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Overcoming the AI Data Eclipse: Obstacles to the Full Adoption of Artificial Intelligence in the Procurement Technology Sector

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Abstract

Artificial Intelligence (AI) has the potential to revolutionize procurement—automating supplier discovery, contract review, risk monitoring, and purchase-to-pay processes. Yet, adoption remains uneven, with many organizations trapped in “pilot purgatory.” A central barrier is the AI Data Eclipse, where incomplete, biased, or inaccessible procurement data blinds AI systems and prevents value realization. This paper is a conceptual review and practitioner framework. We synthesize peer-reviewed literature on AI adoption barriers, position the Data Eclipse as an extension of digital transformation maturity models and data governance frameworks, and illustrate obstacles with case studies from leading firms. We also propose a “POC-to-Platform” roadmap, supported by technical enablers like blockchain-backed supplier verification and dynamic AI governance engines. Finally, we suggest future research priorities on measuring data quality impact, benchmarking explainability, and designing interoperable procurement AI systems.

Keywords: Artificial Intelligence; Procurement; Supply Chain; Data Governance; AI Adoption; Barriers; Trustworthy AI; Data Eclipse.

1. Introduction

AI promises significant benefits for procurement: accelerated supplier identification, contract intelligence, predictive risk sensing, and guided buying. However, organizations often fail to move beyond proofs-of-concept. Multiple surveys report low scaling rates of AI in procurement compared to other enterprise functions.

This paper identifies six categories of obstacles—data, technology, process, people, governance, and the wider ecosystem—and introduces the concept of the AI Data Eclipse: when gaps in procurement data prevent AI from delivering value. We argue that the Eclipse is not a wholly new phenomenon but an extension of digital transformation maturity models and data governance frameworks that emphasize clean, interoperable, and explainable data as prerequisites for automation.

To avoid abuses, Bathsheba Syndrome-type risks (i.e. misuse of power, unethical behavior under weak oversight) must be mitigated via systems built with layered data collection, transparent reporting, anomaly detection, and independent audit mechanisms, suggested by Waditwar (2024). [7].

This paper also looks at the main obstacles holding back adoption. We focus on real-world procurement examples:

- Why spend analytics dashboards often give misleading results.
- Why supplier risk alerts are ignored by buyers.
- Why contract summarization tools “hallucinate” or miss key clauses.

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- Why guided buying systems fail in the long tail of categories.

By understanding these obstacles, procurement leaders can better prepare for successful adoption.

2. Literature Review and Theoretical Framing

2.1. AI Adoption Barriers in Procurement and Supply Chains

Peer-reviewed studies highlight recurring inhibitors:

- Data quality and integration problems.
- Organizational resistance and lack of skills.
- Unclear ROI and poor alignment with procurement processes.
- Weak governance and regulatory uncertainty.

Data quality and integration problems are repeatedly identified as foundational barriers in empirical studies of AI in supply chain management. Hangl et al. (2023) find that inconsistent vendor data across systems significantly reduce AI model performance.[1] . Guida et a. (2023) explores how Artificial Intelligence (AI) can enhance the procurement process, particularly by leveraging data analysis for improved decision-making, risk anticipation, and more efficient procurement workflows. [2]. The contribution lies not in new empirical data but in synthesis, theory extension, and a practitioner roadmap. Balkan & Akyuz (2025) provide a taxonomy of AI/ML methods in procurement decision support and note the frequent challenge of limited labelled data and poor model explainability. [3]

2.2. Data Governance and Digital Transformation Theories

The AI Data Eclipse builds on:

- Data Governance Frameworks: which emphasize lineage, accuracy, and accountability .
- Digital Transformation Maturity Models: which link higher maturity stages to integrated, reliable, and real-time data flows .
- By positioning the Data Eclipse within these theories, we extend their application specifically to procurement.

3. Methodology

This paper is conceptual in nature. It synthesizes existing literature on AI adoption barriers, interprets case study evidence from analyst reports and press releases, and introduces the original framing of the AI Data Eclipse.

