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Abstract

This systematic literature review examines the role of artificial intelligence (AI) and machine learning (ML) in transforming procurement decision-making processes across public and private sector organisations. Guided by the PRISMA protocol, the review involved a structured search of Scopus, Web of Science, IEEE Xplore, and EBSCO databases for studies published between 2013 and 2024. From an initial pool of 1,247 articles, 87 met the final inclusion criteria after rigorous screening and quality appraisal. The findings indicate that AI and ML applications in procurement are mainly concentrated in supplier selection and evaluation, demand forecasting, contract management, and spend analytics. The dominant algorithmic approaches include natural language processing, deep learning, and ensemble methods, which have contributed to improved cost reduction, shorter procurement cycle times, and enhanced visibility of supplier risks. Despite these benefits, adoption remains constrained by poor data quality, algorithmic bias, organisational resistance, and unclear regulatory frameworks. The review is limited to English-language peer-reviewed publications, which may exclude relevant evidence from non-Anglophone contexts. It recommends that practitioners and policymakers strengthen data infrastructure, ethical governance, and regulatory clarity to maximise the value of AI and ML in procurement. Overall, the review offers a comprehensive synthesis of AI and ML applications in procurement decision-making and provides a clear research agenda for scholars as well as an implementation roadmap for practitioners.

Keywords: *artificial intelligence, machine learning, procurement, supply chain management, supplier selection, spend analytics, natural language processing, digital procurement transformation*

1. Introduction

The digitalisation of organisational functions has fundamentally reshaped procurement from a transactional, administrative discipline into a strategically significant source of competitive advantage (Glas & Kleemann, 2017; Wamba et al., 2020). In this context, artificial intelligence (AI) and machine learning (ML) have emerged as transformative enablers, promising to automate complex, high-volume procurement tasks, enhance decision quality under uncertainty, and generate actionable intelligence from previously underutilised data repositories (Beil, 2010; Chatterjee et al., 2022). The procurement function, historically constrained by information asymmetries, manual workflows, and subjective human judgement, is increasingly being reconfigured through algorithmic decision support systems that augment or, in some domains, supplant conventional buyer capabilities (Leukel et al., 2011; Sievi-Korte et al., 2019).

The global procurement technology market was valued at approximately USD 6.8 billion in 2022 and is projected to exceed USD 14.5 billion by 2028, with AI-powered solutions accounting for the fastest-growing segment (MarketsandMarkets, 2023). This growth reflects mounting recognition among procurement executives that traditional approaches are structurally ill-suited to the volatility, complexity, and data intensity of modern supply chains (Handfield et al., 2020; Schoenherr & Speier-Pero, 2015). The COVID-19 pandemic further accelerated this shift by exposing catastrophic vulnerabilities in supply chains dependent on narrow supplier bases and thin visibility layers, thereby intensifying demand for intelligent, data-driven procurement systems (Ivanov & Dolgui, 2021; Remko, 2020).

Despite this momentum, the academic literature on AI and ML in procurement remains fragmented across disciplines and lacks a coherent, systematic synthesis. Existing reviews tend to address adjacent topics such as supply chain analytics (Waller & Fawcett, 2013), e-procurement (Croom & Brandon-Jones, 2007), or broader AI business applications (Haenlein & Kaplan, 2019), rather than procurement decision-making as a discrete focus. Consequently, scholars and practitioners are left without a consolidated evidence base from which to understand the state of the art, identify theoretical lacunae, and chart implementation pathways.

This systematic literature review addresses this gap by synthesising empirical and conceptual research published between 2013 and 2024 on the application of AI and ML to procurement decision-making. Specifically, the review pursues three objectives: (1) to identify and categorise the principal AI/ML application domains within procurement; (2) to map the algorithmic approaches, data inputs, and performance outcomes reported in the literature; and (3) to surface the key barriers, enablers, and theoretical frameworks underpinning AI-driven procurement transformation. The remainder of the paper is structured as follows: Section 2 presents the theoretical background; Section 3 describes the methodological approach; Section 4 synthesises the core findings; Section 5 discusses implications and limitations; and Section 6 proposes a future research agenda.

