



To cite this article: Kamran Pitafi (2026). ARTIFICIAL INTELLIGENCE IN COMMERCIAL DECISION-MAKING A CRITICAL INTEGRATIVE REVIEW AND CONTEXTUAL-FIT FRAMEWORK FOR MANUFACTURING, International Journal of Research in Commerce and Management Studies (IJRCMS) 8 (5): 457-499 Article No. 889 Sub Id 1457

ARTIFICIAL INTELLIGENCE IN COMMERCIAL DECISION-MAKING A CRITICAL INTEGRATIVE REVIEW AND CONTEXTUAL-FIT FRAMEWORK FOR MANUFACTURING

Kamran Pitafi

DOI: <https://doi.org/10.38193/IJRCMS.2026.8531>

ABSTRACT

Artificial intelligence (AI) supports manufacturing decisions involving revenue, suppliers, working capital, capacity and service commitments. Whether evidence from other sectors transfers to these decisions remains uncertain. This critical integrative review examines a reported corpus of 80 review-level publications dated 2015 to 31 August 2026, including a 59-review systematic or systematic-component subset. It distinguishes decision domain, AI decision role, evidence layer and manufacturing-primary scope, and integrates task-technology fit, organizational information processing, socio-technical systems and appropriate reliance. The reported classification identifies 11 manufacturing-primary, function-specific reviews: nine address production planning or scheduling, one demand forecasting and one inventory management. The corresponding restricted subset contains seven, one and one, respectively. These counts describe the selected corpus; they do not estimate field-wide prevalence or independent empirical support. The Manufacturing AI Decision-Fit (MAIDF) framework organizes evidence transfer around four regimes: data adequacy, feedback and actionability, operational coupling, and accountability. Five propositions and a non-compensatory decision workflow specify how these conditions may affect deployment value. The framework remains unvalidated, and the expanded corpus requires a complete record-level audit trail for independent reproduction. Its contribution is a structured account of transfer conditions across commercial decisions, with deployment assessed against a credible baseline and consequential business outcomes.

KEYWORDS: artificial intelligence; manufacturing decision support; commercial decision-making; task-technology fit; MAIDF; production planning; supply-chain management

INTRODUCTION

Manufacturing decisions commit resources before their consequences can be fully observed. Demand forecasts influence materials and capacity; procurement choices shape supplier exposure; inventory policies tie up capital; and pricing decisions create service and delivery obligations. AI can inform each decision, but better model performance does not necessarily produce a better commercial outcome. The relevant question is whether the resulting action improves the economic and operational

performance of the decision system.

Manufacturing often combines long lead times, capital-intensive equipment, intermittent demand, heterogeneous products and negotiated business-to-business relationships. These conditions affect both learning opportunities and the cost of error. A pricing method trained on frequent consumer purchases may receive little usable feedback from occasional industrial contracts. A scheduler that performs well in simulation may be unable to explore safely on a working production line. A supplier-ranking system may require explanations that a procurement committee can challenge before committing expenditure.

Several review streams address parts of this problem. Supply-chain syntheses examine AI capabilities and resilience (Ni et al., 2020; Toorajipour et al., 2021; Culot et al., 2024; Babai et al., 2025; Teixeira et al., 2025; Vlachos and Reddy, 2025). Production reviews cover planning, reinforcement learning, scheduling and digital twins (Panzer and Bender, 2022; Zhou et al., 2022; Estes et al., 2023; Del Gallo et al., 2023; Kriouich and Sarir, 2024). Other reviews examine forecasting, pricing, procurement, supplier selection and inventory (Guida et al., 2023; Chenavaz and Dimitrov, 2025; Gidiagba et al., 2025; Walter et al., 2025; Bergsma et al., 2025). Explainability, governance, generative AI and collaboration cut across these domains (Nimmy et al., 2022; Jackson et al., 2024; Kosasih et al., 2024; Batool et al., 2025; Kumar and Kumar, 2025; Ouerghemmi and Ertz, 2025; Puthanveetil Madathil et al., 2025). The present review connects these streams by examining the conditions under which their findings can inform a manufacturing decision.

Two distinctions are necessary. AI labels refer to different analytical levels: deep learning is a model family, reinforcement learning a learning and decision paradigm, generative AI a capability class, explainability an assurance property, and a decision support system an organizational architecture. Commercial functions also overlap. Supplier selection falls within sourcing, while forecasting, inventory and production planning jointly affect capacity and service. A flat list of technologies and functions obscures these relationships.

Here, commercial decision-making means managerial allocation or commitment decisions affecting revenue, sourcing cost, working capital, service, capacity or network performance. Production planning falls within this boundary when it allocates scarce capacity or determines the economic feasibility of customer commitments. Manufacturing is treated as a set of operating conditions whose relevance must be established for each decision.

1.1 State-of-the-art positioning

Table 1 compares representative reviews by scope and analytical purpose. The comparison positions this paper as an integration of commercial decision domains and evidence-transfer conditions; it does

not establish that no previous framework has addressed related issues. Relevant contributions include Industry 4.0 applications (Zheng et al., 2021), intelligent-manufacturing operations (Zhou et al., 2022), reinforcement learning (Panzer and Bender, 2022; Estes et al., 2023; Rolf et al., 2023), generative AI (Jackson et al., 2024; Ouerghemmi and Ertz, 2025), explainability (Kosasih et al., 2024; Puthanveetil Madathil et al., 2025), prescriptive analytics (Smyth et al., 2024), and supply-chain machine learning (Vlachos and Reddy, 2025). These studies provide the foundations for examining transfer across commercial decisions.

Table 1. Representative state-of-the-art reviews and the gap addressed by this paper.

Review	Scope and context	Principal strength	Gap relative to this paper
Toorajipour et al. (2021)	AI in cross-sector supply-chain management	Broad AI technique and application map	Does not compare manufacturing transfer across commercial decisions.
Zhou et al. (2022)	Production and operations management in intelligent manufacturing	Manufacturing-primary state-of-the-art synthesis	Not focused on commercial decision transfer from cross sector evidence.
Panzer and Bender (2022)	Deep reinforcement learning in production systems	Systematic production-RL synthesis	Single decision family; no cross function transfer model.
Jackson et al. (2024)	GenAI in operations and supply chain management	Capability-based implementation framework	Technology-led rather than manufacturing-transfer-led.
Pan et al. (2026)	AI in manufacturing systems under Industry 5.0	Systematic manufacturing-wide synthesis using a three-stage search strategy	Manufacturing-wide AI map rather than a cross-decision evidence-transfer diagnostic.
Callefi et al. (2026)	GenAI-enabled supply-chain capabilities	TTF-grounded capability hierarchy with secondary cases	GenAI-specific capability prioritization rather than cross technology transfer fit.
Song et al. (2026)	LLMs across SCOR processes	Systematic LLM-SCM application LLM-specific pathways; does framework using CMO/DCT not diagnose manufacturing transfer across decision types.	

Review	Scope and context	Principal strength	Gap relative to this paper
Martuscelli et al. (2026)	AI for operational excellence in manufacturing OM	Manufacturing-primary systematic classification of 67 studies	Broad operational-excellence scope rather than commercialdecision transfer.
Mayerhoff and Schmidt RL for production planning and control (2026)		Systematic synthesis of 196 studies and industrial-maturity evidence	Production-focused; exposes deployment gap but not crossfunction transfer.
This paper	Seven focal commercial decisions across four managerial domains	Systematic-core sensitivity plus the MAIDF decision aid	Technology-agnostic transfer diagnosis linking evidence, context, architecture and decision value.

Recent work makes this positioning more demanding. Callefì et al. (2026) apply task-technology fit to GenAI-enabled supply-chain capabilities, while Song et al. (2026) connect large language models to Supply Chain Operations Reference (SCOR) processes through context-mechanism-outcome and dynamic-capability reasoning. Panja, Zheng and Glock (2026) examine GenAI in logistics and supply chains. Manufacturing reviews address operational excellence (Martuscelli et al., 2026), Industry 5.0 (Pan et al., 2026), and industrial machine-learning operations (MLOps) (Rajashekarappa et al., 2026). MAIDF draws these discussions together at the level of a target decision: what must be similar between the setting that generated the evidence and the setting in which it will be used?

1.2 Research questions and contribution the paper addresses five research questions:

1. How is review-level AI evidence distributed across commercial decision areas relevant to manufacturing?
2. Which predictive, adaptive, generative and assurance roles are represented?
3. Where do reviews have a manufacturing-primary scope, and where does the synthesis depend on cross-sector transfer?
4. Which contextual conditions recur as potential determinants of AI-supported decision value?
5. How can those conditions inform a decision aid and an empirical research agenda?

The contribution combines a decision-role architecture with a distinction between manufacturing-primary and cross-sector evidence. It uses task-technology fit, information-processing, socio-technical and appropriate-reliance research to interpret transfer conditions. The resulting Manufacturing AI Decision-Fit (MAIDF) framework proposes four regimes and a deployment workflow. The reported concentration of dedicated manufacturing reviews in production planning motivates this framework,

while the forecasting and inventory reviews prevent an absolute claim that manufacturing evidence is absent elsewhere.

2. Theoretical foundation: from technology adoption to decision fit

2.1 Task-Technology Fit

Task-technology fit concerns the alignment between technology capabilities and the tasks people perform (Goodhue and Thompson, 1995). For manufacturing AI, this makes prediction quality only one component of usefulness. A more accurate estimate may have little value if the organization cannot act on it, if essential context is missing, or if procedures block the recommended action. Parsons et al. (2025) revisit this alignment in clinical decision support; their work supplies a cross-sector theoretical perspective rather than direct manufacturing evidence. Manufacturing transfer also requires attention to operational interdependence and accountability beyond the immediate task-technology relationship.

2.2 Organizational information processing

Galbraith (1974) links task uncertainty to organizational information-processing requirements. Volatility, multistage lead times and network disruption increase those requirements in manufacturing. AI may expand processing capacity while leaving coordination bottlenecks or binding constraints unresolved. This distinction motivates separate treatment of data adequacy and operational coupling in MAIDF: observing a decision problem and acting successfully on that information are different requirements.

2.3 Socio-technical systems and appropriate reliance

Socio-technical systems theory emphasizes the joint design of technical and social arrangements (Trist and Bamforth, 1951). In AI decision support, task allocation, explanation, escalation and ownership therefore belong within system design. Appropriate-reliance research further asks whether users accept recommendations when warranted and challenge them when necessary (Mehrotra et al., 2024). Kumar and Kumar (2025) place these interactions within adoption and continuing organizational learning in operations and supply chains.

Together, these perspectives motivate four aspects of transfer fit. Figure 1 connects the review design and decision architecture to the theoretical synthesis. The connections express the framework's conceptual derivation; they are not estimated causal relationships.

Callefi et al. (2026) use task-technology fit to organize GenAI-enabled supply-chain capabilities. MAIDF retains that concern with situated use while focusing on evidence transfer across model families and decision domains. Its diagnostic questions concern data, feedback, operational coupling

and accountability in the source and target settings.

Evidence-to-decision-fit architecture

Evidence architecture and claim discipline feed a common theoretical synthesis before transfer fit is assessed.

