

RESEARCH ARTICLE

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Artificial Intelligence in Procurement and Supply Chain Management: A Systematic Literature Review of Performance Outcomes and Operational Efficiency

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ABSTRACT

Purpose. Artificial intelligence (AI) is taking procurement and supply chain management (SCM) from transaction automation to a more strategic and decision-driven approach. The research evidence concerning benefits of such a change in efficiency and organizational performance is still inconclusive, both within and beyond industry, across methods and regions. In this review, we'll compile that evidence and outline the circumstances when AI-powered procurement can add real value.

Design/methodology/approach. The systematic literature review (SLR) was carried out according to the PRISMA 2020 statement. A corpus of 19 studies published during the period 2022–2026 was screened, appraised for quality through an adapted version of Mixed Methods Appraisal Tool (MMAT), and coded descriptively and synthesized thematically. The corpus comprises of econometric panel analysis, structural equation modelling (SEM), fuzzy-set qualitative comparative analysis (fsQCA), Bayesian best-worst multi-criteria decision-making (BBWMCDM), qualitative interviews, case evidence and formal modelling as well as prior reviews.

Findings. The benefits AI delivers are most consistent when applied to process efficiencies: faster invoice and sourcing cycles, improved demand forecasting, reduced stock-out and quicker supplier evaluation. It does actually make a difference to performance, but it depends. When AI is integrated with the strategy, through restructured structures and internal controls, and complemented by human capability, firm-level and resilience gains seem to emerge. Its evidence for better firm performance and operational performance in the supply chain comes from large sample—AI is responsible for better organizational performance and resilience [1] and better firm performance without direct impact on operational performance [2]. In Agentic AI, routines for resource-orchestration are the only means to improve circular procurement performance. The impact of supply chain practices on employee performance and satisfaction is magnified by human-centred AI [4].

Originality/value. The review incorporates a resource-based view, dynamic capability, strategic alignment and socio-technical view and leverages these views to create a capability-conversion framework comprising five propositions. It separates efficiency effects from performance effects, identifies issues in the literature with respect to the quality of the evidence, and establishes research agendas on causal identification, agentic AI and sustainability and developing-economy context.

INTRODUCTION

Procurement has moved beyond a clerical role to become strategic. Procurement contributes approximately 50-60% to the cost of a construction project [5] and now influences the outcomes of cost, resilience, compliance and sustainability on energy, manufacturing, retail, logistic and public projects [6, 7]. Commodity volatility, geopolitical fragmentation, and the disruption caused by the pandemic have also created the limitations of manual, siloed sourcing, at the same time. Concurrently, commodity volatility, geopolitical fragmentation and disruption caused by the pandemic have exposed the limitations of manual and siloed sourcing [1] [8].

AI is the technology most frequently touted to remedy this. Spend analysis, sourcing events, contract analytics, supplier risk, inventory and logistics [9] and [10] are examples of areas where machine learning (ML), natural language processing (NLP), robotic process automation (RPA), predictive analytics have been used, and more recently, generative and agentic AI. The impact claimed by practitioners and academics is significant: errors in forecasting are reduced by up to 50%, cycle times cut by 50% and costs on procurement reduced by 10–25% [11]–[13].

However, there is an inconsistent evidence base. Previous reviews have focused on the mapping of technologies and use cases [9, 14] but seldom looked at distinguishing process efficiency from organizational performance, or at what mechanisms or mechanisms of change are responsible for turning one into the other. However, large-scale studies have yielded mixed results: AI and ML affect firm performance, but not directly the operational performance [2]; agentic AI affects circular procurement directly only when orchestrated in routines [3]. There are several widely published studies, however, that provide consistent improvement rates without much detail regarding the methodology. Thus a critical synthesis is opportune.

This review addresses four research questions (RQs):

RQ1. Which AI applications are being deployed across the procurement and supply chain process, and in which sectors and contexts?

RQ2. What evidence exists that AI improves procurement and supply chain efficiency?

RQ3. What evidence exists that AI improves organizational performance, including firm, operational, resilience, sustainability and employee outcomes, and through which mechanisms?

RQ4. Which enablers, barriers and boundary conditions determine whether AI investments translate into performance?