4. The AI Data Eclipse in Procurement

The AI Data Eclipse is the most pressing challenge in applying AI to procurement. It refers to the situation where AI systems are trained or operate on incomplete, biased, or inaccessible data. Like an eclipse blocking sunlight, these data gaps block AI from generating reliable insights. **Waditwar (2024)** demonstrates how AI-driven models that monitor supplier performance and forecast cost trends allow procurement teams to optimize Total Cost of Ownership (TCO), but that such systems depend heavily on high-quality, timely data – a core aspect of the Data Eclipse phenomenon.[5]

4.1. Causes of the Data Eclipse

- Data Fragmentation – Procurement data lives in separate silos: ERP, supplier portals, spreadsheets, and even email attachments. Without integration, AI cannot see the full picture.
- Bias and Inaccuracy – AI trained on incomplete or skewed supplier performance data may unfairly favor some vendors or categories.
- Regulatory and Privacy Barriers – Data-sharing restrictions prevent organizations from pooling information across suppliers, industries, or borders.
- Supplier Data Discrepancies – Vendors submit inconsistent ESG, compliance, and pricing data, reducing comparability.

4.2. Consequences in Procurement

- Spend Analytics: Dirty or missing data leads to incorrect cost baselines.

- Supplier Risk Sensing: Without full news and ESG coverage, risks are under-detected.
- Contract AI: Missing metadata makes clause extraction unreliable.
- Guided Buying: Long-tail purchases lack enough historical data to generate accurate recommendations.

4.3. Breaking the Eclipse

To solve the Data Eclipse, organizations need:

- Unified Data Aggregation across ERP, SRM, and market intelligence sources.
- Advanced Data Cleansing using machine learning to fix duplicates and errors.
- Blockchain-Backed Supplier Verification for authenticity and traceability.
- Dynamic Governance Engines that ensure compliance with regulations like the EU AI Act in real time.

4.4. Case Study Illustrations

- Nvidia: AI forecasting hindered by incomplete semiconductor supplier data during global chip shortages.
- Apple: JIT procurement disrupted by supply gaps and sustainability compliance challenges.
- Tesla: Raw material sourcing opaque due to limited traceability of lithium/cobalt supply chains.
- Meta: VR hardware procurement faced delays due to inconsistent supplier performance data.
- Google: Cloud procurement challenged by compliance requirements (GDPR, AI Act) limiting AI automation.
- Amazon: AI misaligned inventory planning when real-time supplier feeds were incomplete.
- (*Case evidence drawn from company reports, supply chain analyst coverage, and press releases.*)

5. Related Work and Background

Research in supply chains and e-procurement has identified a repeating set of barriers: poor data quality, lack of skills, unclear ROI, and weak integration with existing systems. Studies also show that people tend not to trust AI if its reasoning is not transparent.

Governments and international bodies are also setting rules for AI. The EU AI Act, the OECD AI Principles, and the new ISO/IEC 42001 AI management system standard all require organizations to show that AI systems are safe, fair, explainable, and auditable. For procurement, this means that systems recommending suppliers or awarding contracts must provide clear evidence of how they reached their decisions. Andhov & Darnall (2025) examine sustainable public procurement, highlighting that governments often lack access to rich supplier ESG data, which constrains AI's use.[6]

6. Where AI in Procurement Breaks Down

AI adoption challenges can be seen clearly across core procurement use-cases.

Table 1 summarizes the relationship between use-cases and the most common obstacles.

Table 1 Procurement Use-Cases and Their Main Obstacles

Procurement Use-Case	Main Obstacles	Example Case	Severity Impact
Spend Intelligence	Data Quality Issues (duplicate suppliers, inconsistent taxonomies)	Apple	High
Supplier Risk Sensing	Sparse/multilingual data, lack of explainability	Nvidia	High
Contract Analytics	Clause variability, OCR errors, hallucinations in LLM's	Google	Medium
Guided Buying / P2P	Thin historical data, frequent exceptions in invoices	Amazon	Medium

6.1. Spend Intelligence

AI tools often fail to provide reliable spend insights because supplier names are spelled differently across systems, cost centers use different codes, and taxonomies are inconsistent. Forecasting models then suffer from "garbage in, garbage out."