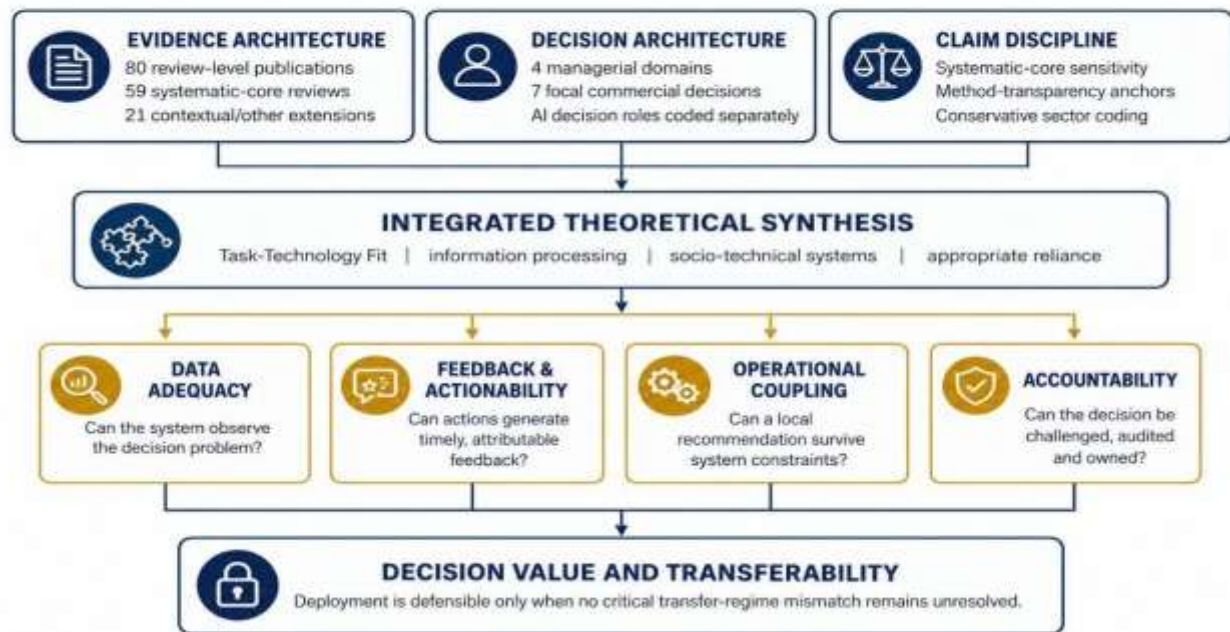


Figure 1: Evidence-to-decision-fit architecture. Evidence design, decision structure and claim discipline converge through an integrated theoretical synthesis before the four MAIDF regimes are derived. AI-assisted preparation attributed in the source manuscript to OpenAI ChatGPT (GPT-5.6 Sol).

2.4 Manufacturing AI Decision-Fit: propositions

The following propositions translate the theoretical synthesis into testable expectations. The four regimes are candidate explanatory dimensions, not empirically established categories or an exhaustive taxonomy. P1-P4 concern decision value within a setting; P5 concerns the credibility of transfer between settings.

P1: Data adequacy. The incremental decision value of AI will increase when data are sufficiently observable, relevant, granular, and representative of the target decision, and will decline when the learning signal is sparse, structurally unstable, or weakly connected to the commercial objective.

P2: Feedback and actionability. Adaptive and prescriptive AI will create greater value when actions generate timely and attributable feedback and when experimentation is operationally and commercially safe; slow, confounded, or relationship-sensitive feedback reduces the suitability of

unconstrained adaptation.

P3: Operational coupling. As capacity, lead-time, process, and network interdependence increase, local model performance becomes a weaker proxy for system-level decision value, increasing the need for integrated simulation, digital-twin, constraint, or coordination mechanisms.

P4: Accountability. As decision stakes, irreversibility, audit requirements, or stakeholder exposure increase, the value of explanation, bounded autonomy, human override, traceability, and explicit ownership increases.

P5: Transfer burden. The credibility of transferring cross-sector AI evidence into manufacturing decreases as mismatch across the four regimes increases; evidence transfer should therefore be justified by decision-architecture similarity rather than by technology similarity alone.

3. Review design and analytical method

3.1 Critical integrative review with a systematic core

This study uses a critical integrative review to connect evidence from management, operations research, industrial engineering, information systems and AI. The purpose is conceptual synthesis and transfer diagnosis rather than pooled effect estimation. Integrative-review guidance supports making the analytical purpose, selection logic and synthesis process explicit (Torraco, 2005, 2016; Snyder, 2019). Systematic-review principles inform transparency, but the present design does not claim the search completeness of a prospectively specified systematic review (Tranfield et al., 2003).

The manuscript reports an 80-publication corpus divided into 59 systematic or systematic-component reviews and 21 other review-level publications. The restricted subset is used to examine the sensitivity of descriptive counts. It is not a quality grade. No prospective registration, complete retrospective database flow, independent-coder agreement coefficient or common quality score is reported. The full 80-record matrix and expanded audit files remain necessary to reproduce this classification; the available earlier supplementary matrix contains 49 records. Counts below are retained as reported results, subject to that documentary limitation.

3.2 Evidence identification, verification, and 2026 update audit

The reported update was completed on 1 September 2026, with eligibility extending to 31 August 2026. It started from a 49-review base covering citation years through 2025 and searched the seven focal decision areas plus crosscutting GenAI, governance, explainability and manufacturing streams. The manuscript identifies public scholarly discovery, publisher platforms, DOI/Crossref records and citation chaining as discovery and verification routes. It does not provide an exhaustive database export history.

Appendix D reproduces the search families reported for the update. The stated expansion adds 31

publications: 30 carrying 2026 citation years and one carrying a 2025 citation year. The reported total is therefore 80. Publisher or DOI identity checks establish bibliographic identity, but cannot by themselves confirm a review's methods, its inclusion eligibility, or the interpretation assigned to it. Those judgments require the corresponding source content and record-level documentation. The earlier S2 log does not document the complete 31-record expansion.

Eligibility is defined as peer-reviewed English-language review evidence relevant to a focal commercial decision or a cross-cutting construct used to interpret manufacturing transfer. The stated period is 2015 to 31 August 2026. Foundational theory, primary studies and institutional material used for background must be distinguished from counted review evidence. The bibliography uses publisher citation years; an exact day-level eligibility boundary additionally requires online publication dates. Issue year alone cannot establish availability by the cutoff. Reviews from other sectors are relevant only where the transfer or theoretical purpose is explicit.

The reported update identifies dedicated manufacturing reviews in demand forecasting (Gomaa, 2026) and inventory management (Royani et al., 2026), alongside production planning and scheduling. On the reported coding, production accounts for nine of 11 manufacturing-primary function-specific reviews and seven of nine in the restricted subset. Thus, the descriptive claim concerns concentration within the corpus, not exclusivity across the literature.

The reported stopping criterion was coverage closure: each focal domain and cross-cutting stream had an identified evidence status, and subsequent additions were judged not to change the coverage pattern or the four proposed regimes. Without a complete sequence of dated searches and dispositions, that stopping decision cannot be independently reproduced. Coverage closure is therefore an author-reported practical stopping rule, not evidence of database or theoretical saturation.

AI assistance was reported for search-term expansion, candidate discovery, bibliographic normalization, consistency checking, language editing, document production and figure preparation. The source manuscript attributes eligibility and coding decisions to the author. The present editorial revision does not constitute independent recoding of the 80-review corpus. Tool use is disclosed in the declarations and figure captions; the author remains responsible for checking source content, retaining the research record and approving the submission.



Figure 2: Reported evidence-identification and update process. Thirty-one reported additional review-level publications were added to the 49-review pre-update corpus, yielding 80 reviews through 31 August 2026; counts describe the analytical corpus rather than a PRISMA database census. AI-assisted preparation attributed in the source manuscript to OpenAI ChatGPT (GPT-5.6 Sol).

3.3 Coding architecture and claim rules

The coding architecture distinguishes review design, evidence layer, focal decision area, sectoral context, manufacturing-primary status and primary AI role. Evidence layer and sectoral status are separate: a contextual review can be manufacturing-primary without becoming a dedicated review of a commercial function. Table 2 defines the rules, and Table 3 illustrates boundary decisions. Independent reproduction requires the complete S1 matrix with one identifiable record per counted review and a source-supported rationale for each classification.

Table 2. Analytical scope, coding rules, and claim discipline.

Dimension	Operational rule	Purpose
Commercial decision boundary	Decisions that allocate or commit revenue, suppliers, inventory, capacity, or network resources with direct economic consequences.	Prevents purely technical manufacturing AI from being counted automatically as commercial decision evidence.



Decision hierarchy	Market/revenue; sourcing/suppliers; internal planning/control; network coordination/resilience.	Avoids treating nested functions as mutually exclusive.
AI decision role	Predictive; prescriptive/adaptive; generative; assurance/governance.	Separates what AI contributes to a decision from algorithm family or implementation architecture.
Evidence layer	Function-specific; cross-functional; contextual.	Prevents broad reviews from inflating dedicated function counts.
Manufacturing-primary	Manufacturing or production is the central sectoral context, not one application among many.	Creates a conservative test of sector-specific evidence.
Systematic core	Review explicitly self-identifies as systematic or contains a substantive systematic review component. Core membership is supplemented by item-level transparency indicators rather than treated as proof of equal quality.	Supports sensitivity analysis while avoiding the assumption that all systematic reviews are methodologically equivalent.
Strong claim rule	Requires support from the systematic core, at least one method-transparent anchor for the decision area, and at least two review publications (independence not established) unless explicitly labelled exploratory.	Reduces dependence on single-review conclusions.
Theory retention rule	A regime is retained only when it recurs across multiple decision domains and has at least one systematic-review anchor.	Makes theory-building traceable to the review evidence.

Illustrative coding decisions. Because the final coding was not independently double-coded prospectively, the paper exposes representative boundary decisions so readers can audit how the rules were applied.

Table 3. Illustrative coding decisions for ambiguous review types.

Review	Evidence layer	Manufacturing primary?	Reasoning
Zhou et al. (2022)	Cross-functional	Yes	Intelligent-manufacturing POM is the organizing sectoral context, but the review spans scheduling, logistics, capacity and related functions; it is not counted as a dedicated production-planning review.
Gomaa (2026)	Function-specific: demand forecasting	Yes	Manufacturing supply chains are the organizing context and demand forecasting is the dedicated decision focus.
Review	Evidence layer	Manufacturing primary?	Reasoning
Royani et al. (2026)	Function-specific: inventory management	Yes	Manufacturing inventory decision-making is the explicit sectoral and functional focus; the review uses PRISMA 2020.
Martuscelli et al. (2026)	Contextual	Yes	Manufacturing operations management is central, but the review spans multiple operational-excellence application domains rather than one focal commercial decision.
Callefi et al. (2026)	Cross-functional	No	The paper develops GenAInabled SCM capabilities across supply-chain contexts rather than a manufacturing-primary dedicated decision review.
Maghanaki, Shahin and Chen (2026)	Contextual	Yes	Manufacturing is central, but the review spans LLM applications across the manufacturing value chain rather than one focal commercial decision.

3.4 Method-transparency and appraisal discipline

Systematic-core membership restricts review design but does not establish equivalent methodological quality. The intended claim rule requires an identifiable search strategy, explicit selection process and defined synthesis method in at least one relevant anchor. The five appraisal fields are search strategy, selection process, independent screening or consensus, primary-study appraisal, and synthesis framework. Table 4 summarizes reported anchors. The earlier S3 file is not a completed five-field appraisal of the expanded corpus, so the full application of this rule remains unverified. Missing reporting should be distinguished from a procedure known not to have been performed.