The review has three contributions. It first distinguishes between efficiency effects and performance effects, and demonstrates that performance effects rely on organizational conversion mechanisms. Second, it combines the elements of resource-based theory, dynamic capability, strategic-alignment and socio-technical theory into a unified capability-conversion model that includes testable propositions. Third, it explicitly evaluates the quality of the evidence and provides information to researchers and managers on where claims are supported by evidence and where they are likely to be beyond evidence.

CONCEPTUAL AND THEORETICAL BACKGROUND

DEFINING AI-ENABLED PROCUREMENT AND SUPPLY CHAIN TRANSFORMATION

AI-powered procurement encompasses the use of learning, reasoning and language technologies to automate, augment or autonomously make source-to-pay and supply chain decisions. The reviewed studies all seem to point to a multi-layered perspective. Process efficiency is improved with operational applications like RPA, automated RFx and invoice matching. Long-term value through strategic applications like contract analytics, supplier risk management and price optimization are shaped by contract analytics [7]. A third, emerging layer is Agentic AI, which is defined as systems that sense, decide and act on the procurement process with little to no human input [3],[5]. Transformation is different from adoption. Adoption is the implementation of a tool.

Transformations involve changes in structures, controls, roles and routines beyond it [1], [15]. This is an important distinction to understand in the review, as the corpus is used repeatedly to confirm that the efficiency gain is due to adoption, and the performance gain due to transformation.

EFFICIENCY VERSUS ORGANIZATIONAL PERFORMANCE

In this review, the outcomes of the processes, cycle time, transaction cost, error rate, forecast accuracy, inventory levels and throughput, are considered as efficiency. Organizational performance refers to higher order outcomes, such as firm financial performance, firm market performance, operational performance, supply chain resilience, circular or sustainability performance and employee performance and satisfaction. Separating the two enables the synthesis to assess if efficiency benefits are realized at the organizational level.

THEORETICAL LENSES IN THE CORPUS

Five theories recur, and each explains a different part of the value chain:

- Resource-based view (RBV). AI creates sustained advantage only when bundled with complementary human and organizational resources that are valuable, rare and hard to imitate [4], [16].
- Dynamic capabilities view (DCV). AI matters as a means to sense, seize and reconfigure under volatility, which explains why its effect appears in firm-level adaptability rather than routine operations [2], [5], [17].
- Resource orchestration theory. Value arises from how managers structure, bundle and leverage resources, so AI's effect runs through scanning, integration and collaboration routines [3], [18].
- Strategic Alignment Model (SAM). Performance depends on the fit between AI capability, strategy, structure and environment; a multiplicative specification implies that weakness in any one element suppresses the whole [7], [19].
- Socio-technical systems (STS) and technology acceptance. AI should augment rather than replace human judgement; perceived usefulness, trust, autonomy and feedback shape whether employees use it well [4], [15], [20].

In addition, the theory of Technology empowerment and organizational change theory provide another understanding of how AI changes hierarchy and control [1] and Industry 5.0 and Construction 5.0 framings further give explicit design considerations to human-centricity and sustainability [5, 8]. The lenses in Section 6 can be used together in the framework.

METHODOLOGY

The review is conducted according to the PRISMA 2020 statement [21] and the evidence-based SLR protocol of Tranfield et al. [22] which includes the following phases: planning, identification, screening, eligibility, quality appraisal, extraction and synthesis. Reports of each stage are provided to audit and extend the process.

REVIEW PROTOCOL AND CORPUS IDENTIFICATION

The review has been developed using a purpose-built core set of 19 records covering AI in procurement and supply chain management published 2022-2026. The corpus is intentionally composed of peer-reviewed empirical research, previous systematic reviews, conference papers and preprints. This blend enables the review to balance high identification evidence with the practitioner literature that carries with it practitioner expectations. For the sake of replication and extension in Scopus and Web of Science, the following search string is used to represent the scope of the corpus:

ELIGIBILITY CRITERIA

Criterion	Inclusion	Exclusion
Topic	AI or AI-dominant digital technology applied to procurement, purchasing, sourcing, inventory or supply chain operations	Generic digitalization with no AI component; AI in unrelated functions
Outcome	Reports or theorizes efficiency, operational, firm, resilience, sustainability or employee outcomes	Purely technical algorithm benchmarking with no organizational outcome
Period	2022–2026	Before 2022
Language	English	Other languages
Document type	Journal articles, reviews, conference papers, preprints with full text	Editorials, abstracts only, non-retrievable full text

SCREENING AND ELIGIBILITY

All 19 records were reviewed on title and abstract for the following criteria and all records satisfied the topic and outcome criteria. Full texts of all 19 were retrieved and assessed. There was no record excluded at eligibility (the corpus was built in scope). The flow is shown in the PRISMA diagram below.