6.2. Supplier Risk Sensing

AI promises to track supplier risks by scanning news, ESG reports, and financial filings. But in practice, the data is sparse, noisy, and multilingual. Buyers demand explainability—"Why was this supplier flagged as high-risk?"—and AI tools often can't provide the evidence clearly.

6.3. Contract Analytics

Contract AI struggles with scanned PDFs, variations in clause language, and jurisdiction-specific rules. Large language models can summarize contracts, but they sometimes hallucinate (make things up) or miss important details. Without reliable citations, legal teams don't trust them.

6.4. Guided Buying and Invoice Automation

AI works well in standardized, high-volume categories (e.g., IT equipment) but struggles with "long-tail" spend where there is little historical data. Exceptions in three-way matching (PO, invoice, goods receipt) still need human intervention, limiting automation.

7. The Six Main Obstacles

The barriers to AI adoption can be grouped into six categories, shown visually in Figure 1.

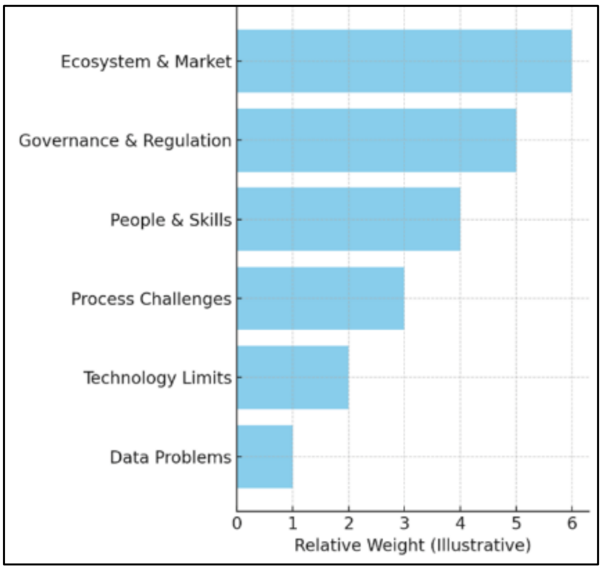

Figure 1 Six Obstacles to AI Adoption in Procurement

7.1. Data Problems

- Supplier master data is messy, with duplicates and missing IDs.
- Contract data lives in scattered systems (ERP, SharePoint, email).
- Labels for training models (e.g., "good supplier performance") are rare.

7.2. Technology Limits

- Black-box models are powerful but not explainable.
- Models break when market conditions change (e.g., COVID supply shocks).
- OCR and document AI still misread complex contracts.

7.3. Process Challenges

- Pilots sit outside real procurement workflows.
- Lack of MLOps pipelines for deploying and monitoring models.
- Overdependence on single vendors locks organizations into rigid solutions.

7.4. People and Skills

- Buyers lack data literacy, and data scientists lack category knowledge.
- Employees fear losing jobs to automation.
- Change management is often overlooked.

7.5. Governance and Regulation

- Uncertainty about whether procurement AI is "high-risk" under the EU AI Act.
- Lack of audit-ready documentation (model cards, data sheets).
- Public trust issues: citizens expect procurement to be transparent.

7.6. Ecosystem and Market

- Supplier digital maturity varies widely, especially in emerging markets.
- No common standards for ESG and supplier data exchange.
- Risk of widening the gap between "AI-ready" and "AI-poor" suppliers.

8. A Roadmap: From Pilot to Platform

To help organizations move beyond pilots, we propose a POC-to-Platform Adoption Framework. It lays out six stages (see Figure 2) that cover readiness checks, data preparation, explainable models, human-in-the-loop design, productionization, and continuous learning.