These indicators should be interpreted separately. Adding them into a common score would conceal differences among review designs and would require its own justification. Their immediate purpose is to show what a source reports and whether it can carry the associated claim. Two review publications may share primary studies, so agreement between them does not establish independent replication.

Table 4. Method-transparency anchors for strong decision-area and cross-cutting claims.

Decision area	Method-transparent anchor	Publicly reported method indicators
Demand forecasting	Gomaa (2026)	Manufacturing-primary systematic review; explicit review objective, manufacturing-supplychain boundary, and structured review process.
Dynamic pricing	Chenavaz and Dimitrov (2025)	Systematic review with Web of Science/Scopus search stages, explicit selection procedure, and 95 peer-reviewed articles.
Procurement	Balkan and Akyuz (2025); Berbig et al. (2026)	Systematic/taxonomic and bibliometric review evidence with explicit corpus-construction procedures.
Supplier selection	Cordeiro et al. (2026)	PRISMA review using Scopus, ScienceDirect, Web of Science and Engineering Village; 27 included studies.
Inventory management	Royani et al. (2026)	PRISMA 2020 systematic review focused on manufacturing inventory decisions.
Production	Mayerhoff and Schmidt (2026)	Systematic review of 196 peer-reviewed RL-PPC

planning/scheduling		studies with explicit industrial-maturity analysis.
	Fatorachian and Kazemi (2026)	
Supply-chain optimization/resilience		Systematic review of 112 studies; staged screening and independent full-text evaluation.
GenAI / LLM supply chains	Song et al. (2026); Panja et al. (2026)	Systematic reviews linking LLM/GenAI capabilities to SCOR/LSCM applications and identifying field-deployment limitations.
Manufacturing-wide AI / governance	Pan et al. (2026); Vyhmeister and Castañé (2026); Rajashekarappa et al. (2026)	Systematic manufacturing/Industry 5.0 and industrial-MLOps reviews supporting deployment, human-centricity, trustworthy-AI and lifecycle boundary claims.

3.5 Synthesis procedure and robustness analyses

The reported synthesis compares findings within decision areas, identifies constraints recurring across areas, relates those constraints to the theoretical foundations, and compares descriptive coverage in the full corpus and restricted subset. This sequence supports conceptual integration. It does not supply causal estimates for the MAIDF propositions.

The sensitivity comparison uses four counts for each decision area: all dedicated reviews, dedicated reviews in the systematic subset, manufacturing-primary dedicated reviews, and manufacturing-primary dedicated reviews in that subset. Agreement between the two profiles indicates stability to this design restriction only. It does not resolve search omissions, classification error, weak primary studies or overlap among reviews.

4. RESULTS: evidence architecture and robustness

4.1 Corpus profile

The updated analytical corpus contains 80 review-level publications: 44 function-specific reviews, 12 crossfunctional reviews, and 24 contextual reviews. Fifty-nine belong to the systematic/systematic-component core and 21 provide other review-level extension. Thirty-three reviews are manufacturing-primary when sectoral context is coded independently of evidence layer. Eleven of these are function-specific, one is cross-functional, and 21 are contextual. Primary AI decision-role coding is used to organize synthesis rather than to estimate field-wide prevalence.

Table 5 reports the function-specific distribution: 15 reviews address supply-chain optimization or resilience, nine production planning or scheduling, five forecasting, four each pricing, procurement and inventory, and three supplier selection. These counts sum to 44. The corresponding systematic-

subset counts sum to 33; the remaining 26 of the reported 59 systematic reviews fall outside the function-specific layer.

The expanded bibliography includes substantial GenAI and manufacturing-wide coverage. Song et al. (2026), Callefì et al. (2026) and Panja et al. (2026) address LLMs and GenAI in supply chains. Other reviews examine manufacturing operations, Industry 5.0, human involvement, trustworthy AI, lifecycle management and sustainability (Martuscelli et al., 2026; Pan et al., 2026; Tzionis et al., 2026; Vyhmeister and Castañé, 2026; Maghanaki, Shahin and Chen, 2026; Chen et al., 2026; Li et al., 2026; Sadeqi Bajestani et al., 2026; Rajashekarappa et al., 2026; Qing and Ramayah, 2026). The selected corpus cannot establish relative publication growth rates for these streams.

4.2 Manufacturing evidence concentration after the 2026 update

Figure 3 and Table 5 show the reported manufacturing-primary pattern. Dedicated reviews occur in production planning or scheduling (nine), forecasting (one) and inventory (one). The systematic subset retains seven, one and one, respectively. Manufacturing-primary describes the review's organizing scope; it does not imply that every primary study reports a live industrial deployment.

Production planning or scheduling accounts for 81.8% (9/11) of manufacturing-primary dedicated reviews and 77.8% (7/9) in the restricted subset. No dedicated manufacturing-primary review is recorded for pricing, procurement, supplier selection or broad supply-chain optimization in this classification. A zero in this table means no review was classified in that cell. It does not demonstrate an absence of manufacturing primary studies, industrial applications or relevant evidence within cross-sector reviews.

Table 5. Coverage sensitivity by focal decision area after the 2026 update.

Decision area	All reviews	Systematic core	Mfg-primary	Mfg-primary core
Demand forecasting	5	2	1	1
Dynamic pricing	4	2	0	0
Procurement	4	3	0	0

Supplier selection	3	3	0	0
Inventory management	4	3	1	1
Production planning/scheduling	9	7	9	7
Supply-chain optimization/resilience	15	13	0	0

Note. Counts are reported classifications awaiting the expanded record-level audit. Zero denotes an empty coded category, not proof that manufacturing evidence is absent.

Dedicated review coverage and manufacturing-primary concentration

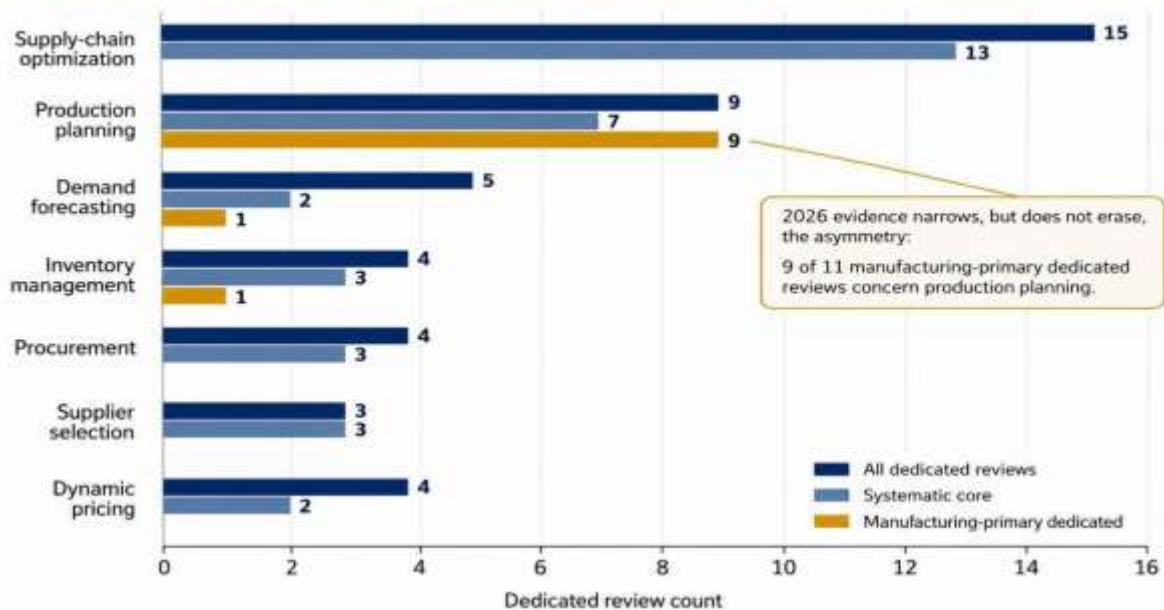


Figure 3: Dedicated review coverage, systematic-core sensitivity and manufacturing-primary concentration through 31 August 2026. The 2026 update adds manufacturing-primary demand-forecasting and inventory reviews, narrowing but not erasing the concentration in production planning/scheduling. AI-assisted preparation attributed in the source manuscript to OpenAI ChatGPT (GPT-5.6 Sol).

5. Critical synthesis by commercial decision domain

5.1 Market and revenue planning

5.1.1 Demand forecasting and demand planning

Demand forecasting is now supported by five dedicated review-level sources. Earlier cross-sector syntheses establish a long technical tradition in predictive analytics and AI forecasting (Seyedan and Mafakheri, 2020; Angos Mediavilla et al., 2022; Douaioui et al., 2024; Walter et al., 2025). Gomaa (2026) materially changes the manufacturing-specificity conclusion by providing a systematic review explicitly focused on AI demand forecasting in manufacturing supply chains.

The combined evidence still does not justify a universal claim that ML or DL outperforms statistical forecasting. The decision-relevant pattern is conditional: flexible learning methods become more attractive with nonlinear, highdimensional and information-rich demand, while sparse, intermittent or regime-shifting demand increases the value of robust baselines, hybrid models and explicit uncertainty treatment. Manufacturing evaluation should therefore connect forecast choice to service, inventory, capacity and production outcomes rather than stop at MAPE, RMSE or predictive accuracy.

A dedicated manufacturing review narrows the transfer problem but does not establish replicated field effectiveness. Comparisons of forecasting architectures must still account for the capacity, inventory and service conditions in which the forecasts are used.

5.1.2 Dynamic pricing

Dynamic pricing now has four dedicated review-level sources in the corpus. den Boer (2015) provides the historical pricing-and-learning survey, while Chenavaz and Dimitrov (2025) provide the systematic AI-focused synthesis. The 2026 update adds Fasihi et al. (2026), a semi-systematic review of 49 studies, and Ozay, Jahanbakht and Wang (2026), a bibliometric map of 1,301 Scopus-indexed publications. Together, these reviews show a shift toward deep learning, contextual-bandit and reinforcement-learning methods, multi-agent approaches, and simulation-driven pricing. However, the application base remains concentrated in data-rich and digitally mediated sectors rather than manufacturing B2B pricing.

The manufacturing transfer burden is therefore still high. Industrial prices are often negotiated, contract-bound, bundled with service, observed at low transaction frequency and constrained by capacity or lead time. Customer relationships persist across transactions, so aggressive online experimentation can impose strategic costs. MAIDF therefore favors predictive win/elasticity estimation, scenario optimization and human approval over unconstrained adaptive pricing unless the feedback and accountability regimes are demonstrably suitable.

5.2 Sourcing and supplier management

5.2.1 Procurement

Guida et al. (2023), Spreitzenbarth, Bode and Stuckenschmidt (2024), Balkan and Akyuz (2025), and Berbig et al. (2026) address procurement applications including spend classification, supplier discovery, document processing, risk analysis and sourcing support. Together they broaden the application map. Their findings also require care where classification depends on ambiguous organizational concepts and human judgment.

Longitudinal decision value remains an important evaluation problem. Enterprise resource planning (ERP) integration, data quality, ownership, traceability and user acceptance affect whether automated tasks improve sourcing. Manufacturing adds interdependencies involving quality, continuity, capacity and sustainability. Evaluation should therefore examine sourcing outcomes, exception handling, decision latency and return on investment over time.

