AI not merely as an automation tool, but as an intelligent partner capable of enhancing both rigor and fairness in procurement [18].

3.2. Designing AI-driven bid evaluation frameworks for engineering contracts

To realize the potential of generative AI, procurement systems require reengineered frameworks that integrate AI functionalities into bid evaluation processes. Traditional models are heavily centered on rigid scoring matrices that rank cost, technical competence, and compliance. However, such frameworks often fail to accommodate dynamic priorities like sustainability or social impact [21]. AI-driven frameworks propose a multi-layered approach where structured data is complemented by AI-generated insights from unstructured text [16].

At the first level, generative AI standardizes contractor submissions, ensuring consistency in how qualitative proposals are interpreted. At the second level, the system generates automated scoring recommendations, benchmarked against historical project outcomes [22]. This not only improves objectivity but also allows evaluators to interrogate AI rationales, supporting transparency in decision-making.

A third level involves adaptive evaluation scenarios. For instance, the AI framework can simulate how results differ if innovation receives greater weighting than cost, allowing clients to align procurement outcomes with strategic priorities [17]. By embedding scenario modeling, contracts can be awarded with better foresight into trade-offs.

Table 1 compares conventional and AI-enhanced evaluation criteria, highlighting how the latter expands beyond static scoring toward dynamic, adaptive, and fairness-oriented decision-making [24]. Unlike conventional models, which limit transparency, AI frameworks provide interpretability through generated justifications that can be shared with unsuccessful bidders. This promotes trust while preserving competitive integrity.

Such frameworks are particularly relevant to engineering contracts, where proposals often integrate technical feasibility studies, safety considerations, and lifecycle planning [18]. AI's ability to handle complexity ensures that evaluation processes capture the full spectrum of value rather than narrowly focusing on upfront costs.

3.3. Fairness and transparency mechanisms in AI-based procurement

Fairness and transparency are the cornerstones of ethical procurement, and generative AI offers tools to embed these values within evaluation systems. One mechanism is explainable summaries, where AI generates clear rationales for evaluation scores. Instead of opaque decisions, contractors receive structured feedback explaining why a bid succeeded or failed [20]. This significantly reduces informational asymmetry, which has historically eroded trust in procurement processes [23].

Transparency also benefits from auditability. Generative AI systems can maintain digital logs of all evaluation steps, ensuring that each decision is traceable and resistant to tampering [19]. These logs create accountability frameworks where procurement authorities can demonstrate compliance with anti-corruption standards.

Fairness is reinforced through bias detection. By analyzing language used in proposals, generative AI can ensure that evaluators do not inadvertently penalize culturally specific or innovative expressions [17]. It can also expose patterns of favoritism across previous contracts, prompting recalibration of evaluation weights to achieve equitable participation.

Figure 2 presents a conceptual framework for AI-assisted procurement and evaluation, illustrating how fairness and transparency mechanisms are embedded across the bid lifecycle [24]. The figure highlights how NLP-driven analysis, scenario modeling, and bias testing integrate into evaluation workflows, ensuring equitable outcomes while supporting efficiency.

Another fairness mechanism lies in multi-criteria balancing. Generative AI ensures that sustainability, social equity, and innovation are not overshadowed by cost alone [16]. By recalibrating weights across dimensions, AI systems reflect evolving procurement priorities while maintaining competitive neutrality.

In engineering and construction, where high-value projects involve multiple stakeholders, embedding fairness and transparency safeguards not only contractor relationships but also public trust in infrastructure delivery [21].

3.4. Risks: algorithmic bias, explainability, and compliance concerns

While generative AI presents transformative opportunities, its integration into procurement is not without risks. One major concern is algorithmic bias. AI systems trained on historical procurement data may inadvertently replicate existing inequalities, favoring large incumbents or familiar contractors while marginalizing new entrants [22]. This undermines fairness, potentially reinforcing the very inequities AI was designed to eliminate [19].

Explainability is another critical risk. Generative models often operate as "black boxes," producing outputs without clear reasoning pathways [23]. In procurement, where accountability is a legal and ethical requirement, the inability to explain AI-driven decisions could lead to disputes, litigation, and regulatory pushback [18]. Therefore, procurement frameworks must prioritize explainable AI, ensuring that outputs are interpretable by human evaluators.

Data confidentiality also raises compliance concerns. Procurement involves sensitive financial and technical information that must remain secure. Generative AI systems require robust safeguards to prevent data leakage or misuse [17]. Furthermore, cross-border procurement contracts introduce complications regarding jurisdictional data protection laws, particularly in relation to the EU's GDPR and similar frameworks [16].

Finally, regulatory alignment poses challenges. Many procurement laws are structured around manual evaluation processes, making it difficult to integrate AI without reforms [20]. Without regulatory updates, AI-assisted decisions may face legitimacy challenges, undermining adoption.