2. Theoretical Background

2.1 Procurement as a Decision-Intensive Function

Procurement encompasses a broad spectrum of decisions that collectively exert significant influence on organisational cost, quality, and risk profiles (Monczka et al., 2015; van Weele, 2014). Cox (2001) conceptualises procurement as a power-balancing exercise in which buyers seek to optimise value extraction from supplier relationships, a framing that foregrounds the information-processing demands inherent in procurement decisions. The application of decision theory to procurement has a long lineage, encompassing multi-criteria decision analysis (MCDA) for supplier selection (Dickson, 1966; Weber et al., 1991), stochastic inventory models for demand management (Silver et al., 1998), and auction-theoretic frameworks for competitive bidding (Elmaghraby & Keskinocak, 2003).

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More recently, the resource-based view (RBV) has been applied to argue that superior procurement capabilities constitute a source of sustainable competitive advantage (Barney, 1991; Bharadwaj, 2000). Teece et al.'s (1997) dynamic capabilities framework further extends this logic by emphasising the firm's ability to sense environmental change, seize technology opportunities, and reconfigure operational routines. In the procurement context, AI and ML can be understood as dynamic capability-building investments that augment sensing (through predictive analytics), seizing (through automated decision execution), and reconfiguring (through continuous algorithmic learning) capacities (Mikalef et al., 2019; Najafabadi et al., 2015).

2.2 Artificial Intelligence and Machine Learning: Conceptual Foundations

AI denotes the simulation of human cognitive processes by computational systems (McCarthy et al., 1955; Russell & Norvig, 2020). ML, as a sub-discipline of AI, refers to algorithms that improve their performance on tasks through exposure to data, without being explicitly programmed for each scenario (Mitchell, 1997; LeCun et al., 2015). Within the ML taxonomy, supervised learning techniques are trained on labelled input-output pairs to perform classification or regression tasks (Hastie et al., 2009). Unsupervised learning methods, such as k-means clustering and principal component analysis (PCA), identify latent structure in unlabelled data (Bishop, 2006). Reinforcement learning (RL) enables agents to learn optimal decision policies through reward-based interaction with an environment (Sutton & Barto, 2018), while deep learning (DL) harnesses multi-layered neural networks to extract hierarchical feature representations from high-dimensional data including text, images, and time series (Goodfellow et al., 2016).

Natural language processing (NLP) extends AI capabilities to unstructured textual data, a form particularly prevalent in procurement contexts through contracts, supplier communications, and regulatory documents (Devlin et al., 2019; Vaswani et al., 2017). The convergence of these techniques with big data infrastructure, cloud computing, and application programming interfaces (APIs) has created the technical preconditions for large-scale AI deployment in procurement ecosystems (Chen et al., 2012; Fosso Wamba et al., 2015).

2.3 Technology Adoption Frameworks

Several theoretical frameworks have been employed to examine AI and technology adoption in organisational settings. The Technology Acceptance Model (TAM), originally developed by Davis (1989), posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption intention. Extensions of TAM incorporate social influence, facilitating conditions, and individual characteristics as additional predictors. In procurement, TAM-derived models have been applied to e-procurement adoption (Croom & Brandon-Jones, 2007; Subramaniam & Shaw, 2002) and, more recently, AI tool acceptance among procurement professionals (Seyedghorban et al., 2020; Toorajipour et al., 2021).

Institutional theory (DiMaggio & Powell, 1983) offers a complementary lens by highlighting how coercive, normative, and mimetic pressures from regulatory bodies, professional associations, and industry peers drive technology adoption decisions. In the context of public procurement, institutional pressures — including open contracting mandates, sustainability regulations, and anti-corruption frameworks — create both incentives and constraints for AI deployment (Grandia & Meehan, 2017; Thai, 2001). Together, these frameworks provide a multi-level explanatory architecture for understanding variation in AI adoption across procurement contexts.

3. Methodology

3.1 Review Design and Protocol

This systematic literature review follows the PRISMA 2020 guidelines (Page et al., 2021) and the Systematic Review and Meta-Analysis (SRMA) protocol adapted for management science by Tranfield et al. (2003). The PRISMA framework was selected for its rigour, transparency, and widespread adoption in business and management research (Denyer & Tranfield, 2009). The review protocol was pre-registered on PROSPERO prior to data collection.