5.2.2 Supplier selection

Supplier-selection evidence expands sharply. In addition to Gidiagba, Tartibu and Okwu (2025), Cordeiro et al. (2026) conduct a PRISMA systematic review of ML for supplier qualification and performance prediction, while Gupta, Chadha and Srivastava (2026) synthesize AI and hybrid multi-criteria approaches. The new reviews strengthen evidence that ML can support classification, ranking and multi-criteria decision support, but they also report heterogeneity of metrics, data quality limitations, interpretability concerns and limited real-world validation.

The core problem remains construct validity. Supplier choice has no single observable ground truth because financial, quality, delivery, sustainability, technology and risk priorities change with strategy and disruption. Accordingly, the accountability regime is central: ranking stability, criterion provenance, sensitivity analysis, explanation and explicit override rights are as important as predictive fit.

5.3 Internal planning and control

5.3.1 Inventory management

Inventory management now has four dedicated review-level sources, including a new manufacturing-primary systematic review. Royani et al. (2026) use PRISMA 2020 to compare statistical, AI and hybrid methods specifically for manufacturing inventory decisions. Their synthesis supports a context-fit interpretation: statistical methods remain effective under stable historical patterns and strong interpretability needs, AI becomes more attractive with large-scale nonlinear and dynamic data, and hybrid approaches may balance accuracy and explainability.

The context dependence described in these reviews motivates MAIDF's data-adequacy and accountability questions. It does not validate the framework. Inventory value depends on service targets, shortage costs, working capital, lead times and feasible replenishment actions. Policy-level comparisons against statistical and operations research baselines are therefore needed before interpreting forecast improvement as a commercial benefit.

5.3.2 Production planning and scheduling

Production planning and scheduling remain the strongest manufacturing-primary domain, now with nine dedicated reviews and seven in the systematic core. The 2026 additions are particularly important. Mayerhoff and Schmidt (2026) synthesize 196 peer-reviewed RL studies for production planning and control and find validation to be overwhelmingly simulation-centric, with rare physical testbeds and no reviewed case of sustained closed-loop autonomous control in continuous live production. Schneider et al. (2026) similarly review RL in production control and expose uneven coverage of control tasks and logistical target variables. Waubert de Puiseau et al. (2026) add a 143-study deep-RL machine-scheduling review and again report limited use of real data and stochastic/large-scale settings.

These findings motivate evaluation beyond simulator performance. Policies must cope with incomplete state information, disturbances, changing priorities and operator intervention, as well as integration with manufacturing execution systems (MES) and ERP. Shadow-mode evaluation, calibrated simulation, constrained or offline learning, and recovery testing are candidate safeguards whose adequacy depends on the deployment setting.

5.4 Network coordination, optimization, and resilience

Supply-chain optimization/resilience remains the largest dedicated cluster, now with 15 reviews and 13 in the systematic core. Fatorachian and Kazemi (2026) add a systems-theory synthesis of 112 studies and emphasize integration, information sharing and real-time decision-making; Noor et al. (2026) synthesize 103 ML studies and organize applications and adoption barriers using SCOR. These additions strengthen evidence for broad AI capability while also foregrounding technical, human and contextual barriers.

Transfer to a manufacturing network depends on its structure, data-sharing arrangements, supplier concentration, product characteristics and lead times. Cross-sector reviews help identify capabilities and recurring barriers. Their application to a particular network still requires evidence about operational interdependence and decision ownership.

Table 6. Critical synthesis by focal decision area after the 2026 update.

Decision area	What review evidence supports	Manufacturing transfer constraint	Priority evidence gap
Demand forecasting	ML/DL can add value under nonlinear or high-dimensional data; a 2026 manufacturing systematic review now exists.	Sparse/intermittent demand, regime shifts, and weak linkage from forecast error to decision economics.	Replicated manufacturing field studies linking forecast choice to service, inventory and capacity outcomes.
Dynamic pricing	Learning-based pricing is mature across data-rich sectors; 2026 evidence broadens cross-industry mapping.	Negotiated B2B relationships, low transaction frequency, contracts, and capacity/lead-time coupling.	Manufacturing/B2B pricing studies with causal or quasiexperimental evaluation.
Procurement	AI supports classification, sourcing, risk detection, document processing and decision augmentation.	ERP/process integration, ownership, data quality, user acceptance and accountability.	Longitudinal manufacturing decision-quality and ROI evidence.
Supplier selection	ML and hybrid MCDM can support classification, ranking and sustainability-oriented choice.	No single ground truth; criteria, provenance, metric heterogeneity and interpretability affect ranking validity.	Stability, sensitivity, override and outcome validation under changing supplier conditions.
Inventory management	Statistical, AI and hybrid policies have context-dependent strengths; manufacturing-specific review evidence now exists.	Accuracy is not inventory economics; service cost, action spaces and lead-time/multiechelon dynamics matter.	Manufacturing policy trials using service-cost and working-capital outcomes.

Decision area	What review evidence supports	Manufacturing transfer constraint	Priority evidence gap
Production planning/scheduling	Strong manufacturing review base for RL, scheduling, digital twins and XRL; 2026 SLR covers 196 RL-PPC studies.	Simulation dominance, sim-to-real transfer, safety, integration and human override.	Sustained live deployment evidence across sites and disturbances.
Supply-chain optimization/resilience	Broad evidence spans prediction, integration, risk, resilience, XAI, prescriptive analytics, ML and GenAI.	Cross-sector heterogeneity, datasharing rights, network coupling and evidence overlap.	Interorganizational field studies using shared data and systemlevel KPIs.

5.5 Cross-review contradictions and unresolved tensions

Table 7 sets out tensions between capability claims and deployment conditions. These are interpretive contrasts across heterogeneous reviews. They should not be read as directly comparable statistical contradictions between matched studies.

Table 7. Contradictions and unresolved tensions across review streams.

Tension	Evidence emphasizing capability	Countervailing evidence or boundary	MAIDF interpretation
Forecasting superiority	Algorithm-focused reviews document strong ML/DL performance in nonlinear and high-dimensional settings.	Manufacturing and inventory reviews stress data regime, baselines, interpretability and downstream decision loss; no universal superiority follows (Gomaa, 2026; Royani et al.,	Data adequacy and economic decision loss condition whether accuracy gains translate into value.



2026).			
AI maturity vs. deployment	2026 SCM and manufacturing reviews map a rapidly expanding application space.	Field evidence remains thin in several streams; Panja et al. (2026) report simulation/artificial-data dominance and Mayerhoff and Schmidt (2026) find rare physical/live RL deployment.	Capability breadth is not deployment maturity; feedback, coupling and actionability matter.
Explainability vs. appropriate reliance	Manufacturing XAI reviews emphasize transparency and challenge ability (Tzionis et al., 2026).	Trustworthy-AI evidence shows many industrial applications remain at low technology readiness levels; explanation alone cannot establish safe reliance.	Accountability requires evidence that explanation improves detection, override and recovery.
GenAI capability vs. decision validity	Recent IJPR reviews identify LLM/GenAI capability pathways across SCM (Callefi et al., 2026; Song et al., 2026).	Grounding, data governance, domain integration and field validation remain material constraints (Panja et al., 2026; Maghanaki et al., 2026).	Generative capability must be bounded by data adequacy, validated tools and explicit accountability.

6. Cross-cutting evidence: human-AI collaboration, governance, and generative AI

6.1 Human-AI collaboration and appropriate reliance

Human users are part of the decision system rather than passive recipients of model output. Kumar and Kumar (2025) review human-AI collaboration in operations and supply chains, while Mehrotra et al. (2024) emphasize appropriate rather than maximal trust. The 2026 manufacturing literature reinforces the point: Tzionis et al. (2026) organize XAI around manufacturing applications, and Vyhmeister and Castañé (2026) find much Industry 5.0 trustworthy-AI evidence at early technology-readiness levels.

Collaboration should be evaluated through the quality of acceptance, challenge, override and

escalation decisions. An explanation may be useful when it helps identify an error or recover from one. Persuasive explanations can also encourage reliance without improving correctness. Accordingly, explanation quality and appropriate reliance need separate assessment.

6.2 Governance and accountability

Governance affects the architecture of the decision system. Batool et al. (2025) review governance frameworks, and Vyhmeister and Castañé (2026) examine trustworthy AI in Industry 5.0. The practical requirements vary by decision: forecasting raises provenance and drift questions; supplier ranking requires defensible criteria; pricing requires review of commercial and applicable regulatory constraints; and production control needs safe intervention and recovery. MAIDF uses these differences to frame accountability before deployment.

MAIDF captures this through accountability: who must understand, approve, challenge, audit and own the decision; how reversible the decision is; and what recovery mechanism exists. A technology can fit the computational task and still be unfit for the accountability architecture in which the task is performed.

6.3 Generative AI and large language models

Recent reviews broaden the GenAI evidence map without establishing deployment maturity. Song et al. (2026) systematically map LLM capabilities across SCOR processes; Panja, Zheng and Glock (2026) review 43 GenAI studies across logistics and supply-chain functions; Bahroun et al. (2026) provide a PRISMA-guided 98-study analysis of generative AI for supply-chain transformation; and Callefi et al. (2026) derive a TTF-grounded hierarchy of GenAI-enabled supply-chain capabilities. Manufacturing-focused reviews now examine LLMs, GenAI and human-in-the-loop architectures across smart manufacturing and the broader value chain (Maghanaki, Shahin and Chen, 2026; Chen et al., 2026; Li et al., 2026; Sadeqi Bajestani et al., 2026; Ilieva and Iliev, 2026).

This evidence distinguishes at least four commercial roles: knowledge/interface augmentation, scenario and synthetic-data generation, design and engineering co-creation, and decision orchestration across retrieval, optimization, digital twins, enterprise systems and human experts. The literature is nevertheless explicit about maturity limits. Panja et al. (2026) report that most included studies rely on simulation or artificial datasets, while manufacturing reviews emphasize grounding, domain integration, data privacy, interpretability and human oversight. Fluent generation is therefore not equivalent to valid decision support.

Relative to these recent frameworks, MAIDF is intentionally technology-agnostic. It does not prescribe one LLM architecture or capability sequence. Instead, it asks whether the underlying data,

feedback, operational and accountability conditions support the intended decision role. Low-stakes knowledge synthesis may require provenance and retrieval; scenario generation may require simulation validation; and consequential recommendations may require bounded tools, deterministic optimization components, explicit uncertainty and human approval.

7. Manufacturing AI Decision-Fit as a decision aid

7.1 Operational definitions

Figure 4 presents MAIDF as a proposed transfer framework. Its non-compensatory rule is a precautionary design choice: strength in one regime should not offset an unresolved, high-consequence mismatch in another. Abundant data do not make hazardous experimentation acceptable, and accurate forecasts do not remove capacity constraints. The rule has not been empirically calibrated, and satisfying all four checks is not proof of safety or economic value.