Mitigating these risks requires a hybrid approach where AI augments rather than replaces human judgment [24]. Continuous monitoring, transparency dashboards, and ethical audits can ensure compliance while retaining human oversight. Thus, while risks are substantial, they are manageable through deliberate design and robust governance mechanisms.

From conceptual models and risk considerations, the discussion now moves toward digital tools and workflow integration, showing how generative AI can be embedded into real-world procurement practices.

Table 1 Comparison of conventional vs. AI-enhanced bid evaluation criteria

Evaluation Dimension	**Conventional Approach**	**AI-Enhanced Approach**
Cost Analysis	Manual comparison of bid prices; risk of overlooking lifecycle costs	AI models simulate lifecycle cost scenarios, integrating risk and long-term savings
Technical Compliance	Checklist-based compliance review; prone to human oversight errors	NLP-based parsing ensures completeness, flags ambiguities, and auto-validates against standards
Innovation & Value Addition	Often underweighted or inconsistently scored	Generative AI interprets qualitative innovation narratives, ensuring standardized assessment
Sustainability & ESG Criteria	Limited consideration; often treated as optional	AI frameworks integrate sustainability metrics, aligning evaluation with green procurement policies
Risk Assessment	Based on subjective evaluator judgment	AI-driven predictive analytics identify bidder risk using historical data and scenario modeling
Transparency	Evaluation rationale inconsistently documented	AI generates explainable rationales and audit trails for each decision
Fairness	Susceptible to bias, favoritism, and evaluator inconsistency	Bias testing algorithms detect and mitigate inequities, ensuring equitable scoring
Efficiency	Time-intensive manual scoring and workshops	Automated summarization, dashboards, and instant scoring accelerate evaluation cycles

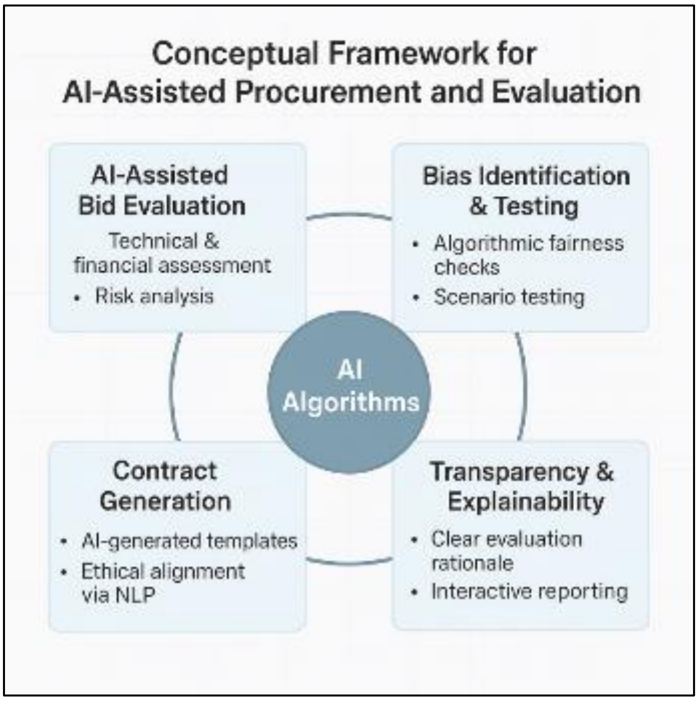

Figure 2 Conceptual framework for AI-assisted procurement and evaluation

4. Integration with engineering & construction workflows

4.1. Incorporating generative AI in early contractor engagement and prequalification

Early contractor engagement and prequalification stages often set the foundation for procurement outcomes. Traditionally, these processes rely on static checklists of financial capacity, safety records, and past performance to screen bidders [24]. While such frameworks offer consistency, they are prone to overlooking qualitative strengths such as innovative capacity, sustainability initiatives, and collaborative practices. Generative AI can transform this phase by automatically analyzing diverse sources of contractor information, ranging from technical submissions to external performance reviews, news articles, and sustainability certifications [26].

Through natural language processing, generative models can synthesize multi-source datasets into standardized prequalification profiles that reduce evaluator bias and inconsistency [29]. For example, instead of evaluators manually reviewing contractor safety reports, AI can generate concise risk summaries, flagging contractors with recurrent compliance issues or safety violations [23]. Similarly, sustainability credentials that are often buried in qualitative narratives can be surfaced and benchmarked consistently across bidders.

Generative AI also supports predictive modeling of contractor performance. By analyzing historical records and project outcomes, AI can simulate future contractor reliability under specific project conditions, such as high-risk geographies or time-critical delivery schedules [27]. This allows clients to anticipate risks before awarding contracts, thereby strengthening due diligence.