Fig 1: PRISMA 2020 flow diagram of study selection

Figure 1. PRISMA 2020 flow diagram. All 19 records passed screening and eligibility; quality appraisal limited two low-quality studies to descriptive mapping.

QUALITY APPRAISAL

Each study was rated using an adapted MMAT [23] that rated five design-specific criteria: clarity of question, appropriateness of design, measurement validity, analytic rigour and coherence between data and conclusions. Studies were rated high (5), moderate (3–4) or low (≤ 2). It was also checked whether there is a documented search and selection process in prior reviews.

Two studies were given a low rating. The cost reductions, time and capacity gains are both 10% across all five organizations and all of the tasks reported by Jain [12] are the same and the reference list is not much related to procurement and no sampling, instrument or test statistics. Cooper [11] states the percentage increase in forecasting accuracy (e.g., 30–40%) accurately in a qualitative interview study, but does not provide any explanation for these percentages. Both were used in descriptive mapping for RQ1 and RQ4 but not for weighing the evidence in RQ2 and RQ3. The Quality Ratings are listed in Table 1.

DATA EXTRACTION AND SYNTHESIS

Bibliographic information, sector and country, design, sample, theory, applications of AI, type of outcome, key effects, and stated limitations were all gathered in a structured extraction form. Descriptive mapping and reflexive thematic analysis [24] were used. Codes were developed inductively from findings, organized into themes in relation to the RQs, and then organized deductively to the theory lenses in Section 2. In order to avoid the attempt of a meta-analysis, due to the heterogeneity of designs and measures, effect sizes are reported narratively with the sources of design.

DESCRIPTIVE RESULTS

The corpus is contemporary, and methodologically varied but not all empirical. In 2025-26, 74% (14/19) of studies were published, indicating a quick-growing field. Seven are quantitative empirical research, one is based on multi-criteria decision making, one is qualitative, three are based on case or triangulated evidence, two are conceptual or formal modelling, and five are reviews.

Temporal distribution. 2022: 2 studies; 2023: 2; 2024: 1; 2025: 8; 2026: 6.

Geographic and sectoral spread: Empirical settings include the countries of China [1, 8], India [3], Jordan [4], Romania [15], the United States and Canada [2, 25] and sub-Saharan Africa [13]. Industries covered are manufacturing, energy, critical infrastructure, construction, customs and public logistics, retail, garments and footwear and informal trade.

Theory use: The lenses most commonly found are RBV and DCV; resource orchestration, SAM, STS, technology acceptance, and technology empowerment are found in one or two studies each. In eight studies, mostly review papers and papers aimed at practitioners, no explicit theory is employed.

Table 1. Profile and quality appraisal of the reviewed studies

Study	Design	Context	Sample / data	Theory	Main outcome	Quality
Guo et al. [1]	Panel econometrics (text-mined AI index, IV, Heckman)	Chinese A-share manufacturers, 2013–2022	18,617 firm-years	Technology empowerment ; organizational change	Supply chain resilience	High
Bag et al. [3]	CB-SEM; serial mediation	Indian firms with circular procurement	500 firms	Resource orchestration	Circular procurement performance	High
Garg et al. [2]	PLS-SEM + fsQCA	US and Canadian B2B/B2G firms	180 managers	DCV	Firm and operational performance	High
Oncioiu et al. [15]	PLS-SEM	Romanian logistics (3PL, retail, manufacturing)	217 specialists	TAM; TOE-type readiness	Operational redesign in circular logistics	Moderate
Alkhawalda h [4]	CB-SEM with moderation	Jordanian customs, e-commerce supply chains	338 officers	RBV; STS; contingency	Employee performance; job satisfaction	Moderate
Nazir [25]	Cross-sectional survey; regression	Critical infrastructure (energy, water, telecoms, transport)	286 professionals	Predictive analytics; optimization	Procurement optimization performance	Moderate
Jain [12]	Claimed mixed methods	Oracle ERP users	5 organizations	None	Cost, cycle time, supplier score	Low
Wu et al. [8]	Probability analysis + Bayesian	Chinese garment and	14 experts	Industry 5.0	Resilience and	Moderate