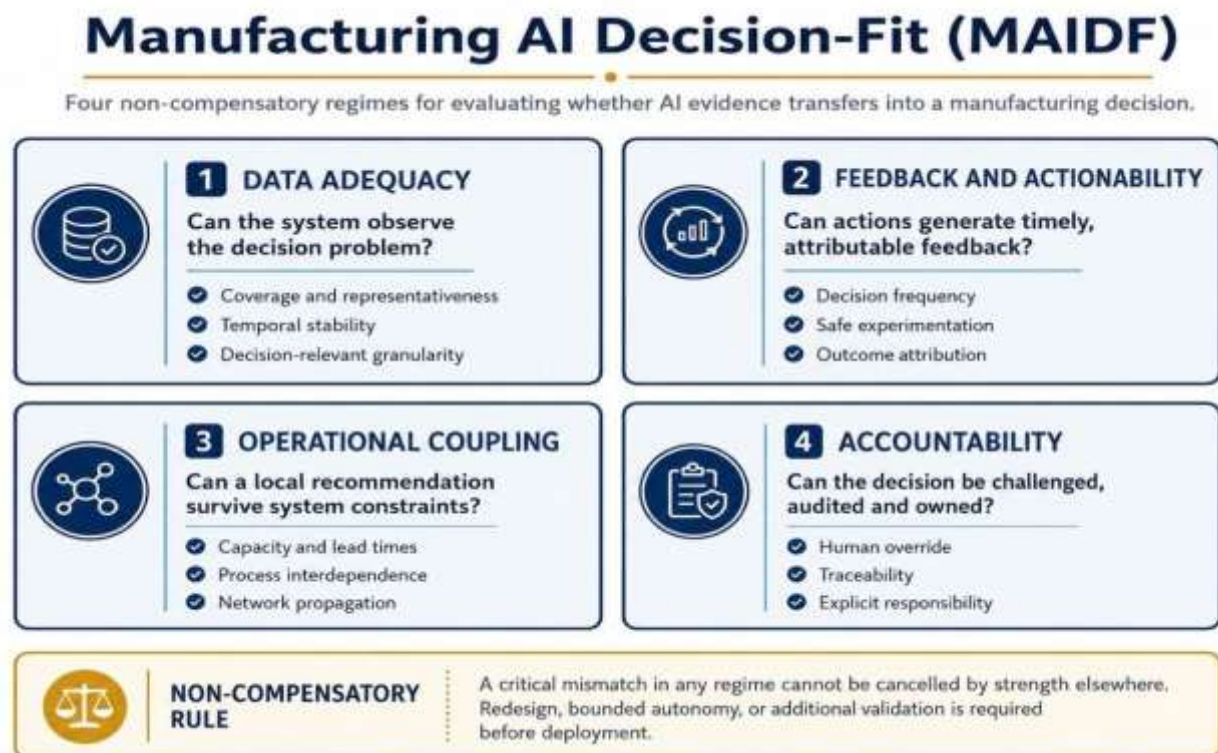


Figure 4: Manufacturing AI Decision-Fit (MAIDF) framework. Transferability is assessed across four non-compensatory regimes before deployment value is evaluated. AI-assisted preparation attributed in the source manuscript to OpenAI ChatGPT (GPT-5.6 Sol).

Table 8. Operationalization of the four MAIDF regimes.

Regime	Key diagnostic questions	Evidence of fit	High-risk mismatch
Data adequacy	Are decision-relevant variables observable? Is history representative? Are data granular and timely enough for the proposed role?	Stable feature definitions, sufficient comparable cases, data lineage, measurable decision target.	Sparse/nonstationary observations, missing contextual variables, target leakage, proxy objectives disconnected from economics.
Feedback / actionability	How quickly are outcomes observed? Can effects be attributed to actions? Can the organization experiment safely?	Short/traceable feedback, repeated decisions, reversible trials, clear action-response link.	Long contractual cycles, confounded outcomes, strategic relationship costs, unsafe exploration.
Operational coupling	Which capacity, lead-time, process, supplier, or network constraints can invalidate a local recommendation?	Integrated constraints, digital twin/simulation, system-level objective, stress-tested interactions.	Locally optimal recommendations that create downstream bottlenecks or amplify disruption.
Accountability	Who must understand, approve, challenge, audit, or own the decision? How reversible is error?	Audit trail, uncertainty communication, escalation, human override, monitoring, defined ownership.	High-stakes/irreversible action with opaque rationale, unclear ownership, or no recovery mechanism.

7.2 Measurement guidance, interactions, and scope

The four regimes are not asserted to be exhaustive or statistically independent. Organizational readiness, competitive dynamics, regulation, cybersecurity and sustainability can act as antecedents, moderators, or consequences of the four regimes and should be added if empirical validation demonstrates incremental explanatory value. MAIDF instead proposes a parsimonious starting structure whose components can be measured and falsified. Candidate operational measures include: Data adequacy: missingness, coverage of decision-relevant variables, feature-definition stability, comparable historical episodes, drift magnitude, label/target validity, and data lineage completeness. Feedback/actionability: median decision-to-outcome latency, decisions per period, proportion of outcomes attributable to the focal action, reversibility of experiments, and share of recommendations

that can actually be implemented.

Operational coupling: number and criticality of binding capacity/lead-time constraints, network dependency depth, disturbance-propagation measures, and the gap between local and system-level objective values.

Accountability: financial and regulatory exposure, decision reversibility, number of approval and escalation layers, audit obligations, override rights, and time-to-recovery after an AI-supported error. Interactions should be expected rather than suppressed. Data adequacy is less valuable for adaptive learning when feedback is too slow to attribute outcomes; operational coupling increases the consequences of feedback errors; and high accountability can convert a technically feasible autonomous policy into a bounded human-in-the-loop architecture. Future validation should therefore test both the main effects in P1 to P4 and interactions among regimes, with P5 treated as the higher-order transfer proposition.

7.3 Decision-aid workflow

Figure 5 sets out the proposed workflow. Specify the decision objective and a credible baseline, identify AI's intended role, and examine all four regimes. An unresolved critical mismatch leads to redesign, restricted autonomy or further validation. Architecture selection can then consider shadow mode, bounded decision support or autonomous execution as appropriate. Deployment value must subsequently be evaluated through economic, operational, human and governance outcomes. The workflow is a decision aid, not a validated approval instrument.

MAIDF decision-aid workflow

Decision definition, AI role, fit screening, architecture selection and value validation.

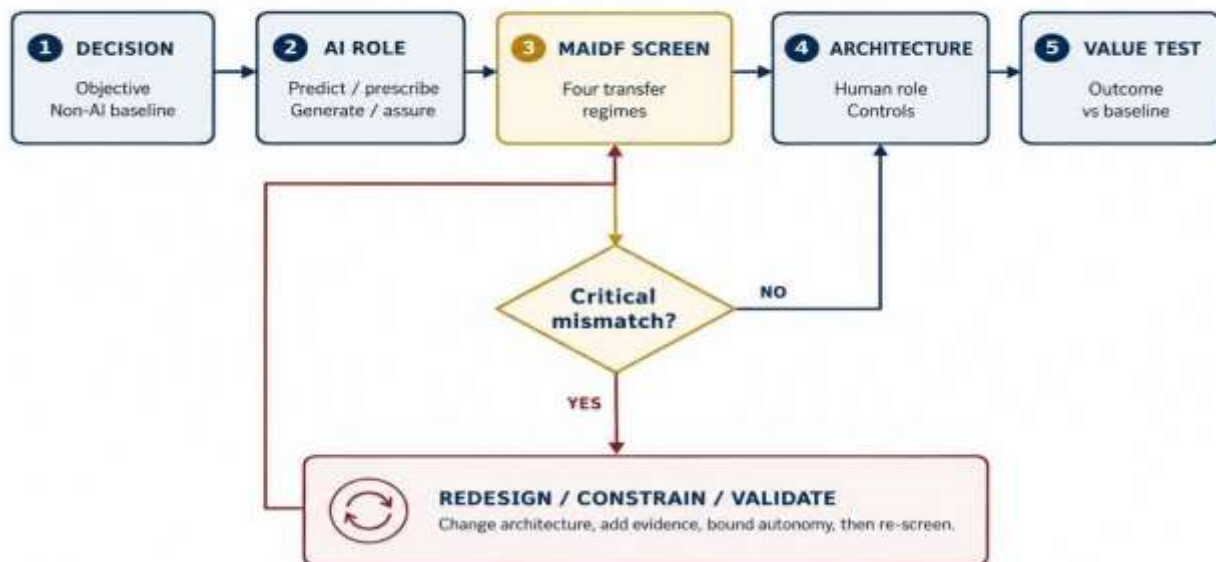


Figure 5: MAIDF decision-aid workflow. A critical unresolved mismatch branches to redesign, constrained autonomy or further validation before the architecture proceeds to value testing. AI-assisted preparation attributed in the source manuscript to OpenAI ChatGPT (GPT-5.6 Sol).

7.4 Worked manufacturing applications

Table 9 interprets three review anchors through MAIDF. These applications illustrate how the proposed regimes inform architecture and evaluation choices; they are not empirical case studies or independent validation of the framework. The outcomes in the final column are proposed evaluation measures, not observed effects.

Table 9. Evidence-linked MAIDF demonstrations using updated review anchors.

Decision	Regime profile	Implication for AI architecture	Proposed evaluation measures
Manufacturing demand forecasting - Gomaa (2026)	Manufacturing-specific review evidence now exists, but transfer still depends on demand sparsity, exogenous data quality and the downstream planning objective.	Use AI complexity only when data adequacy and downstream service/capacity value justify it; retain robust statistical/hybrid baselines.	Forecast error plus service, inventory, capacity and stability outcomes.
Manufacturing inventory -Royani et al. (2026)	Statistical methods remain competitive in stable/transparent regimes; AI is stronger in larger, nonlinear, dynamic data; hybrids are promising.	Select statistical, AI or hybrid architecture from data regime and accountability needs, then connect predictions directly to inventory policy.	Service level, shortage cost, working capital, interpretability and policy stability.
Production RL -Mayerhoff and Schmidt (2026)	196-study review is simulation centric; physical testbeds are rare and sustained live closed-loop autonomy was not reported.	Treat high coupling and unsafe exploration as a deployment gate: use digital twins'/shadow mode, offline/safe RL, constraints and operator override.	Throughput, tardiness, recovery, safety, override quality and sustained live robustness.

8. DISCUSSION

8.1 From an evidence gap to a graded transferability problem

The reported distribution directs attention to transferability across commercial functions. Manufacturing-primary review coverage includes forecasting and inventory, while production planning retains the largest dedicated cluster. The classification should inform where further scrutiny is needed, rather than ranking the actual industrial effectiveness of AI across functions.

Manufacturing specificity is an external-validity question. Evidence from another sector may be useful when the source and target share relevant data, feedback, operational and accountability conditions. Conversely, a manufacturing label alone provides little assurance when those conditions differ.

MAIDF makes that comparison explicit.

8.2 Theoretical contribution relative to recent fit and supply-chain frameworks

MAIDF extends established fit reasoning to evidence transfer. Task-technology fit links capabilities to task requirements; information-processing theory connects uncertainty to organizational information needs; sociotechnical systems theory places technical choices within work arrangements; and appropriate reliance addresses how people use or challenge recommendations. The proposed integration remains open to comparison with existing readiness and fit constructs.

Recent reviews help define the contribution boundary. Calfe et al. (2026) extend TTF with a GenAI capability pathway in SCM; Song et al. (2026) combine SCOR, context-mechanism-outcome logic and dynamic capabilities for LLM applications; Fatorachian and Kazemi (2026) use systems theory to interpret AI-enabled supply-chain integration. The proposed distinction has three parts. First, its unit of analysis is evidence transfer into a target decision rather than technology adoption or capability accumulation. Second, it separates feedback/actionability and operational coupling because industrial learning signals and system constraints can invalidate otherwise good task-technology fit. Third, it treats accountability as part of fit before deployment, not as an ex-post governance layer.