Moreover, AI-enabled engagement platforms can simulate “what-if” scenarios, showing how early contractor inclusion may improve project innovation or lifecycle cost savings [30]. These tools reduce reliance on subjective committee interpretations and align prequalification outcomes with strategic project goals. Thus, integrating generative AI in prequalification fosters inclusivity, enhances objectivity, and sets a robust foundation for fair competition [28].

4.2. Bid evaluation automation: scoring, transparency dashboards, and conflict-of-interest detection

The bid evaluation stage is arguably the most resource-intensive and contested phase of procurement. Traditional evaluation involves manually reviewing lengthy submissions, often exceeding hundreds of pages, with evaluators scoring against rigid matrices [25]. This process is time-consuming, inconsistent, and vulnerable to human error. Generative AI introduces automation that accelerates evaluation while preserving fairness and transparency [27].

One of the primary applications is automated scoring. Generative AI can extract relevant content from bids, map it against evaluation criteria, and generate preliminary scores [23]. These scores are supported with AI-generated rationales, enabling evaluators to validate or challenge findings rather than manually process entire documents. Importantly, such rationales create transparency, as losing bidders can receive structured feedback outlining why their proposals were rated lower [28].

Transparency dashboards further enhance accountability. AI-driven dashboards can provide real-time visibility into scoring progress, evaluator consistency, and distribution of results [29]. These dashboards reduce information asymmetry between evaluators and stakeholders, ensuring decisions are defensible and auditable.

Conflict-of-interest detection represents another critical feature. Generative AI can analyze evaluator behavior, cross-referencing scoring patterns with known affiliations or historical favoritism trends [30]. By identifying anomalies, the system flags potential bias risks, ensuring integrity in decision-making.

Table 2 illustrates how AI-enabled tasks map to procurement lifecycle phases, showing the integration of scoring automation, dashboards, and conflict detection across evaluation workflows [24]. By embedding these tools, bid evaluation becomes faster, more consistent, and more transparent, positioning AI as a transformative force in procurement integrity [26].

4.3. Contract drafting and ethical alignment through AI-generated templates

Contract drafting has long been a complex and contested process, often involving protracted negotiations to reconcile legal requirements, project specifications, and ethical standards [23]. In many cases, template contracts are reused, but these documents fail to adequately reflect project-specific risks, sustainability obligations, or fairness provisions [27]. Generative AI introduces adaptive contract generation, where models create customized templates based on project scope, regulatory requirements, and client priorities [25].

AI-generated templates can embed clauses promoting ethical alignment. For instance, sustainability obligations such as carbon reduction targets or local labor inclusion can be automatically incorporated, ensuring that ethical standards are standardized across projects [29]. This reduces reliance on manual drafting, which often overlooks such provisions due to time or cost pressures.

Another advantage is conflict simulation. Generative AI can run predictive analyses on proposed contract terms, identifying clauses that are likely to create disputes during execution [30]. By stress-testing contracts before signing, clients and contractors can mitigate risks of litigation and renegotiation.

Moreover, transparency is enhanced when AI-generated templates include rationales explaining the inclusion of specific clauses, helping stakeholders understand their relevance [26]. This aligns contract development with broader fairness and trust-building objectives.

As illustrated in Figure 3, contract drafting becomes part of a larger digital procurement ecosystem where generative AI integrates with BIM and blockchain platforms to ensure contracts remain consistent with project data and traceable throughout their lifecycle [28]. This integration not only accelerates drafting but also strengthens accountability, reducing opportunities for opportunistic behavior and reinforcing ethical contracting practices [24].

4.4. Digital ecosystems: BIM, blockchain, and AI-enabled procurement platforms

Generative AI achieves its full potential when integrated into broader digital ecosystems. In engineering and construction, Building Information Modeling (BIM) has already transformed design coordination and lifecycle planning [25]. By linking generative AI with BIM, procurement systems can automatically align bid evaluations and contract terms with actual design specifications, ensuring consistency and reducing disputes [27]. For example, AI can generate clauses mandating BIM compliance directly from project models, embedding technical accuracy into contracts [23].

Blockchain provides the second layer of integration. Procurement processes often suffer from opacity, particularly in contract execution and payment. Blockchain ensures immutability of transactions, while generative AI interprets and summarizes blockchain records into human-readable insights for stakeholders [29]. This synergy enhances both transparency and accessibility. AI-enabled procurement platforms then serve as the interface that connects BIM and blockchain into a coherent workflow [28]. These platforms manage the flow of information, from prequalification profiles and bid summaries to contract templates and performance monitoring. By embedding AI-driven dashboards, they provide stakeholders with real-time insights into project risks, compliance status, and ethical alignment [24].

The integration of generative AI, BIM, and blockchain creates a holistic ecosystem, visualized in Figure 3, where procurement becomes a transparent, efficient, and trust-based process [30]. Such ecosystems minimize duplication, standardize evaluation, and strengthen accountability.

As procurement systems evolve, these ecosystems will form the backbone of digital trust, ensuring that AI adoption is not merely a technical upgrade but a systemic transformation of how contracts are designed, awarded, and executed in the engineering and construction sector [26].