Study	Design	Context	Sample / data	Theory	Main outcome	Quality
Cooper [11]	BWM + Pareto Qualitative semi-structured interviews	footwear supply chains Cross-industry	Not reported	None	sustainability priorities Adoption benefits and barriers	Low
Saihi et al. [6]	Triangulation : literature, industry reports, cases	Multi-industry strategic procurement	Multiple cases	DT in procurement	Efficiency, innovation, resilience	Moderate
Zope et al. [26]	Comparative analysis with case illustrations	Global supply chains	Illustrative cases	None	Efficiency, supplier relations, risk	Moderate
Nicoletti [5]	Literature synthesis + international cases	Construction	Cases (e.g., Crossrail, Masdar City)	DCV; Construction 5.0	Efficiency, sustainability, resilience	Moderate
Theodorou and Theodorou [7]	Formal multiplicative model	Energy and utilities	Illustrative industry cases	SAM	Procurement performance (modelled)	Moderate
Akinlade et al. [27]	Conceptual framework	Multi-industry	None	Strategic alignment (implicit)	Efficiency–strategy alignment	Moderate
Berbig et al. [10]	SLR + bibliometrics, AI-assisted	Global procurement	89 articles	—	Research trends and gaps	High
Althabatah et al. [9]	SLR (PRISMA)	Procurement 4.0	111 Scopus articles	—	Technology value propositions	High
Rainy and Chowdhury [14]	Scoping review (PRISMA-ScR)	Digital retail	86 sources	—	AI vendor performance evaluation	Moderate
Lawal and Isiyaku [13]	Narrative review	African informal supply chains	Literature and cases	—	Inventory and procurement efficiency	Moderate
Moreno [28]	Integrative review	Cross-sector SCM	Literature	—	Efficiency, resilience, decisions	Moderate

Table 1: Profile and quality appraisal of the reviewed studies

This is a warning-distributed distribution. For inferential statements about organizational performance, only six of the studies rely on a sufficiently large sample, and none of these studies explicitly tests for endogeneity—only one [1] does so using instrumental-variable and selection-correction tests. The vast

majority of performance claims in other places are based on cross-sectional perceptual data or illustrative cases.

THEMATIC SYNTHESIS

The four themes which emerged, one for each research question are: Summed up, there is a common theme across them: AI can consistently enhance process efficiency, but, only in the presence of organisational conversion mechanisms can organizational performance be enhanced.

THEME 1 — AI APPLICATIONS ACROSS THE PROCUREMENT AND SUPPLY CHAIN PROCESS (RQ1)

AI is moving beyond transactional automation towards decision support and autonomous agents. This transition is reported by Berbig et al. [10] in 89 articles, where research effort shifted to supplier management, and comprehensive implementation frameworks are few. In reviewing 111 papers, Althabatah et al. [9] conclude that the research on e-procurement and blockchain is most prevalent while AI is the fastest growing stream. The mapping of application clusters identified in the corpus is given in Table 2.

Application cluster	Typical techniques	Process stage	Representative studies
Spend analysis and automated sourcing (RFx)	ML classification, NLP	Source	Theodorou and Theodorou [7]; Saihi et al. [6]
Supplier and vendor evaluation	Supervised and unsupervised ML, NLP sentiment, anomaly detection	Source / manage	Rainy and Chowdhury [14]; Jain [12]; Zope et al. [26]
Supplier and supply risk analytics	Predictive analytics, risk scoring, early warning	Source / manage	Nazir [25]; Cooper [11]; Akinlade et al. [27]
Contract management and analytics	NLP extraction, smart contracts	Contract	Theodorou and Theodorou [7]; Nicoletti [5]
Price optimization and negotiation support	Optimization, generative AI	Source / contract	Theodorou and Theodorou [7]; Nazir [25]
Demand forecasting and inventory optimization	Ensemble ML, deep learning, RFID and IoT	Plan / replenish	Lawal and Isiyaku [13]; Wu et al. [8]; Alkhawaldah [4]
Transaction automation (P2P, invoice, PO)	RPA, intelligent document processing	Purchase-to-pay	Jain [12]; Zope et al. [26]
Logistics and decision configuration	Predictive algorithms, digital twins	Deliver	Oncioiu et al. [15]; Moreno [28]; Garg et al. [2]
Agentic and autonomous procurement	Multi-agent systems, LLM agents	End-to-end	Bag et al. [3]; Nicoletti [5]
Circular and sustainable sourcing	Lifecycle analytics, traceability, blockchain-AI	Source / reverse flows	Bag et al. [3]; Wu et al. [8]; Nicoletti [5]