8.3 Implications for manufacturing executives

The practical sequence should begin with the decision, not the model. Executives should ask four questions before model selection:

Data: Are available signals observable, representative, timely and decision-relevant enough to justify the proposed model complexity?

Feedback: How quickly and safely can the organization observe whether an AI-supported action was correct, and can the outcome be attributed to that action?

Operational coupling: Which capacity, lead-time, supplier, process or network constraints can invalidate a locally optimal recommendation?

Accountability: Who must understand, approve, challenge, audit or own the decision when outcomes are adverse?

The evaluation standard changes accordingly. Forecasting should be linked to service, inventory and capacity outcomes; scheduling to robustness and recovery; supplier selection to ranking stability and explanation; GenAI to grounding and error containment. Model accuracy remains relevant but becomes an intermediate metric rather than the business outcome.

8.4 Implications for industrial research infrastructure

The 2026 evidence strengthens the case for realistic industrial test infrastructure. Mayerhoff and Schmidt (2026) show that RL-PPC validation remains simulation-centric; Panja et al. (2026) find

substantial reliance on simulation and artificial datasets in GenAI supply-chain research; trustworthy-AI reviews show many industrial applications

remain at relatively early readiness levels, and Rajashekarappa et al. (2026) identify data quality, drift, integration and lifecycle-automation gaps in industrial MLOps. Shared testbeds, controlled industrial data spaces, lifecycle monitoring and multi-site replication are therefore central to moving from capability demonstrations to transferable evidence.

A minimum reporting standard for manufacturing AI field studies should include the decision objective and non-AI baseline; data provenance and temporal split; feedback latency and attribution; binding operational constraints; human role and override rights; governance/audit requirements; deployment mode and monitoring; and economic plus operational outcomes. Reporting these elements would make future studies directly codable against MAIDF and improve cross-firm transferability.

8.5 Prioritized research agenda

Table 10. Prioritized research agenda for manufacturing AI decision value.

Priority	Core question	Recommended design	Expected contribution
Manufacturing/B2B dynamic pricing	How do negotiation, contracts, low transaction frequency, capacity and lead times alter adaptive pricing value?	Multi-firm archives; Quasi experiments; capacity-constrained design science.	Tests the remaining high transfer-burden pricing gap and P2/P3.
Replicated manufacturing forecasting	Do AI forecasts improve service, inventory and capacity outcomes across multiple manufacturers?	Longitudinal multi-site studies with statistical/hybrid baselines.	Moves the new 2026 manufacturing review evidence from single-review presence to replicated external validity.
Policy-level inventory validation	Do AI/hybrid policies improve service-cost outcomes under real lead-time and replenishment constraints?	Paired statistical/OR/AI policy trials with cost-sensitive evaluation.	Tests the context-fit claims synthesized by Royani et al. (2026).

Sim-to-real production AI	When do RL/digital-twin policies remain robust under incomplete state information, disruptions and operator intervention?	Physical testbeds; shadow mode; safe offline RL; stress testing.	Addresses the deployment gap quantified by Mayerhoff and Schmidt (2026).
Human-AI decision architecture	When should managers accept, challenge or override AI recommendations?	Controlled field experiments; process tracing; calibrated-reliance and recovery metrics.	Replaces adoption attitude with measurable collaborative decision performance.
Grounded GenAI decision support	How should GenAI interfaces connect to retrieval, optimization, digital twins and enterprise controls?	Design science; red teaming; grounded tasks; tool-use audits; human approval.	Separates fluent generation from valid commercial decisions.
MAIDF construct validation	Do the four regimes predict incremental decision value beyond generic TTF and readiness constructs?	Construct development; multidomain field studies; moderated performance models; replication.	Tests the framework as theory rather than leaving it as a descriptive aid.
Second-order evidence overlaps	How much apparent replication is caused by primary studies appearing in multiple reviews?	Citation-overlap matrices and corrected covered area in future umbrella updates.	Improves confidence in review level robustness claims.

9. LIMITATIONS AND BOUNDARY CONDITIONS

The review uses purposive integrative synthesis rather than an exhaustive database census. Search services, execution dates and complete retrieval sets are not available for the full historical corpus. Moreover, the recovered supplementary files describe the earlier 49-review base rather than the complete 80-review expansion. The reported counts and sensitivity classifications require reconciliation against the expanded evidence matrix before they can be independently reproduced.

Review-level synthesis inherits publication and reporting biases from primary studies. Overlap among reviews creates further dependence: 80 publications cannot be interpreted as 80 independent evidence bases. Corrected covered area was not computed. A primary-study overlap matrix would be needed to quantify the degree of duplication.

Restricting the corpus to systematic or systematic-component reviews cannot substitute for critical

appraisal. The five proposed transparency indicators do not provide a completed assessment of every included review, and reporting completeness alone does not establish low risk of bias. These limitations restrict the strength of cross review conclusions.

Function-specific scope, manufacturing-primary status and primary AI role require judgment. No retained prospective independent-coder log supports an agreement statistic. The expanded coding matrix and source excerpts are needed to inspect boundary decisions. Independent recoding should precede stronger claims about classification reliability.

MAIDF has not been validated as a measurement instrument or causal model. Its four regimes may overlap, and the definition and threshold of a critical mismatch remain context-dependent. Organizational readiness, competition, cybersecurity, regulation and sustainability may add explanatory value. Comparative field testing is needed to establish whether MAIDF improves decisions beyond established fit and readiness approaches.

The review is restricted to English-language peer-reviewed material for counted evidence and has a cutoff of 31 August 2026. Relevant non-English, practitioner, grey-literature and later 2026 developments may therefore be missed, particularly for proprietary industrial deployments.

The evidence base is time-sensitive. Publisher citation years and first-online dates may differ, so historical eligibility should be checked against the actual availability date. The update's date restriction and incomplete retrieval trail create additional omission risk.

10. CONCLUSION

The review links AI-supported commercial decisions in manufacturing to the conditions under which evidence can be transferred into practice. The reported corpus includes dedicated manufacturing reviews in forecasting and inventory alongside a larger production-planning cluster. This pattern concerns the scope of selected reviews and should not be interpreted as a census of industrial applications.

MAIDF organizes the transfer question around data adequacy, feedback and actionability, operational coupling, and accountability. It connects established fit and organizational theories to a specific target decision, keeping algorithm performance distinct from economic and operational value. The five propositions and non-compensatory workflow provide an agenda for empirical testing, not a validated deployment guarantee.

The practical implication is to examine source-target conditions before selecting the degree of

autonomy, then compare outcomes against a credible baseline. Independent reproduction of the corpus classification and field validation of the framework remain necessary before stronger claims about generalizability or decision improvement can be made.

Data availability statement and supplementary material

The numerical synthesis reports 80 review-level publications. The presently available supplementary records comprise an earlier 49-review matrix, its structured search audit and its methodological-anchor summary. These do not provide the complete record-level basis for the expanded counts. Independent reproduction requires the updated S1 evidence matrix, S2 search and disposition record, and S3 appraisal records, reconciled to the tables and figures. No complete public repository for those expanded files is identified in this version. The study reports using published literature rather than proprietary, personal or individual-level data.

Declarations

Funding. This research received no external funding.

Competing interests. The author has held senior commercial roles for approximately two decades with consumer electronics manufacturers, including LG Electronics and Panasonic, with regional profit-and-loss responsibility. These roles inform the practitioner perspective. The author reports no current commercial, advisory, or financial relationship with any organization whose evidence is synthesized, and no organization reviewed or influenced the analysis before submission.

Ethics. This study synthesizes published literature and public institutional information. It did not recruit human participants or use personal data.

Author contributions. Kamran Pitaifi: conceptualization; methodology; investigation; evidence curation; formal synthesis; writing -original draft; writing -review and editing; visualization; project administration.

AI-assisted tools. The source manuscript reports using OpenAI ChatGPT (GPT-5.6 Sol, accessed 1 September 2026) for search-term expansion, candidate discovery, bibliographic and consistency checks, language refinement, editorial restructuring, document production and code-assisted figure preparation. This version also received AI-assisted editorial review, language revision, source spot-checking and formatting through OpenAI ChatGPT/Codex on 16 September 2026. No new empirical observations, search-history counts or coding-agreement statistics were generated. The model version for this later assistance is not verified in the available record. The author must confirm the tool history, applicable terms, accuracy, originality, references and final wording before submission, and retains responsibility for the research and its interpretation. Figure captions preserve the source manuscript's

AI-assistance attribution.

Appendix A. Evidence-set summary

Table 11. Compact profile of the updated analytical corpus.

Evidence layer / review grouping	n	Primary AI role	n
Function-specific	44	Predictive	17
Cross-functional	12	Broad/mixed	23
Contextual	24	Prescriptive/adaptive	14
Systematic/systematic-component core	59	Assurance/governance	13
Other review-level extension	21	Generative	13

Manufacturing-primary profile. Thirty-three reviews are coded manufacturing-primary after applying sectoral context independently of evidence layer. Eleven are function-specific: nine production planning/scheduling, one demand forecasting, and one inventory management. One is cross-functional and 21 are contextual manufacturing reviews. Twenty-three manufacturing-primary reviews fall in the systematic/systematic-component core, including nine of the 11 function-specific reviews. The 2026 update therefore narrows the earlier asymmetry without removing the dominant production-planning concentration.

Appendix B. Coding dictionary

Appendix Table B1. Coding dictionary.

Field	Rule
Function-specific	Review is centrally organized around one focal decision area; passing mentions do not qualify.
Cross-functional	Review spans multiple operations/supply-chain decision areas and is used as supporting evidence rather than forced into a single function.



Contextual	Review informs manufacturing context, GenAI, XAI, trust, governance, or human-AI collaboration without inflating function counts.
Manufacturing-primary	Manufacturing or production is the central review context; general SCM reviews containing manufacturing primary studies do not qualify.
Predictive role	AI estimates future or latent states, classifies, or forecasts.
Prescriptive/adaptive role	AI recommends actions, optimizes decisions, or learns policies from interaction.
Generative role	AI generates text, scenarios, code, explanations, or interactive decision-support content.
Assurance/governance role	Primary focus is explainability, trust, human-AI interaction, oversight, auditability, or governance.
Broad/mixed role	Review deliberately spans multiple AI roles without one dominant analytical orientation.
Publication year	Publisher citation year used for consistency.

Appendix C. Final verification-update summary

The manuscript reports a 1 September 2026 update adding 31 publications to the 49-review base: 30 with 2026 citation years and one with a 2025 citation year. The bibliography includes manufacturing forecasting (Gomaa, 2026), inventory (Royani et al., 2026), production control (Mayerhoff and Schmidt, 2026; Schneider et al., 2026), and broader manufacturing and supply-chain reviews. The corresponding expanded record-level audit is not supplied with the available earlier supplementary files. The reported update history therefore remains subject to author reconciliation.

The reported function-specific manufacturing counts are nine production-planning reviews, one forecasting review and one inventory review. Their restricted-subset equivalents are seven, one and one. These values reconcile arithmetically with Table 5; arithmetic consistency does not verify inclusion or coding decisions.

Appendix D. Search query families and retrieval boundary

The following query families are retained from the manuscript's reported search strategy. They describe topical coverage, but are not a complete reproducible search log: exact service-specific

syntax, execution dates, retrieved records and dispositions are required as well. A 2026 citation-year filter alone cannot establish an exact online publication cutoff.