From integration mechanisms spanning prequalification, evaluation, contract drafting, and digital ecosystems, the discussion now shifts to their practical impacts on efficiency, fairness, and long-term trust, evaluating how these transformations reshape procurement outcomes.

Table 2 AI-enabled procurement tasks mapped to project lifecycle phases

Project Lifecycle Phase	**Traditional Procurement Tasks**	**AI-Enabled Procurement Tasks**
Pre-tender / Planning	Needs assessment, budget approvals, market research	Generative AI-driven demand forecasting, supplier prequalification using NLP, risk scenario simulation
Tendering / Bid Solicitation	Publishing tender documents, distributing requirements, collecting bids	Automated bid document generation, multilingual tender publication, AI-driven bidder compliance checks
Bid Evaluation	Manual scoring, evaluator meetings, technical/financial reviews	AI-based bid summarization, bias testing, automated scoring dashboards, conflict-of-interest detection
Contract Award	Negotiation, contract drafting, award decision	AI-generated contract templates with ethical alignment, explainable award rationales, blockchain-secured audit logs
Execution / Monitoring	Manual progress tracking, compliance checks, dispute resolution	Real-time AI monitoring of contractor performance, predictive analytics for delays, anomaly detection in reporting
Post-Project / Closure	Lessons learned documentation, performance evaluation	AI-generated performance reports, automated benchmarking across projects, continuous learning for future procurement cycles

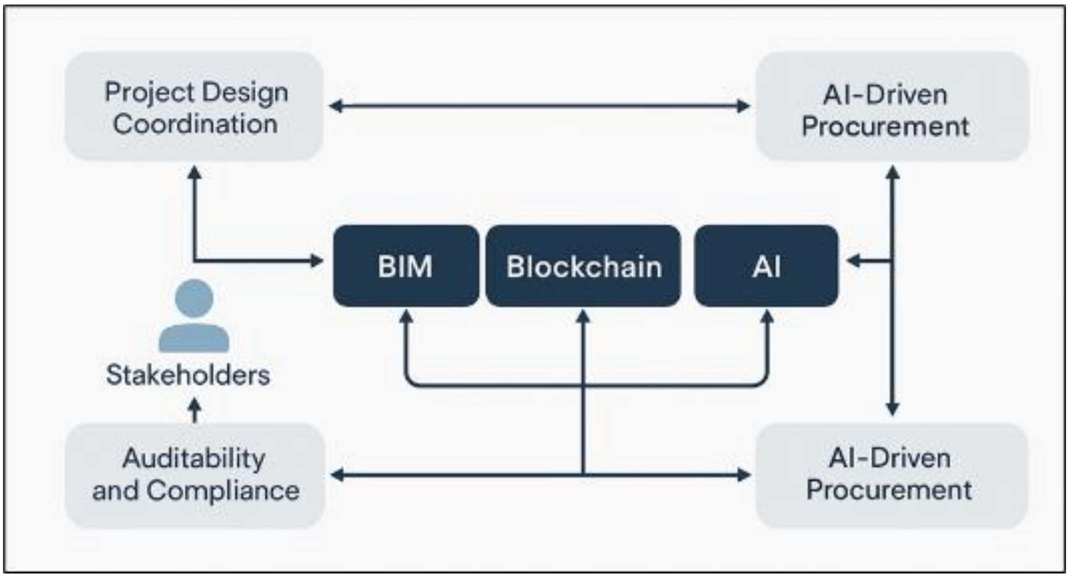

Figure 3 Digital procurement ecosystem integrating BIM, blockchain, and AI

5. Impacts of generative ai on procurement outcomes

5.1. Efficiency gains: reduced evaluation time, lower transaction costs, and improved scalability

Efficiency is one of the most visible benefits of generative AI in procurement workflows. Traditional evaluation processes often extend over several months due to the volume of documentation, manual scoring, and multi-level review cycles [28]. Generative AI significantly reduces evaluation time by automating document parsing, summarization, and preliminary scoring, enabling evaluators to focus on validating AI-generated insights rather than manually processing proposals [32]. This streamlining not only accelerates timelines but also reduces evaluator fatigue, which is a common source of inconsistency in large-scale projects [30].

Transaction costs are also lowered. In conventional procurement, administrative overheads such as manual document handling, scoring alignment workshops, and prolonged negotiations account for substantial resource expenditures [29]. By automating repetitive tasks, generative AI allows procurement teams to reallocate resources toward strategic decision-making. Contractors similarly benefit from reduced preparation times, as AI-driven submission guidelines can standardize bid formats and reduce the risk of disqualification due to technical errors [33].