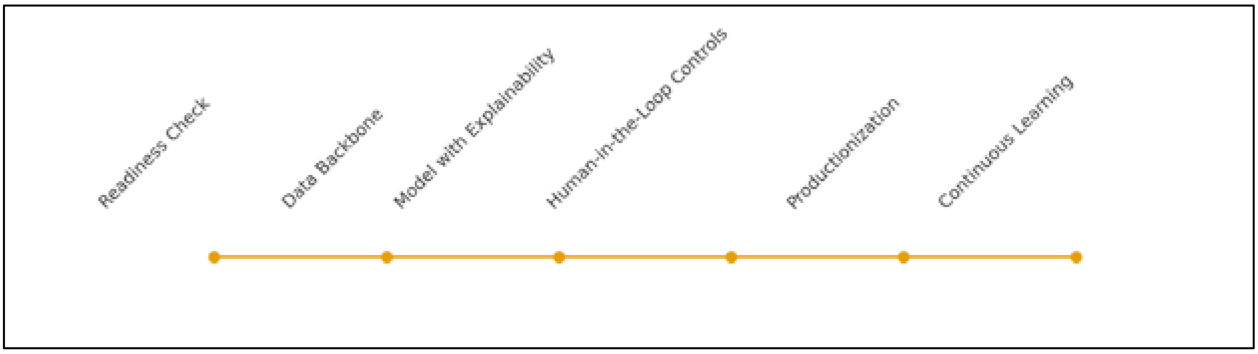

Figure 2 POC-to-Platform Adoption Roadmap

This roadmap provides procurement teams with a practical way to scale AI while staying compliant with upcoming regulations such as the EU AI Act.

- Readiness Check – Classify the AI use-case by risk level. Decide where humans must stay in the loop.
- Data Backbone – Build a clean supplier and contract master with unique IDs and data-quality rules.
- Model with Explainability – Require an "explainability bill of materials": model card, data sheet, bias tests, and challenge sets.
- Human-in-the-Loop Controls – Define when AI makes suggestions vs. when buyers must approve.
- Productionization – Integrate models into CLM, ERP, and P2P workflows with monitoring for drift.
- Continuous Learning – Collect feedback, retrain, and share transparency reports (especially for public procurement).

Recent work by Waditwar (2025) shows that applying NLP, anomaly detection, and predictive analytics within government contracts helps identify compliance and risk factors more effectively than manual review, underlining both the promise and limitations of current contract AI tools. [4]

9. The Data Eclipse in Action

9.1. Nvidia – Semiconductor Supply Chains

- *Current Strategy:* Nvidia relies heavily on AI-driven demand forecasting and supplier collaboration.
- *The Eclipse:* Chip shortages and geopolitical export restrictions create blind spots in supplier capacity and delivery schedules. AI systems mis-predict demand when upstream supplier data is incomplete.
- *Solution:* Blockchain-backed supplier verification and predictive analytics could provide greater transparency across multi-tier suppliers.

9.2. Apple – Just-in-Time Global Procurement

- *Current Strategy:* Apple depends on tightly coordinated Asian suppliers with a just-in-time (JIT) model.
- *The Eclipse:* Any missing data on logistics bottlenecks or sustainability compliance leads to disruptions, as seen during the pandemic. AI cannot optimize procurement without reliable upstream data.
- *Solution:* AI-driven sustainability tracking and real-time alerts could reduce over-dependence on single suppliers.

9.3. Tesla – Battery and Raw Material Sourcing

- *Current Strategy:* Tesla uses vertical integration for EV batteries, with localized supplier networks.
- *The Eclipse:* Gaps in raw material traceability (e.g., lithium, cobalt) create procurement risks. AI forecasting falters without authentic supplier data on material origins.
- *Solution:* Blockchain-verified raw material procurement and AI demand analytics could ensure better visibility and ethical sourcing.

9.4. Meta – Hardware Supply Chain for VR/AR

- *Current Strategy:* Meta procures hardware components for its Oculus/Quest devices using AI-based supply tracking.
- *The Eclipse:* Supplier inconsistency and lack of performance data reduce reliability of AI-led supplier scoring.
- *Solution:* AI-powered supplier performance benchmarking combined with negotiation automation could improve results.