1. Demand forecasting/planning: ("artificial intelligence" OR "machine learning" OR "deep learning") AND (manufactur* OR "supply chain") AND ("demand forecasting" OR "demand planning") AND (review OR "systematic review")
2. Dynamic pricing: ("artificial intelligence" OR "machine learning" OR "reinforcement learning") AND "dynamic pricing" AND (review OR bibliometric OR "systematic review")
3. Procurement/purchasing: ("artificial intelligence" OR "machine learning") AND (procurement OR purchasing) AND (review OR "systematic review")
4. Supplier selection: ("artificial intelligence" OR "machine learning") AND ("supplier selection" OR "supplier qualification") AND (review OR "systematic review")
5. Inventory management/control: ("artificial intelligence" OR "machine learning") AND (manufactur* OR "supply chain") AND ("inventory management" OR "inventory control") AND (review OR "systematic review")
6. Production planning/control/scheduling: ("artificial intelligence" OR "reinforcement learning") AND ("production scheduling" OR "production planning" OR "production control") AND (review OR "systematic review")
7. Supply-chain optimization/resilience: ("artificial intelligence" OR "machine learning") AND "supply chain" AND (optimization OR resilience OR integration) AND (review OR "systematic review")
8. Generative AI / LLM supply chains: ("generative AI" OR "large language model" OR LLM) AND ("supply chain" OR logistics) AND (review OR "systematic review")
9. Generative AI / LLM manufacturing: ("generative AI" OR "large language model" OR LLM) AND manufactur* AND (review OR survey OR "systematic review")
10. Governance / XAI / trustworthy AI: ("explainable AI" OR "trustworthy AI" OR governance) AND (manufactur* OR industry) AND (review OR "systematic review")

REFERENCES

- Albayrak Ünal, Ö., Erkeyman, B., & Usanmaz, B. (2023). Applications of artificial intelligence in inventory management: A systematic review of the literature. *Archives of Computational Methods in Engineering*, 30(4), 2605–2625. <https://doi.org/10.1007/s11831-022-09879-5>
- Angos Mediavilla, M., Dietrich, F., & Palm, D. (2022). Review and analysis of artificial intelligence methods for demand forecasting in supply chain management. *Procedia CIRP*, 107, 1126–1131. <https://doi.org/10.1016/j.procir.2022.05.119>
- Babai, M. Z., Arampatzis, M., Hasni, M., Lolli, F., & Tsadiras, A. (2025). On the use of machine learning in supply chain management: A systematic review. *IMA Journal of Management*

- Mathematics*, 36(1), 21–49. <https://doi.org/10.1093/imaman/dpae029>
- Bahroun, Z., Saihi, A., Asad, R., & Tanash, M. (2026). A systematic analysis of generative artificial intelligence for supply chain transformation. *Supply Chain Analytics*, 13, 100188. <https://doi.org/10.1016/j.sca.2025.100188>
- Balkan, D., & Akyuz, G. A. (2025). Artificial intelligence (AI) and machine learning (ML) in procurement and purchasing decision-support (DS): A taxonomic literature review and research opportunities. *Artificial Intelligence Review*, 58, 341. <https://doi.org/10.1007/s10462-025-11336-1>
- Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: A systematic literature review. *AI and Ethics*, 5, 3265–3279. <https://doi.org/10.1007/s43681-024-00653-w>
- Berbig, D., Kania, A., Mroczek-Dąbrowska, K., & Bremser, K. (2026). Artificial intelligence in procurement: A systematic and AI-assisted literature review. *Business Process Management Journal*. <https://doi.org/10.1108/BPMJ-10-2025-1701>
- Bergsma, R., de Ruijt, C., & Bhulai, S. (2025). A systematic review of machine learning approaches in inventory control optimization. *Operations Research Perspectives*, 15, 100367. <https://doi.org/10.1016/j.orp.2025.100367>
- Callefi, M. H., Magalhães, E., Lopes Negrão, L. L., Thüerer, M., Siegler, J., Tomašević, I., & Godinho Filho, M. (2026). Building a pathway of GenAI-enabled capabilities for supply chain management. *International Journal of Production Research*, 64(16), 6874–6906. <https://doi.org/10.1080/00207543.2026.2636664>
- CESMII. (2026). *Data sharing, AI-ready data and data-first smart manufacturing: An industry coalition experience: NIST/NSF workshop study*. Smart Manufacturing Institute. <https://www.cesmii.org/data-sharing-ai-ready-data-and-datafirst-smart-manufacturing-an-industry-coalition-experience-nist-nsf-workshop-study/>
- Chen, C., Li, L., Wang, T., Wang, Z., Leng, J., Shao, H., & Cheng, L. (2026). Leveraging large language models for smart manufacturing: Reviews, enablers, challenges, and opportunities. *Journal of Manufacturing Systems*, 85, 593–612. <https://doi.org/10.1016/j.jmsy.2026.02.008>
- Chenavaz, R. Y., & Dimitrov, S. (2025). Artificial intelligence and dynamic pricing: A systematic literature review. *Journal of Applied Economics*, 28(1), 2466140. <https://doi.org/10.1080/15140326.2025.2466140>
- Cordeiro, L. N., Lordsleem Junior, A. C., Costa, T. C. A., & Rabbani, E. R. K. (2026). Evaluating machine learning models compared to traditional supplier qualification process techniques in supply chain management: A systematic literature review. *Brazilian Journal of Operations & Production Management*, 23(1), 3022. <https://doi.org/10.14488/BJOPM.3022.2026>
- Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry*, 162, 104132. <https://doi.org/10.1016/j.compind.2024.104132>
- Del Gallo, M., Mazzuto, G., Ciarapica, F. E., & Bevilacqua, M. (2023). Artificial intelligence to solve

- production scheduling problems in real industrial settings: Systematic literature review. *Electronics*, 12(23), 4732. <https://doi.org/10.3390/electronics12234732>
- den Boer, A. V. (2015). Dynamic pricing and learning: Historical origins, current research, and new directions. *Surveys in Operations Research and Management Science*, 20(1), 1–18. <https://doi.org/10.1016/j.sorms.2015.03.001>
- Douaioui, K., Oucheikh, R., Benmoussa, O., & Mabrouki, C. (2024). Machine learning and deep learning models for demand forecasting in supply chain management: A critical review. *Applied System Innovation*, 7(5), 93. <https://doi.org/10.3390/asi7050093>
- Erlenbusch, F., & Stricker, N. (2025). Explainable reinforcement learning in job-shop scheduling: A systematic literature review. *Procedia CIRP*, 132, 25–30. <https://doi.org/10.1016/j.procir.2025.01.005>
- Esteso, A., Peidro, D., Mula, J., & Díaz-Madroñero, M. (2023). Reinforcement learning applied to production planning and control. *International Journal of Production Research*, 61(16), 5772–5789. <https://doi.org/10.1080/00207543.2022.2104180>
- Fasihi, Z., Rezaei-Pandari, M., Torkaman, F., & Razzazi, M. (2026). The AI-driven evolution of dynamic pricing: A semisystematic review and novel hierarchical classification. *Applied Operations and Analytics*, 2(1), 1–31. <https://doi.org/10.1080/29966892.2026.2682621>
- Fatorachian, H., & Kazemi, H. (2026). Optimizing supply chains with AI: A systematic review through the lens of systems theory. *Cogent Engineering*, 13(1), 2639206. <https://doi.org/10.1080/23311916.2026.2639206>
- Fonseca, L. M., Esposito, L., Murino, T., & Busu, M. (2026). Artificial intelligence-enabled sustainability in SME supply chains: A systematic and bibliometric literature review. *Management & Marketing*, 21, 19. <https://doi.org/10.1007/s44491-026-00020-x>
- Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28–36. <https://doi.org/10.1287/inte.4.3.28>
- Ganesh, A. D., & Kalpana, P. (2022). Future of artificial intelligence and its influence on supply chain risk management: A systematic review. *Computers & Industrial Engineering*, 169, 108206. <https://doi.org/10.1016/j.cie.2022.108206>
- Gálvez del Postigo Gallego, L., Lazarova-Molnar, S., del Real Torres, A., & Acevedo Galicia, L. E. (2025). Decision support within digital twins in manufacturing ecosystems: A review. *IET Collaborative Intelligent Manufacturing*, 7(1), e70041. <https://doi.org/10.1049/cim2.70041>
- Gidiagba, J., Tartibu, L., & Okwu, M. (2025). A systematic review of machine learning applications in sustainable supplier selection. *Decision Analytics Journal*, 14, 100547. <https://doi.org/10.1016/j.dajour.2025.100547>
- Gomaa, A. H. (2026). Artificial intelligence for demand forecasting in manufacturing supply chains: A systematic literature review, research gap analysis, and future directions. *Supply Chain Management Research*, 026270018. <https://doi.org/10.36922/SCMR026270018>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS*

Quarterly, 19(2), 213–236. <https://doi.org/10.2307/249689>

Guida, M., Caniato, F., Moretto, A., & Ronchi, S. (2023). The role of artificial intelligence in the procurement process: State of the art and research agenda. *Journal of Purchasing and Supply Management*, 29(2), 100823. <https://doi.org/10.1016/j.pursup.2023.100823>

Gupta, S. K., Chadha, S., & Srivastava, A. (2026). A systematic review of artificial intelligence revolution in supplier selection for multi-criteria decision-making. *SN Computer Science*, 7, 366. <https://doi.org/10.1007/s42979-026-04960-3>

Gutierrez, J. C., Polo Triana, S. I., & León Becerra, J. S. (2025). Benefits, challenges, and limitations of inventory control using machine learning algorithms: Literature review. *OPSEARCH*, 62(3), 1140–1172. <https://doi.org/10.1007/s12597-024-00839-0>

Helu, M. M., & Hedberg, T. D. (2020). *Connecting, deploying, and using the smart manufacturing systems test bed*. NIST Advanced Manufacturing Series 200-2. <https://doi.org/10.6028/NIST.AMS.200-2>

Ilieva, G., & Iliev, Y. (2026). Generative AI in manufacturing and industrial contexts: A systematic review of applications, challenges, and future directions. *Electronics*, 15(15), 3485. <https://doi.org/10.3390/electronics15153485>

Itu, A. (2026). Resilient and intelligent supply chains: Advances and challenges in AI-driven optimization and forecasting. *Applied Sciences*, 16(9), 4285. <https://doi.org/10.3390/app16094285>

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation. *International Journal of Production Research*, 62(17), 6120–6145. <https://doi.org/10.1080/00207543.2024.2309309>

Kassa, A., Kitaw, D., Stache, U., Beshah, B., & Degefu, G. (2023). Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research. *Computers & Industrial Engineering*, 186, 109714. <https://doi.org/10.1016/j.cie.2023.109714>

Kosasih, E. E., Papadakis, E., Baryannis, G., & Brintrup, A. (2024). A review of explainable artificial intelligence in supply chain management using neurosymbolic approaches. *International Journal of Production Research*, 62(4), 1510–1540. <https://doi.org/10.1080/00207543.2023.2281663>

Kriouich, M., & Sarir, H. (2024). Artificial intelligence application in production scheduling problem systematic literature review: Bibliometric analysis, research trend, and knowledge taxonomy. *SN Operations Research Forum*, 5, 29. <https://doi.org/10.1007/s43069-024-00312-0>

Kumar, N., & Kumar, R. R. (2025). Human-AI collaboration in operations and supply chain management: A systematic literature review. *Management Review Quarterly*. Advance online publication. <https://doi.org/10.1007/s11301-025-005759>

Li, D., Liu, S., Wang, B., Yu, C., Zheng, P., & Li, W. (2025). Trustworthy AI for human-centric smart manufacturing: A survey. *Journal of Manufacturing Systems*, 78, 308–327.