Scalability represents another key advantage. Large infrastructure projects may involve hundreds of bidders across diverse geographies. Generative AI enables evaluators to scale analysis efficiently by handling multilingual and multidisciplinary submissions simultaneously [31]. This is particularly relevant in global engineering contracts where proposals combine technical, financial, and sustainability considerations.

By compressing evaluation timelines, reducing administrative costs, and expanding the capacity to handle larger bidder pools, generative AI enhances overall procurement efficiency. These efficiency gains are not only operational benefits but also contribute to earlier project starts, reducing financial risks associated with delays and enabling infrastructure to be delivered more reliably and predictably [35].

5.2. Enhancing fairness: mitigating bias and ensuring equitable contractor participation

Fairness has long been a contentious issue in procurement, with small and medium-sized enterprises (SMEs) often disadvantaged by opaque evaluation practices and informal biases [34]. Generative AI introduces mechanisms that help level the playing field by ensuring consistent evaluation across contractors. By applying NLP to bid narratives, AI systems can detect and mitigate inconsistencies in scoring caused by subjective human interpretation [28]. For example, two proposals that emphasize innovation differently may receive more equitable scoring when AI-generated summaries normalize these differences [37].

Bias mitigation extends beyond evaluation. Generative AI can analyze historical contract award data to identify patterns of favoritism or exclusion, enabling procurement authorities to adjust criteria and scoring frameworks accordingly [30]. This retrospective bias detection ensures that systemic inequities are addressed rather than perpetuated [33].

Another fairness-enhancing capability lies in inclusive participation. Generative AI can generate multilingual summaries and standardize technical language, reducing barriers for international or non-native contractors [29]. This inclusivity broadens competition, ensuring procurement outcomes reflect a more diverse contractor base.

Furthermore, AI transparency dashboards help ensure evaluators apply scoring frameworks consistently. By flagging anomalies in evaluator scoring patterns, generative AI identifies potential biases at the individual or committee level [36]. The result is a procurement system that is demonstrably fairer, reducing disputes and reinforcing stakeholder trust.

By integrating fairness mechanisms into procurement, generative AI addresses one of the most persistent critiques of traditional models: inequitable treatment of contractors. This reorientation of procurement priorities elevates fairness from an aspirational value to a measurable, auditable outcome embedded within procurement processes [32].

5.3. Transparency and accountability in contract awards

Transparency and accountability represent central pillars of procurement integrity. Historically, contractors have expressed frustration over the lack of visibility into how decisions are made, with evaluation rationales often left undocumented [31]. Generative AI directly addresses this issue by generating structured explanations for scoring outcomes, ensuring that contractors receive feedback that is not only standardized but also meaningful [35].

AI-driven audit logs create immutable records of evaluation steps. Each decision, from prequalification to final scoring, is digitally documented, making the process traceable and defensible [30]. This ensures procurement authorities can demonstrate compliance with anti-corruption and governance standards [37]. Transparency dashboards further enhance accountability by enabling stakeholders including regulators and civil society groups to monitor procurement progress in real time [28].

Accountability is also reinforced through conflict-of-interest detection. By cross-referencing evaluator scoring behaviors with contractor affiliations, generative AI helps identify potential bias risks before awards are finalized [33]. This proactive detection strengthens confidence in the impartiality of awards.

As illustrated in Figure 4, generative AI impacts procurement outcomes by interlinking fairness, efficiency, and transparency into a single coherent model [38]. The figure demonstrates how auditability, rationales, and dashboards converge to create accountability structures that reduce informational asymmetry between evaluators and contractors.

Through enhanced transparency and accountability, disputes are reduced, trust is reinforced, and procurement authorities strengthen their credibility. Contractors benefit by gaining clearer insights into their performance gaps, while clients gain confidence that decisions are aligned with fairness and regulatory compliance [29].