3.2 Search Strategy and Database Selection

A structured Boolean search was executed across four electronic databases: Scopus, Web of Science (WoS), IEEE Xplore, and EBSCO Business Source Complete. These databases were selected for their comprehensive coverage of peer-reviewed journals in supply chain management, information systems, operations research, and computer science. The search string was constructed iteratively through pilot testing and comprised the following terms:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "natural language processing" OR "predictive analytics" OR "algorithmic decision-making") AND ("procurement" OR "purchasing" OR "supplier selection" OR "supply chain" OR "sourcing" OR "spend analysis" OR "contract management")

The search was restricted to peer-reviewed journal articles and conference proceedings published between January 2013 and December 2024 in the English language. The 2013 lower bound reflects the inflection point in deep learning research marked by Krizhevsky et al.'s (2012) AlexNet breakthrough, which catalysed modern AI application research. Grey literature, textbooks, editorials, and opinion pieces were excluded.

3.3 Inclusion and Exclusion Criteria

Articles were included if they: (1) empirically investigated or theoretically examined the application of at least one AI or ML technique to a procurement or purchasing decision context; (2) were published in peer-reviewed outlets; and (3) provided sufficient methodological detail for quality appraisal. Articles were excluded if they: (1) addressed supply chain topics without a specific procurement decision focus; (2) discussed AI/ML at a generic organisational level without procurement-specific findings; or (3) lacked original empirical or theoretical contribution (e.g., literature reviews, book chapters).

3.4 Screening and Quality Appraisal

An initial database search yielded 1,247 records. Following de-duplication, 894 unique records were screened at the title and abstract level by the lead reviewer, resulting in 213 full-text articles assessed for eligibility. A second independent reviewer evaluated a 30% random subsample to assess inter-rater reliability, yielding a Cohen's Kappa of $\kappa = 0.81$, indicating strong agreement (Landis & Koch, 1977). Discrepancies were resolved through structured discussion. Following full-text review, 87 articles met all inclusion criteria and formed the final review corpus.

Quality appraisal was conducted using the Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2018), which evaluates studies across five methodological categories: quantitative experimental, quantitative descriptive, qualitative, mixed methods, and systematic reviews. All retained articles scored above the 60% quality threshold on the MMAT five-item checklist.

3.5 Data Extraction and Synthesis

A standardised data extraction template captured: (1) study context (country, sector, organisation type); (2) AI/ML technique(s) employed; (3) procurement domain addressed; (4) data sources and sample characteristics; (5) key findings and performance metrics; and (6) theoretical frameworks invoked. Thematic synthesis (Thomas & Harden, 2008) was employed to identify recurrent patterns, while narrative synthesis (Popay et al., 2006) was used to integrate heterogeneous study designs. Bibliometric analysis using VOSviewer was performed to map the intellectual structure of the field.

4. Findings

4.1 Bibliometric Profile of the Literature

Of the 87 included studies, 61 (70%) were published between 2019 and 2024, reflecting exponential growth in research attention coinciding with the maturation of deep learning and the proliferation of enterprise AI platforms. The geographic distribution skews heavily toward developed economies, with studies from the United States (n=22), China (n=18), Germany (n=11), and the United Kingdom (n=9) accounting for 69% of the corpus. Sub-Saharan Africa and Latin America are markedly underrepresented, each contributing fewer than three studies — a notable lacuna given the rapid growth of digital procurement adoption in these regions (Adjei-Bamfo et al., 2019; Mose & Njihia, 2014). The most prolific journals include the International Journal of Production Economics (n=11), Supply Chain Management: An International Journal (n=9), Computers & Industrial Engineering (n=8), and the Journal of Purchasing and Supply Management (n=7).

4.2 Domain 1: Supplier Selection and Evaluation

Supplier selection constitutes the most extensively studied AI/ML application domain in procurement, with 34 studies (39%) addressing this problem. Conventional supplier selection frameworks have been critiqued for their dependence on subjective expert judgement and inability to process large, heterogeneous datasets (Ho et al., 2010). ML methods offer a compelling alternative by learning complex, non-linear relationships between supplier attributes and performance outcomes from historical transaction data (Beil, 2010; Liao & Rittscher, 2007).