Table 2: AI application clusters in procurement and supply chain management

The context determines the balance. For integrated utilities, contract analytics become an important feature for managing long-term infrastructure contracts. For transmission utilities, asset availability becomes an important concern, and for renewables, supplier risks and sustainability become important features. In Africa's informal supply chains, the architecture that matters is mobile-first, voice-supported, and offline-capable, owing to the constraints of connectivity, illiteracy, and lack of money [13]. In construction, the combination of AI with BIM, IoT and blockchain technology becomes important.

THEME 2 — EFFICIENCY EFFECTS (RQ2)

Efficiency is the best-supported outcome in the corpus. Gains cluster in four areas:

- **Cycle time and transaction cost.** The automation of procurement has led to a reduction in processing times by more than 30% in engineering and construction companies [5]. Digital sourcing has brought down transactional sourcing times by 30%–50% in industry triangulation [6].

- **Forecasting and inventory.** Forecasting through AI usage reduces the number of stock-outs by 30-50% and excess inventories by 20-40% under informal conditions [13]. There is anecdotal proof that analytics-driven purchasing practices result in 30% lower cost of inventory and 20% higher order fulfillment [6].
- **Sourcing cost.** Saving reported ranges from 10-25% by means of vendor selection, demand consolidation and negotiation assistance [13] while approximately 15% savings in case studies [26].
- **Decision quality.** For critical infrastructures, predictive risk analytics ($\beta = .31$), AI-based predictive analytics ($\beta = .27$), real-time data integration ($\beta = .23$), and quantum-based optimization ($\beta = .18$) together account for 68.4% of the variance in procurement optimization effectiveness [25].
- **Two cautions apply.** First, many efficiency figures come from reviews, case summaries or industry sources rather than controlled comparisons, so they indicate direction more reliably than magnitude. Second, the lowest-quality studies report the most uniform gains. Jain [12], for instance, reports exactly 10% cost reduction, 50% time reduction and 50% capacity increase for every organization. Such uniformity is implausible and inflates the apparent consensus.

THEME 3 — ORGANIZATIONAL PERFORMANCE EFFECTS AND MECHANISMS (RQ3)

There is a positive but indirect relationship between AI and organizational performance. It can be clearly seen that the most effective designs prove that AI operates through organizational processes and not alone. Table 3 presents the main evidence.

Study	Path or effect	Estimate	Interpretation
Guo et al. [1]	AI → supply chain resilience	$\beta = 0.0067$, $p < .01$; robust to IV and Heckman	AI raises resilience in manufacturing
Guo et al. [1]	AI → executive ratio (flattening)	$\beta = -0.0072$, $p < .05$	Mechanism: flatter structure
Guo et al. [1]	AI → internal control index	$\beta = 0.134$, $p < .01$	Mechanism: stronger internal control
Garg et al. [2]	AI/ML → firm performance	$\beta = 0.29$, $p < .01$	Strategic, firm-level gain
Garg et al. [2]	AI/ML → operational performance	$\beta = -0.06$, $p = .48$ (n.s.)	No direct operational gain
Oncioiu et al. [15]	AI-enabled decision configuration → operational redesign	$\beta = 0.459$	Decision support drives redesign
Oncioiu et al. [15]	Strategic readiness → operational transformation	$\beta = 0.374$	Readiness matters
Nazir [25]	Four AI capabilities → procurement optimization	$R^2 = 0.684$	Integrated analytics explain most variance
Alkhawaldah [4]	Logistics and fulfilment → employee performance	$\beta = 0.412$, $p < .001$	Supply chain practices lift employees
Alkhawaldah [4]	AI systems × logistics → employee performance	$\beta = 0.145$, $p < .01$	AI amplifies the effect
Alkhawaldah [4]	Employee performance → job satisfaction	$\beta = 0.633$, $p < .001$	Performance feeds satisfaction

Table 3: Key quantitative evidence on AI and organizational performance

Firm versus operational performance. According to Garg et al. [2], AI and ML enhance performance of firms but not their operational performance and do not moderate the impact of information sharing, decision synchronization and logistic efficiency. However, in the fsQCA analysis performed by the authors, logistics efficiency together with AI create sufficient configuration for high performance of firms. Going through the DCV, the benefit of AI can be attributed to sensing and reconfiguration, which is reflected in strategic adaptability.