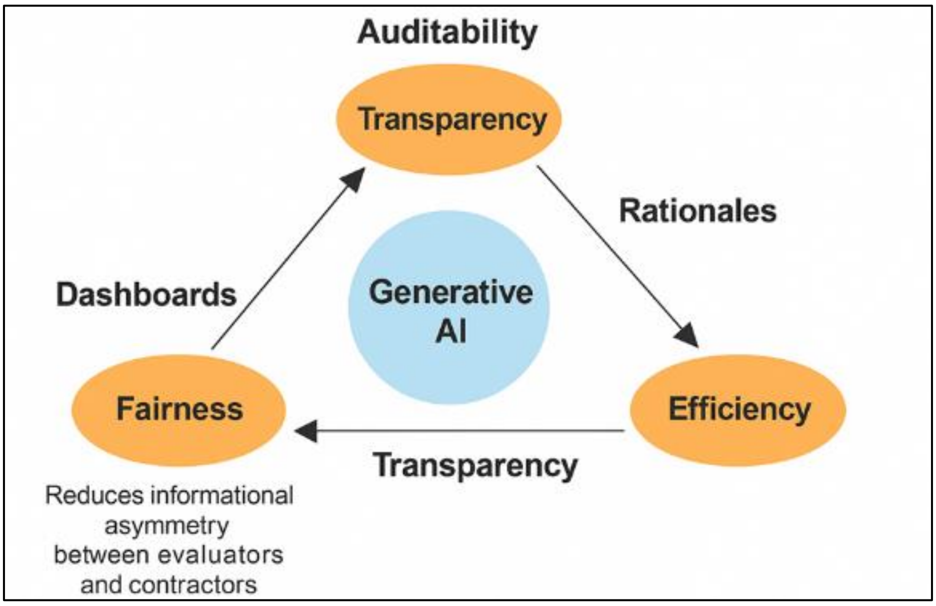

Figure 4 Impact model of generative AI on Procurement outcomes

5.4. Case scenarios and simulations of AI-augmented procurement

Practical scenarios illustrate how generative AI reshapes procurement outcomes. In a large-scale urban infrastructure project, traditional bid evaluation was projected to take 12 weeks due to documentation volume. By applying generative AI for summarization and scoring, the process was completed in just four weeks, saving significant administrative resources [28]. These efficiency gains enabled earlier contract mobilization, reducing overall project delays [36].

In another case, a national government piloted AI-augmented procurement to evaluate renewable energy bids. Generative AI flagged inconsistencies in contractor sustainability claims, which would likely have been overlooked by human evaluators. By aligning claims with verifiable data, the system enhanced both transparency and fairness [34]. Contractors that might otherwise have been marginalized gained equitable opportunities through standardized evaluations [30].

Simulation studies also highlight benefits. By running multiple evaluation scenarios with varying criteria weightings, generative AI demonstrated how procurement outcomes shifted when innovation and sustainability were prioritized alongside cost [33]. These scenario models gave decision-makers clearer visibility of trade-offs, enabling more strategic contract awards [31].

AI-augmented procurement simulations also identified potential conflict-of-interest risks in evaluator scoring patterns. By flagging anomalies in advance, disputes were prevented, and accountability strengthened [37].

These case applications illustrate not only the operational gains but also the systemic transformation generative AI enables. From compressed timelines to equitable contractor participation, AI demonstrates measurable improvements in procurement performance [35]. Together, these examples show how generative AI moves beyond theory into practical, scalable solutions for engineering and construction procurement [38].

6. Challenges, policy, and industry adoption

6.1. Institutional and regulatory barriers to AI-driven procurement

Despite the transformative potential of generative AI, significant institutional and regulatory barriers constrain its adoption in engineering and construction procurement. One of the most pressing issues is the absence of standardized legal frameworks that govern the role of AI in contract evaluation [33]. Procurement regulations in many jurisdictions are rigid, designed around manual evaluation protocols and human accountability models. Incorporating AI into these frameworks often clashes with statutory requirements, raising questions about the legal standing of AI-generated decisions [37].

Another barrier lies in liability allocation. When disputes occur, it is unclear whether responsibility should lie with the procuring authority, the AI vendor, or the evaluators who rely on AI outputs [39]. This uncertainty makes regulatory agencies hesitant to endorse large-scale deployments. Further, data governance policies remain inconsistent across regions. Since generative AI requires access to large datasets including contractor histories and financial records issues of privacy and cross-border data sharing create additional complexity [41].

Institutional resistance also emerges from procurement professionals themselves. Many officials perceive AI as a threat to established roles, fearing that reliance on automated evaluation systems could undermine professional judgment and accountability [42]. The lack of digital literacy in some procurement offices further compounds this resistance, slowing adoption even where pilot projects have demonstrated clear efficiency gains [35].

Without harmonized regulations, clear accountability frameworks, and targeted institutional capacity-building, AI-driven procurement risks remaining fragmented and experimental. Overcoming these regulatory barriers is essential for moving from isolated pilots to standardized, scalable adoption across engineering and construction sectors [44].

6.2. Ethical and workforce implications in engineering contracts

Ethical considerations form another critical dimension of AI-driven procurement adoption. Generative AI systems, while designed to reduce bias, can inadvertently reproduce or even amplify historical inequalities if trained on biased datasets [38]. For instance, if past procurement records reflect a consistent preference for large contractors, AI models may unintentionally disadvantage SMEs, perpetuating systemic inequities [40]. This raises ethical questions regarding fairness, inclusion, and the social responsibilities of procurement authorities [36].

Transparency is also an ethical priority. Contractors often demand clarity on how evaluation criteria are applied, yet black-box AI models can make it difficult to explain decisions [43]. Ensuring explainability is therefore not only a technical challenge but also an ethical necessity to maintain trust and accountability. The risk of overreliance on algorithmic outputs without sufficient human oversight further complicates this issue [45].