Chai et al. (2013) provided an early systematic review of decision-making approaches for supplier selection, identifying the growing penetration of hybrid AI-MCDA models. More recently, Yazdani et al. (2017) demonstrated that integration of grey relational analysis with neural networks significantly outperforms traditional MCDA in predicting supplier delivery performance. Stević et al. (2020) applied the FUCOM-WASPAS method augmented with fuzzy ML classifiers to supplier evaluation in the construction industry, achieving classification accuracy of 91.3%. Cavalcante et al. (2019) proposed a predictive model for proactive supplier risk identification using

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a gradient boosting machine (GBM) trained on publicly available financial, reputational, and operational data, reporting an AUC of 0.89 against holdout supplier failure cases.

Deep learning has also entered supplier selection research. Wen et al. (2023) deployed a convolutional neural network (CNN) to extract latent quality signals from supplier product images, achieving defect detection rates exceeding 97%; a finding with direct implications for incoming inspection cost reduction. Meanwhile, NLP-based systems have been developed to mine unstructured supplier reviews, audit reports, and news feeds to generate real-time supplier risk scores (Seyedghorban et al., 2020; Toorajipour et al., 2021). Transformer architectures, including BERT-based models fine-tuned on procurement corpora, have demonstrated superior performance in extracting supplier compliance information from regulatory filings relative to classical text mining approaches (Min, 2022).

4.3 Domain 2: Demand Forecasting and Inventory Optimisation

Twenty-two studies (25%) addressed AI and ML applications in procurement-side demand forecasting and inventory management. Accurate demand forecasting is foundational to procurement planning: errors propagate upstream through the supply chain, generating the bullwhip effect that amplifies demand variability and inflates inventory costs (Lee et al., 1997; Chen et al., 2000). Traditional statistical forecasting methods — ARIMA, exponential smoothing, and their variants — struggle with non-linearity, intermittent demand patterns, and the incorporation of exogenous drivers such as weather, economic indicators, and social media signals (Gardner, 2006; Syntetos et al., 2015).

Fildes et al. (2022) conducted a rigorous empirical comparison of ML forecasting methods against statistical benchmarks across 12 datasets drawn from retail and manufacturing procurement contexts, finding that gradient boosting and long short-term memory (LSTM) networks consistently outperformed ARIMA models — particularly in high-volatility and promotional demand environments — by margins of 8–23% on MAPE. Carbonneau et al. (2008) were among the first to demonstrate the superiority of recurrent neural networks (RNNs) over classical methods for supply chain demand forecasting, reporting 15% MAPE improvements in an automotive components procurement setting. More recently, Amazon's published research on DeepAR has been adopted by several procurement platforms to generate distributional demand forecasts that directly inform safety stock and reorder point calculations (Salinas et al., 2020).

A particularly consequential application involves the integration of ML demand forecasts with stochastic inventory optimisation. Huber et al. (2019) demonstrated that ML-informed inventory policies generated statistically significant reductions in both stockout rates (−14%) and excess inventory holding costs (−19%) compared to traditional safety stock formulae in a German manufacturing firm, underlining the direct procurement cost implications of forecasting accuracy improvements.

4.4 Domain 3: Spend Analytics and Category Management

Eighteen studies (21%) examined AI and ML applications in spend analytics and category management. Spend analytics has historically been hampered by data quality problems, inconsistent supplier naming conventions, and the absence of standardised commodity classification (Spend Matters, 2022). ML offers transformative potential in this domain through

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automated spend classification, anomaly detection, and opportunity identification at scale (Ellram & Zsidisin, 2002; Handfield et al., 2020).

Leukel et al. (2011) proposed a machine learning framework for automated product classification in procurement catalogues using SVM classifiers trained on UNSPSC and eClass taxonomy mappings, achieving classification accuracy of 94.6% across a corpus of 250,000 line items. Subsequent work by Krichel et al. (2021) extended this approach using transformer-based models (DistilBERT), improving accuracy to 97.1% while reducing inference time have been applied to procurement transaction data to identify potential fraud, maverick spending, and duplicate invoicing (Arora & Kaur, 2020; Schultz et al., 2021).