9.5. Google – Cloud Procurement and Compliance

- *Current Strategy:* Google Cloud uses AI for vendor management and automated procurement approvals.
- *The Eclipse:* Security and regulatory compliance gaps prevent AI from having full access to supplier risk data. This makes it harder to assess compliance in real-time.
- *Solution:* A dynamic AI compliance engine could continuously monitor evolving regulations (e.g., GDPR, EU AI Act) and adapt procurement workflows.

9.6. Amazon – Real-Time Global Retail Procurement

- *Current Strategy:* Amazon runs one of the world's most automated procurement systems, combining robotics and AI.
- *The Eclipse:* At massive scale, even small gaps in supplier data or late updates can throw off AI-driven demand-supply synchronization.
- *Solution:* AI-powered real-time supply-demand balancing, supported by unified supplier data, ensures inventory efficiency.

10. Conclusion

Artificial Intelligence will not transform procurement overnight. The journey from experimentation to enterprise-wide adoption is complex, requiring not only technical innovation but also organizational readiness and governance maturity. The AI Data Eclipse—the condition where incomplete, inconsistent, or inaccessible procurement data blinds AI systems—remains the most fundamental barrier. Overcoming this challenge is less about building "smarter" models and more about creating the right foundation of clean, reliable, and trustworthy data pipelines.

To move forward, companies must recognize that AI in procurement is as much a data problem and a governance problem as it is a technological one. Without integration across ERP, SRM, and external market intelligence sources, AI models will continue to deliver partial or biased insights. Without strong governance frameworks, such as those mandated by the EU AI Act and ISO/IEC 42001, organizations risk non-compliance, ethical lapses, and erosion of stakeholder trust. And without meaningful human-AI collaboration, procurement professionals may resist adoption or misuse automated outputs.

The way forward is a staged, systemic approach. Firms should first establish golden supplier and contract master data repositories, then embed explainability mechanisms (model cards, data sheets, bias audits), and finally integrate AI into procurement workflows with human oversight and continuous monitoring. Those that succeed will not only achieve cost savings and efficiency gains but will also position procurement as a driver of transparency, resilience, and sustainability in global supply chains.

10.1. Managerial Implications

For practitioners, this study highlights that:

- Investments in data governance yield greater long-term returns than isolated AI pilots.
- Building cross-functional teams (procurement + data science + legal/compliance) is critical for adoption.
- Trust and explainability must be prioritized to ensure stakeholder buy-in, especially in regulated environments.
- The AI Data Eclipse is not inevitable—it can be addressed through deliberate strategies in integration, governance, and ecosystem collaboration.

10.2. Future Research Directions

Measuring Data Quality Impact: Develop metrics and empirical studies that quantify how errors in supplier master data propagate through AI models, affecting sourcing outcomes, supplier scoring, and cost baselines.

Benchmarking Explainability: Establish benchmarks and industry standards that define what counts as “sufficiently explainable” AI in sourcing, contract management, and public procurement decisions.

Cross-Company Data Collaboratives: Explore legal, technical, and governance mechanisms (e.g., federated learning, blockchain) that allow companies to share procurement intelligence without breaching competition laws or privacy regulations.

Socio-Technical Trust Models: Examine how buyer perceptions of transparency, fairness, and accountability influence adoption. Future work should integrate insights from behavioral science and organizational psychology into procurement AI design.

AI for Ethical Procurement: Investigate how AI can support ESG compliance, supplier diversity, and sustainability objectives while minimizing risks of bias and exclusion.

Public Sector Applications: Expand research on AI in government procurement, where the need for transparency, auditability, and ethical safeguards is even greater than in the private sector.

By pursuing these avenues, both researchers and practitioners can advance toward an AI-powered procurement ecosystem that is transparent, reliable, scalable, and socially responsible. Overcoming the AI Data Eclipse is not merely a technical task—it is an organizational transformation that will determine how procurement contributes to competitiveness, resilience, and ethical value creation in the digital age.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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