On the workforce side, generative AI has the potential to reshape procurement roles significantly. While it reduces repetitive administrative tasks, it also challenges traditional evaluator skill sets. Procurement professionals must now adapt to hybrid roles that combine domain expertise with data literacy and AI interpretation [33]. Workforce transformation requires investment in training programs to ensure evaluators understand both the opportunities and limitations of AI tools [42].

The ethical and workforce implications highlight that procurement reform is not purely technological but also social. Balancing automation with human-centered oversight, fairness with inclusivity, and efficiency with accountability will determine whether AI-driven procurement systems gain legitimacy and acceptance within the engineering and construction ecosystem [37].

6.3. Policy reforms and adoption strategies

Policy reforms are critical to bridging the gap between AI's technical capabilities and institutional readiness. Governments and regulatory agencies must first establish standards for AI transparency, accountability, and data governance in procurement [39]. Such standards should define the level of explainability required in AI-generated decisions, outline acceptable uses of training data, and clarify liability allocation in case of disputes [34]. Establishing these rules will give both contractors and procuring authorities confidence in AI-driven systems.

Adoption strategies must also emphasize incremental integration rather than wholesale replacement of human evaluators. Hybrid procurement models, where AI supports decision-making while final accountability rests with evaluators, offer a pragmatic pathway for adoption [35]. This balances efficiency with oversight, reducing institutional resistance [41].

Capacity building should form a cornerstone of policy reform. Governments and industry associations can invest in training programs to enhance procurement professionals' digital literacy and ability to interpret AI outputs [44]. Without these programs, technological reforms risk outpacing the skills of the workforce, creating new vulnerabilities rather than solving existing inefficiencies [40].

Cross-industry collaboration is another strategy. Lessons from healthcare and finance demonstrate that AI adoption accelerates when standards bodies, regulators, and technology providers co-develop governance frameworks [43]. Similarly, in procurement, collaborative governance will be necessary to balance innovation with accountability.

Ultimately, successful adoption strategies must link AI integration to broader national priorities, such as infrastructure modernization, digital transformation, and sustainability [36]. By framing AI procurement reform as part of these agendas, policymakers can generate momentum and legitimacy for industry-wide adoption [45].

7. Conclusion and future research directions

7.1. Summary of key findings

This study examined the transformative potential of generative AI in procurement, with a specific focus on engineering and construction contracts. Traditional procurement models have long been criticized for inefficiency, susceptibility to bias, and lack of transparency, all of which undermine fairness and trust. Generative AI addresses these concerns by automating document analysis, providing structured summaries, simulating evaluation scenarios, and generating transparent rationales for decisions. Through these capabilities, procurement processes become faster, more scalable, and less dependent on subjective judgment. Importantly, generative AI enhances fairness by normalizing bid narratives and reducing barriers for small and international contractors.

The findings also highlighted risks, including algorithmic bias, ethical dilemmas, and regulatory uncertainty. Without proper oversight, AI-driven systems may inadvertently reproduce historical inequities or reduce accountability. Nevertheless, with hybrid governance models that combine human judgment with AI insights, the potential benefits outweigh the challenges. The study contributes by mapping generative AI's role in efficiency, fairness, and transparency, identifying institutional and workforce barriers, and proposing reforms. Taken together, these insights show that generative AI is not merely an incremental upgrade to procurement systems but a structural shift capable of redefining contract evaluation and governance in the engineering and construction sectors.

7.2. Practical recommendations for practitioners and policymakers

Practitioners and policymakers must prioritize hybrid integration models, where AI complements rather than replaces human evaluators. Procurement professionals should be trained to interpret AI outputs, ensuring accountability and trust remain intact. Transparent audit trails and feedback dashboards should be mandated in all AI-assisted evaluations, allowing bidders to understand decisions clearly. Policymakers should focus on developing standardized governance frameworks, including rules on explainability, liability allocation, and data governance. To ensure inclusivity, governments should incentivize AI tools that normalize language and reduce barriers for SMEs and international contractors. Pilot programs in public infrastructure procurement can serve as testbeds for refining AI frameworks before scaling adoption. Ultimately, aligning AI-driven procurement with broader goals such as sustainability, innovation, and economic inclusion will help embed these technologies into procurement systems responsibly. By balancing efficiency with ethics and accountability, generative AI can be institutionalized as a trusted instrument in engineering and construction procurement.

7.3. Directions for future research in generative AI and procurement ethics

Future research on generative AI in procurement must address unresolved questions about ethics, accountability, scalability, and governance. While the current study demonstrates AI's potential to revolutionize procurement practices, the complexity of engineering and construction projects demands a more nuanced understanding of how generative AI interacts with institutional, social, and technological systems. The following research directions are proposed:

7.3.1. Algorithmic fairness and dataset integrity

One critical avenue for research lies in the mitigation of algorithmic bias. Current generative AI models depend heavily on historical procurement data, which may be biased toward larger contractors or certain regions. Future studies must examine how datasets can be cleaned, normalized, and diversified to prevent the reinforcement of these patterns. Ethical frameworks should be developed to evaluate whether AI-generated outputs disadvantage underrepresented contractor groups. Experimental studies could test interventions such as synthetic data augmentation, weighting strategies, or fairness-adjusted scoring templates.