Resilience. The biggest study in the corpus shows that AI enhances the resilience of supply chain operations for 18,617 firm-years with higher impacts among high-tech, downstream, capital-intensive, technology-intensive, eastern region, and growth/maturity stage companies [1]. The rationale behind this is organizational since AI decreases hierarchy and enhances internal controls. Wu et al. [8] confirm the same finding through Bayesian expert prioritization where continuous IoT monitoring, flexible automation, and predictive big data analytics are identified as resilience enhancers.

Circular and sustainability performance. Agentic AI influences circular procurement success in three orchestrated processes: resource scanning and evaluation, cross-functional systems, and supplier collaboration [3]. On the same note, Oncioiu et al. [15] conclude that AI-driven decision configuration, organizational readiness, and transformation context influence operational redesign for circular logistics. Sustainability successes in construction and energy industries have been documented through life cycle analysis and waste reduction, albeit through case studies [5], [7].

Employee outcomes. In the public sector, AI-based purchasing and inventory systems enhance the influence of logistics, information and demand management on the performance of employees and in doing so improve their job satisfaction [4]. Including the AI moderator increased the variance explained by satisfaction from 0.51 to 0.54. This effect is contingent on autonomy, trust in AI output and feedback possibility.

THEME 4 — ENABLERS, BARRIERS AND BOUNDARY CONDITIONS (RQ4)

The corpus agrees closely on what determines conversion. Table 4 groups the factors.

Dimension	Enablers	Barriers	Key sources
Strategic	Alignment of AI portfolio with cost, quality, flexibility and dependability priorities; executive sponsorship	Technology-led adoption without strategic intent	Theodorou and Theodorou [7]; Akinlade et al. [27]; Cooper [11]
Organizational	Flatter structures; strong internal control; cross-functional integration; supplier collaboration routines	Hierarchical rigidity; siloed functions; change resistance	Guo et al. [1]; Bag et al. [3]; Oncioiu et al. [15]
Human	Digital literacy; training; trust; task autonomy; human-in-the-loop design	Skills gaps; fear of job loss; over-reliance on automation	Alkhawaldah [4]; Moreno [28]; Lawal and Isiyaku [13]
Data and technology	Clean, integrated data; ERP and legacy interoperability; real-time integration	Fragmented data; integration complexity; high implementation cost	Nazir [25]; Rainy and Chowdhury [14]; Zope et al. [26]
Governance and ethics	Explainability; auditing; privacy-by-design; algorithmic-bias controls	Opaque decisions; cybersecurity risk; regulatory uncertainty	Saihi et al. [6]; Wu et al. [8]; Nicoletti [5]
Environmental	Supportive policy; digital infrastructure; regional innovation ecosystems	Weak connectivity; unreliable power; informal markets	Guo et al. [1]; Lawal and Isiyaku [13]

Table 4: Enablers and barriers to AI-enabled performance

Three boundary conditions are significant. Firstly, misalignment is multiplicative: if any of AI capability, strategic alignment, organizational readiness or environmental fit is poor, then poor performance results, even with high AI capability [7]. Secondly, context reduces the effect size: effects are weaker in labor-intensive firms, start-ups, underdeveloped locations and bureaucratic organizations [1], [4]. Thirdly, risks of implementation reduce actual gains: poor data quality, bias, resistance, gaps in governance and vendor lock-in reduce ex ante value [7].

INTEGRATIVE FRAMEWORK AND PROPOSITIONS

The synthesis leads to a framework for AI capability-conversion. AI capability creates efficiency directly; however, organizational performance needs mechanisms of conversion, which depend on alignment and

context. The framework incorporates RBV (complementary resources), DCV and resource orchestration (reconfiguration of resources), SAM (alignment/fit), and STS (human augmentation).