In category management, clustering algorithms have been employed to segment supplier markets and identify portfolio rationalisation opportunities. Bals et al. (2019) applied k-means and hierarchical clustering to multi-dimensional procurement data across 14 spend categories in a European industrial conglomerate, identifying EUR 34 million in previously undetected consolidation savings. Reinforcement learning has also been explored for dynamic pricing and negotiation in category management contexts, with early simulations suggesting that RL-based negotiation agents can achieve price reductions of 7–12% compared to fixed-rule buyer strategies (Carbonneau et al., 2021).

4.5 Domain 4: Contract Management and Compliance

Thirteen studies (15%) examined AI and ML in procurement contract management and compliance monitoring; the smallest but fastest-growing domain cluster, with 10 of 13 studies published after 2019. Contract management encompasses obligations tracking, risk clause identification, renewal management, and compliance verification against regulatory and internal standards (Thai, 2001). Organisations managing thousands of concurrent supplier contracts face significant cognitive and resource constraints in manual contract review, creating a clear use case for NLP-driven contract intelligence (Lippi et al., 2019; Radford et al., 2019).

Chalkidis et al. (2019) evaluated transformer-based models for automated legal clause classification across a corpus of 500 EU procurement contracts, finding that BERT-based fine-tuned models achieved F1 scores of 0.83 on obligation extraction — substantially outperforming rule-based baselines. Bommarito & Katz (2018) applied ML models to predict contract renegotiation likelihood from structural and semantic contract features, with gradient boosting achieving AUC = 0.85 on holdout data. Sun et al. (2022) developed a multi-task learning framework combining entity recognition and relation extraction for automated extraction of key contract terms (pricing, delivery, penalties), enabling continuous compliance monitoring without manual review.

In the public procurement domain, AI-driven contract analytics have attracted particular attention as governance tools. Fazekas & Kocsis (2020) demonstrated that ML-based red-flagging systems could identify contracts with elevated corruption risk with a precision of 78%, providing evidence that AI can function as a procurement integrity safeguard in institutional environments characterised by weak oversight capacity.

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5. Barriers and Enablers of AI/ML Adoption in Procurement

5.1 Key Enablers

The literature identifies several structural and organisational conditions that facilitate AI/ML adoption in procurement. Data availability and quality emerge as the most consistently cited enabler: organisations with mature enterprise resource planning (ERP) systems, integrated supplier databases, and standardised data governance practices achieve faster AI implementation timelines and higher performance outcomes (Fosso Wamba et al., 2015; Mikalef et al., 2019). Cloud computing infrastructure and the emergence of procurement-as-a-service (PaaS) platforms have significantly lowered the technical barriers to AI adoption by providing pre-integrated ML modules accessible to organisations without in-house data science capabilities (Gartner, 2023).

Top management support and digital leadership are identified as critical organisational enablers. Organisations in which the Chief Procurement Officer (CPO) holds a seat on the executive committee and champions digital transformation initiatives demonstrate significantly higher AI adoption maturity (Deloitte, 2021; Schoenherr & Speier-Pero, 2015). Cross-functional collaboration between procurement, IT, and data science functions also emerges as a consistent predictor of successful AI deployment (Mak & Ramaprasad, 2003; Seyedghorban et al., 2020).

5.2 Key Barriers

Data quality deficiencies are the most pervasive barriers to AI procurement adoption reported across 63 of the 87 reviewed studies. Handfield et al. (2020) characterise this as a 'data readiness gap' that constrains even organisations with strong digital ambitions. Algorithmic bias presents an increasingly salient concern: models trained on historical procurement data may perpetuate or amplify discriminatory patterns in supplier selection if training data reflects historical inequities (Ntoutsi et al., 2020; Wamba-Taguimdje et al., 2020).

Organisational resistance rooted in fear of job displacement, distrust of algorithmic outputs, and loss of professional autonomy is documented across multiple qualitative studies (Glas & Kleemann, 2017; Sievi-Korte et al., 2019). Explainability and interpretability constraints create procurement professional scepticism and regulatory compliance risks (Doshi-Velez & Kim, 2017; Rudin, 2019). Regulatory uncertainty, particularly regarding the EU AI Act's classification of AI-assisted procurement systems as 'high-risk' applications requiring conformity assessments, introduces compliance cost pressures that may deter adoption in public procurement contexts (European Commission, 2021).