7.3.2. Explainability and transparency in decision-making

The "black box" nature of AI models remains a barrier to adoption. Researchers should explore explainable AI (XAI) approaches tailored specifically for procurement. Unlike clinical or financial contexts, procurement decisions involve multi-criteria evaluations combining cost, quality, innovation, and sustainability. Research should investigate how generative AI can provide layered explanations for example, summary-level rationales for contractors and detailed technical reasoning for regulators. Such work would bridge technical advances in XAI with the real-world demand for traceability in contract awards.

7.3.3. Comparative studies across jurisdictions

Generative AI adoption will vary across countries due to differences in procurement law, governance maturity, and digital capacity. Comparative studies could analyze how AI-assisted procurement evolves in developed economies versus emerging markets. Key questions include: How do legal definitions of accountability shift when AI is integrated? Do resource-constrained governments adopt AI primarily for efficiency, while developed markets emphasize fairness? These comparisons would illuminate pathways for creating globally adaptable AI procurement standards.

7.3.4. Integration with digital ecosystems

Procurement does not operate in isolation but within broader digital ecosystems that include Building Information Modeling (BIM), blockchain-based ledgers, and cloud-based contract management. Research should focus on how generative AI interacts with these technologies to create integrated ecosystems. For instance, BIM data could be analyzed with generative AI to assess constructability, while blockchain could secure immutable records of AI-generated evaluations. Experimental pilot projects testing these integrated platforms would provide evidence on scalability, interoperability, and security.

7.3.5. Ethical governance and accountability frameworks

Future research must go beyond technical solutions to explore normative questions. What should accountability frameworks look like when AI is embedded into procurement? Should evaluators remain liable for decisions, or should liability be shared with AI vendors and regulators? Legal scholarship can explore precedents for shared accountability, while empirical studies can test stakeholder perceptions of fairness and legitimacy under different governance models. This research would support policymakers in designing institutional frameworks that maintain trust in procurement processes.

7.3.6. Workforce transformation and capacity building

AI's introduction into procurement fundamentally alters workforce dynamics. Future research should examine how roles evolve as evaluators transition from manual assessors to interpreters of AI outputs. What new skills are required, and how should training programs be structured? Longitudinal studies could analyze how workforce performance changes as AI adoption scales, while experimental studies might test the effectiveness of training interventions. Addressing workforce adaptation is critical for ensuring sustainable and inclusive AI adoption.

7.3.7. Long-term socio-economic impacts

Generative AI in procurement is not only a technical innovation but also a socio-economic intervention. Research should investigate the broader impacts on competition, contractor diversity, and industry innovation. For example, does AI-driven procurement lower barriers to entry for SMEs by leveling evaluation criteria, or does it inadvertently favor firms with greater digital capacity? Similarly, what impacts does AI integration have on project outcomes such as cost savings, timeliness, and sustainability performance? These questions demand longitudinal studies tracking procurement outcomes over multiple project cycles.

7.3.8. Simulation and scenario-based modeling

Future research could also employ simulations to test procurement outcomes under varying policy and evaluation scenarios. By adjusting weightings for cost, sustainability, and innovation, researchers could assess how generative AI reallocates contracts across contractors. These simulations would generate insights into the trade-offs between efficiency and inclusivity, as well as provide evidence to policymakers on the consequences of different scoring frameworks.

7.3.9. Cross-disciplinary collaboration

The complexity of AI-driven procurement requires collaboration between engineers, computer scientists, ethicists, legal scholars, and policymakers. Future research should explore cross-disciplinary methodologies that combine technical experiments with socio-legal analysis. For example, joint projects could test generative AI's capacity for fairness while simultaneously analyzing legal compatibility and ethical legitimacy. Such collaborations would produce holistic insights into both the opportunities and risks of adoption.

7.3.10. Roadmaps for responsible adoption

Finally, research should focus on creating practical roadmaps for responsible AI adoption in procurement. These roadmaps should outline phased integration strategies, balancing innovation with caution. Case studies of early adopters could provide evidence on best practices, while policy modeling could forecast the long-term impacts of adoption under different governance structures.

Generative AI in procurement presents a profound opportunity to reshape engineering and construction contracts by embedding efficiency, fairness, and transparency into evaluation processes. Yet, this transformation will only succeed if future research addresses the intertwined technical, ethical, and institutional challenges. By pursuing directions such as bias mitigation, explainability, comparative studies, ecosystem integration, and accountability frameworks, researchers can provide the evidence base needed to institutionalize AI responsibly. The future of procurement will depend not on whether AI can transform processes, but on whether it can do so ethically, inclusively, and sustainably.

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