AI raises efficiency directly; performance needs conversion

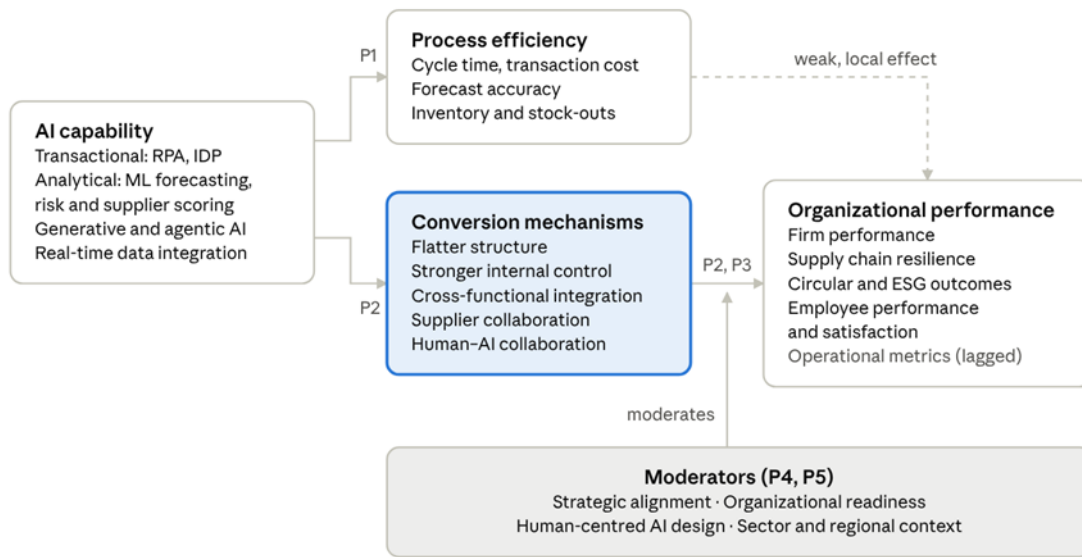


Fig 2: AI capability-conversion framework

Figure 2. AI capability-conversion framework. AI capability improves efficiency directly (P1), but organizational performance runs through conversion mechanisms (P2, P3), whose strength depends on alignment, readiness, human-centred design and context (P4, P5).

The framework yields five testable propositions:

- **P1 (Efficiency path).** AI capability in procurement has a direct positive effect on process efficiency, including cycle time, transaction cost, forecast accuracy and inventory levels. Grounded in: Nazir [25]; Saihi et al. [6]; Lawal and Isiyaku [13].
- **P2 (Conversion path).** The effect of AI capability on organizational performance is mediated by organizational conversion mechanisms: structural flattening, internal control, cross-functional integration and supplier collaboration routines. Grounded in: Guo et al. [1]; Bag et al. [3]; Oncioiu et al. [15].
- **P3 (Strategic locus).** AI's performance effect appears first at the strategic level (firm performance, resilience) and only later or weakly in routine operational metrics. Grounded in: Garg et al. [2]; Guo et al. [1].
- **P4 (Multiplicative alignment).** Strategic alignment and organizational readiness moderate the AI-performance relationship multiplicatively, so a deficit in either suppresses returns regardless of AI sophistication. Grounded in: Theodorou and Theodorou [7]; Oncioiu et al. [15].
- **P5 (Human augmentation).** Human-centred AI design, through autonomy, trust and feedback, strengthens the effect of supply chain practices on employee performance, which in turn sustains satisfaction and adoption. Grounded in: Alkhawaldah [4]; Nicoletti [5].

DISCUSSION

RECONCILING THE EVIDENCE

The seeming paradox of large efficiency claims combined with small performance effects is resolved when efficiency and performance are disentangled. Efficiency benefits are local and immediate: a faster invoice process or an improved forecast. Performance benefits happen when the local efficiency improvements affect decision making, control, and collaboration at the organization. In researches where adoption alone is measured, efficiency is discovered, while performance appears in researches that assess the organization's mechanisms. The interpretation follows from the productivity paradox reasoning about the need for complementary investments, and improves the earlier review papers that simply mapped technology types but did not test conversion [9], [10].

The empirical findings also reveal a progression of stages. The transactional AI (RPA, documents processing) is common and generates efficiency. The analytical AI (forecasting, risk analysis, vendor evaluations) produces better decisions. The orchestrating AI, including agentic systems, produces performance only if mechanisms of scanning, integrating, and collaboration are in place [3]. Organizations that bypass the organization-building effort of the second stage will never benefit from the third one.