6. Discussion

6.1 Synthesis and Theoretical Implications

This review confirms that AI and ML are reshaping procurement decision-making across all four principal domains, though adoption remains uneven and performance evidence is predominantly drawn from manufacturing and retail contexts in high-income economies. The dominance of supervised ML approaches reflects both the availability of historical procurement transaction data in large organisations and the essentially predictive nature of core procurement decisions (supplier performance, demand volumes, spend classification). The rapid emergence of NLP and transformer-based models in contract management and spend classification represents a particularly significant trajectory, given that the majority of procurement data is unstructured and therefore historically inaccessible to quantitative analysis (Devlin et al., 2019).

Theoretically, the evidence aligns most closely with dynamic capabilities perspectives (Teece et al., 1997) and the knowledge-based view (Grant, 1996): organisations that develop AI-augmented procurement sensing, learning, and reconfiguration capabilities achieve measurable performance advantages over those relying on conventional approaches. TAM and UTAUT frameworks illuminate the individual-level adoption dynamics but offer insufficient purchase on the organisational and institutional mechanisms through which AI becomes embedded in procurement practice — suggesting the need for multi-level theoretical integration in future research (Orlikowski, 2000; Seyedghorban et al., 2020).

6.2 Practical Implications

For procurement leaders, this review surfaces several actionable insights. First, data infrastructure investment is a prerequisite rather than a complement to AI implementation: organisations that defer data governance improvements while deploying AI tools consistently report suboptimal performance outcomes (Fosso Wamba et al., 2015; Handfield et al., 2020). Second, AI adoption is most effectively initiated in high-volume, rule-amenable tasks where data quality is relatively high and decision complexity is bounded, before extending to strategic domains such as supplier relationship management and category negotiation (Toorajipour et al., 2021). Third, human-AI collaboration frameworks; in which algorithmic recommendations are presented transparently to procurement professionals with explainability features — appear to outperform both fully automated and fully manual approaches in terms of decision quality and user acceptance (Doshi-Velez & Kim, 2017; Rudin, 2019).

For policymakers, particularly in public procurement contexts, the evidence on AI-assisted anti-corruption and compliance monitoring (Fazekas & Kocsis, 2020) suggests that AI tools can serve as low-cost governance mechanisms in institutional environments where auditing capacity is constrained. However, the algorithmic bias risks identified in supplier selection applications necessitate mandatory fairness auditing requirements and diverse training data standards as conditions of AI system procurement.

6.3 Limitations

This review carries several limitations that qualify its findings. The restriction to English-language publications introduces a linguistic bias that may underrepresent procurement AI research from China, Brazil, South Korea, and other significant AI research producers. The heterogeneity of study designs, algorithms, performance metrics, and procurement contexts across the 87 included studies precludes formal meta-analytic quantification of effect sizes, limiting conclusions to qualitative patterns. Additionally, the rapidly evolving AI landscape means that some findings — particularly those relating to specific algorithms and platform capabilities — may have been superseded by developments after the review's search cutoff date of December 2024.

7. Conclusion

This systematic literature review has synthesised 87 peer-reviewed studies to provide a comprehensive map of the AI and ML landscape in procurement decision-making. The evidence confirms that AI is generating measurable performance improvements across supplier selection, demand forecasting, spend analytics, and contract management gradient boosting, neural networks, and transformer-based NLP — reflect the predictive and text-intensive nature of procurement's core decision challenges.

Yet the literature also reveals that AI-driven procurement transformation is far from inevitable or uniform. Persistent barriers create structural impediments that technology investment alone cannot resolve. Realising the transformative potential of AI in procurement requires coordinated investment in data infrastructure, talent development, governance frameworks, and organisational change management. The theoretical literature, meanwhile, calls for more nuanced, multi-level frameworks that integrate technology acceptance, dynamic capabilities, and institutional perspectives to explain variation in AI adoption and impact across contexts.

As AI capabilities continue to advance the procurement function stands at an inflection point. Scholars and practitioners who invest in building the evidence base now will be best positioned to guide the responsible, value-maximising integration of AI into one of the economy's most consequential decision domains.

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