RESEARCH AGENDA

Gap	Why it matters	Suggested research question	Suggested design
Causal identification	Most evidence is cross-sectional and perceptual	Does AI adoption cause performance change, and with what lag?	Panel data, difference-in-differences, natural experiments
Objective outcome data	Self-reported performance invites common-method bias	Do AI effects hold on audited cost, ERP log and supplier data?	Multi-source data linking surveys to system logs
Agentic AI governance	Autonomous agents shift decision rights	How should decision rights, accountability and controls be allocated between agents and buyers?	Case studies; design science; experiments
Operational null effect	Firm-level gains without operational gains are unexplained	Through which mechanisms, and over what time, do operational effects emerge?	Longitudinal mediation; fsQCA configurations
Sustainability measurement	Circular and ESG effects are largely case-based	Does AI improve verified emissions, waste and circularity outcomes?	Lifecycle data combined with procurement records
Developing and informal economies	Evidence is concentrated in China, India and OECD contexts	Which low-cost, mobile-first AI designs deliver value under weak infrastructure?	Field trials in Africa, South Asia and MENA
Public procurement	Accountability and transparency rules differ	How does AI affect integrity, competition and value for money?	Administrative data; comparative policy analysis
Human–AI collaboration	Over-reliance and de-skilling are understudied	When does AI augment rather than erode buyer judgement?	Behavioural experiments; ethnography
Measurement standards	Constructs and KPIs vary across studies	Can a validated AI-procurement maturity and value scale be developed?	Scale development; Delphi studies

Table 5: Future research agenda

MANAGERIAL IMPLICATIONS

- Start from strategy, not technology. Map each AI use case to a declared priority (cost, quality, flexibility, dependability or sustainability) and fund the portfolio accordingly [7].
- Budget for conversion. Invest in structural redesign, internal control and cross-functional integration alongside the tool; these carry the performance effect [1].
- Build orchestration routines before deploying agents. Structured resource scanning, integrated procurement systems and supplier collaboration routines are prerequisites for agentic AI value [3].
- Measure at two levels. Track efficiency KPIs (cycle time, cost per PO, forecast error) and performance KPIs (firm results, resilience, circularity, employee outcomes) separately, so that early efficiency gains are not mistaken for strategic impact.
- Design for people. Preserve buyer autonomy, explain AI outputs and create feedback channels; employee trust conditions the payoff [4].

- Discount for implementation risk. Treat data quality, bias, cybersecurity and vendor lock-in as an explicit discount on business cases, and phase deployment from assessment to pilot to scale [7].

POLICY IMPLICATIONS

Policymakers can accelerate inclusive adoption through digital-infrastructure investment, AI-skills programs and shared platforms for smaller firms, which benefit least from AI today [1], [13]. Clear rules on data protection, algorithmic accountability and cross-border data flows would reduce the regulatory uncertainty cited across sectors [5], [8].

LIMITATIONS

Four shortcomings affect this review. The first one is that the 19-study corpus was selected through purposive sampling and not exhaustive data export from a database, which could mean that the selection is biased towards certain areas and countries. The second one is that the corpus contains preprints and papers published in non-indexed journals; while quality appraisal takes care of this issue, it does not completely eliminate it. The third one is that the heterogeneity of the measures makes meta-analysis impossible; therefore, effect sizes are compared descriptively. The fourth one is that some of the 2026 studies are early view and can be modified.

CONCLUSION

Procurement processes assisted by AI lead to efficiency improvements and organizational performance with certainty and conditionalities, respectively. From the analysis of 19 articles, it is possible to note that the application of AI results in cycle time reduction, better forecasting ability, lower levels of inventory and better supplier evaluation. The impact on organizational performance, resilience, circularity and the well-being of employees, on the other hand, operates via organizational conversion, which consists of organizational flattening, stronger internal controls, cross-departmental integration, interaction with suppliers and human-centric design. In the absence of these processes, the efficiency benefits remain within a limited scope.

The capability/conversion framework together with five propositions gives grounds for cumulative studies. The quality appraisal revealed cases of excessive reporting of the benefits compared with evidence. For managers, the conclusion is clear – AI should be considered a capability, not a tool. For researchers, the challenge lies in conducting causal, multi-source and longitudinal studies, particularly about agentic AI, sustainability and emerging economies.

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