<https://doi.org/10.1016/j.jmsy.2024.11.020>

Li, Y., Zhao, H., Jiang, H., Pan, Y., Liu, Z., Wu, Z., Shu, P., Tian, J., Yang, T., Xu, S., Lyu, Y., Blenk, P., Pence, J., Rupram, J., Banu, E., Song, K., Zhu, D., Wang, X., & Liu, T. (2026). Large language models for manufacturing. *Journal of Manufacturing Systems*, 86, 516–545.

<https://doi.org/10.1016/j.jmsy.2026.02.014>

Ma, Y., Zheng, S., Yang, Z., Zheng, P., Leng, J., & Hong, J. (2025). Leveraging large language models in next generation intelligent manufacturing: Retrospect and prospect. *Journal of Manufacturing Systems*, 82, 809–840. <https://doi.org/10.1016/j.jmsy.2025.07.019>

Maghanaki, M., Shahin, M., & Chen, F. F. (2026). Large language models in manufacturing: A comprehensive review. *The International Journal of Advanced Manufacturing Technology*.

<https://doi.org/10.1007/s00170-026-18711-4>

Martuscelli, L., Fantozzi, I. C., Leoni, L., & Schiraldi, M. M. (2026). Artificial intelligence for operational excellence in operations management: A systematic literature review and classification framework in manufacturing. *Production Planning & Control*, 1–37.

<https://doi.org/10.1080/09537287.2026.2638482>

Mayerhoff, J., & Schmidt, M. (2026). Reinforcement learning for autonomous production planning and control: A systematic literature review. *Journal of Manufacturing Systems*, 86, 546–568.

<https://doi.org/10.1016/j.jmsy.2026.03.023>

Mehrotra, S., Degachi, C., Vereschak, O., Jonker, C. M., & Tielman, M. L. (2024). A systematic review on fostering appropriate trust in human-AI interaction: Trends, opportunities and challenges. *ACM Journal on Responsible Computing*, 1(4), Article 26, 1–45. <https://doi.org/10.1145/3696449>

Montealegre-López, N. (2025). Exploring the role of trust in AI-driven decision-making: A systematic literature review. *Management Review Quarterly*. Advance online publication.

<https://doi.org/10.1007/s11301-025-00526-4>

Moosavi, S., Farajzadeh-Zanjani, M., Razavi-Far, R., Palade, V., & Saif, M. (2024). Explainable AI in manufacturing and industrial cyber-physical systems: A survey. *Electronics*, 13(17), 3497.

<https://doi.org/10.3390/electronics13173497>

Nayernia, H., Bahemia, H., & Papagiannidis, S. (2022). A systematic review of the implementation of Industry 4.0 from the organisational perspective. *International Journal of Production Research*, 60(14), 4365–4396. <https://doi.org/10.1080/00207543.2021.2002964>

Naz, F., Agrawal, R., Kumar, A., Gunasekaran, A., Majumdar, A., & Luthra, S. (2022a). Reviewing the applications of artificial intelligence in sustainable supply chains: Exploring research propositions for future directions. *Business Strategy and the Environment*, 31(5), 2400–2423.

<https://doi.org/10.1002/bse.3034>

Naz, F., Kumar, A., Majumdar, A., & Agrawal, R. (2022b). Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research.

Operations Management Research, 15, 378–398. <https://doi.org/10.1007/s12063-021-00208-w>

- Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. *International Journal of Machine Learning and Cybernetics*, 11(7), 1463–1482. <https://doi.org/10.1007/s13042-019-01050-0>
- Nimmy, S. F., Hussain, O. K., Chakraborty, R. K., Hussain, F. K., & Saberi, M. (2022). Explainability in supply chain operational risk management: A systematic literature review. *Knowledge-Based Systems*, 235, 107587. <https://doi.org/10.1016/j.knosys.2021.107587>
- Noor, M., Fei, W., Ullah, K., Khan, S., & Shah, M. (2026). Harnessing machine learning for supply chain management: A systematic review and future research framework. *Computers & Electrical Engineering*, 135, 111189. <https://doi.org/10.1016/j.compeleceng.2026.111189>
- Ordibazar, A. H., Hussain, O., Chakraborty, R. K., Irannezhad, E., & Saberi, M. (2025). Artificial intelligence applications for supply chain risk management considering interconnectivity, external events exposures and transparency: A systematic literature review. *Modern Supply Chain Research and Applications*, 7(2), 148–179. <https://doi.org/10.1108/MS CRA-102024-0041>
- Ouerghemmi, C., & Ertz, M. (2025). Integrating large language models into digital manufacturing: A systematic review and research agenda. *Computers*, 14(8), 318. <https://doi.org/10.3390/computers14080318>
- Ozay, D., Jahanbakht, M., & Wang, S. (2026). AI-based dynamic pricing: A cross-industry bibliometric review of trends, challenges, and future directions. *Journal of Theoretical and Applied Electronic Commerce Research*, 21(8), 280. <https://doi.org/10.3390/jtaer21080280>
- Pan, Y., Huang, Z., Lev, B., Xu, L., & Olson, D. L. (2026). A literature review on the artificial intelligence in manufacturing systems under Industry 5.0. *International Journal of Production Research*, 64(12), 5120–5161. <https://doi.org/10.1080/00207543.2026.2623537>
- Panja, S., Zheng, T., & Glock, C. H. (2026). Potentials of generative AI in logistics and supply chain management: A guiding review on applications and future research directions. *International Journal of Production Research*. <https://doi.org/10.1080/00207543.2026.2680586>
- Panzer, M., & Bender, B. (2022). Deep reinforcement learning in production systems: A systematic literature review. *International Journal of Production Research*, 60(13), 4316–4341. <https://doi.org/10.1080/00207543.2021.1973138>
- Parsons, C. S., Zuiderwijk, A., Orchard, N. A., Oosterhoff, J. H. F., & de Reuver, M. (2025). Task-technology fit of artificial intelligence-based clinical decision support systems: A review of qualitative studies. *BMC Medical Informatics and Decision Making*, 25, 397. <https://doi.org/10.1186/s12911-025-03237-8>
- Puthanveetil Madathil, A., Luo, Z., Liu, S., Walker, S., Madarkar, R., & Qin, Y. (2025). A review of explainable artificial intelligence in smart manufacturing. *International Journal of Production Research*, 63(23), 8654–8697. <https://doi.org/10.1080/00207543.2025.2513574>
- Qing, C., & Ramayah, T. (2026). Artificial intelligence adoption in sustainable manufacturing: A systematic review of antecedents, mediators, moderators, and outcomes. *Sustainable Development*, 1–

32. <https://doi.org/10.1002/sd.71254>

Rajashekarappa, M., Turanoglu Bekar, E., Karlsson, A., Bokrantz, J., Subramaniyan, M., & Skoogh, A. (2026). Industrial MLOps: A systematic review of architectures and implementation challenges. *Production & Manufacturing Research*, 14(1), 2658878. <https://doi.org/10.1080/21693277.2026.2658878>

Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., & Ivanov, D. (2023). A review on reinforcement learning algorithms and applications in supply chain management. *International Journal of Production Research*, 61(20), 7151–7179. <https://doi.org/10.1080/00207543.2022.2140221>

Royani, A. D., Sholihin, M., Dewi, D., Novika, N., Sorayya, A., Hanifah, W. N., Trilana, R. R. A., & Buton, P. (2026). The role of statistical methods and artificial intelligence in inventory management for manufacturing industries: A systematic literature review. *Frontiers in Big Data*, 9, 1799073. <https://doi.org/10.3389/fdata.2026.1799073>

Sadeqi Bajestani, M., Mun, D., & Kim, D. B. (2026). Human-in-the-loop and large language models in smart manufacturing: Current applications, challenges, and perspectives. *Journal of Manufacturing Systems*, 86, 913–941. <https://doi.org/10.1016/j.jmsy.2026.04.027>

Samuels, A. (2025). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review. *Frontiers in Artificial Intelligence*, 7, 1477044. <https://doi.org/10.3389/frai.2024.1477044>

Schaefer, F., Leutheuser, V., & Voigt, K.-I. (2026). Human-technology relationship: AI adoption in manufacturing. *Procedia Computer Science*, 277, 384–393. <https://doi.org/10.1016/j.procs.2026.02.080>

Schneider, J., Pfannschmidt, C., Nyhuis, P., & Schmidt, M. (2026). The role of reinforcement learning in production control: A systematic literature review. *IEEE Access*, 14, 34375–34389. <https://doi.org/10.1109/ACCESS.2026.3668903>

Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: Methods, applications, and research opportunities. *Journal of Big Data*, 7, 53. <https://doi.org/10.1186/s40537-020-00329-2>

Shafiee, S. (2025). Generative AI in manufacturing: A literature review of recent applications and future prospects. *Procedia CIRP*, 132, 1–6. <https://doi.org/10.1016/j.procir.2025.01.001>

Shahzadi, S., Jia, F., Chen, L., & John, A. (2024). AI adoption in supply chain management: A systematic literature review. *Journal of Manufacturing Technology Management*, 35(6), 1125–1150. <https://doi.org/10.1108/JMTM-09-2023-0431>

Smyth, R., Dennehy, D., Fosso Wamba, S., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. *International Journal of Production Research*, 62(23), 8537–8561. <https://doi.org/10.1080/00207543.2024.2341415>

- Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Song, Z., Xie, Y., Yang, L., & Zhao, Y. (2026). Large language models in supply chain management: A systematic literature review and application framework. *International Journal of Production Research*, 64(16), 7144–7184. <https://doi.org/10.1080/00207543.2026.2641103>
- Spreitzenbarth, J. M., Bode, C., & Stuckenschmidt, H. (2024). Artificial intelligence and machine learning in purchasing and supply management: A mixed-methods review of the state-of-the-art in literature and practice. *Journal of Purchasing and Supply Management*, 30(1), 100896. <https://doi.org/10.1016/j.pursup.2024.100896>
- Teixeira, A. R., Ferreira, J. V., & Ramos, A. L. (2025). Intelligent supply chain management: A systematic literature review on artificial intelligence contributions. *Information*, 16(5), 399. <https://doi.org/10.3390/info16050399>
- Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, 122, 502–517. <https://doi.org/10.1016/j.jbusres.2020.09.009>
- Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, 4(3), 356–367. <https://doi.org/10.1177/1534484305278283>
- Torraco, R. J. (2016). Writing integrative literature reviews: Using the past and present to explore the future. *Human Resource Development Review*, 15(4), 404–428. <https://doi.org/10.1177/1534484316671606>
- Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207–222. <https://doi.org/10.1111/1467-8551.00375>
- Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting: An examination of the psychological situation and defences of a work group in relation to the social structure and technological content of the work system. *Human Relations*, 4(1), 3–38. <https://doi.org/10.1177/001872675100400101>
- Tzionis, G., Mouratidis, P., Kougka, G., Gialampoukidis, I., Vrochidis, S., Kompatsiaris, I., & Vlachopoulou, M. (2026). A review of explainable AI methods and their application in manufacturing systems. *Discover Applied Sciences*, 8, 52. <https://doi.org/10.1007/s42452-025-07908-z>
- Vlachos, I., & Reddy, P. G. (2025). Machine learning in supply chain management: Systematic literature review and future research agenda. *International Journal of Production Research*, 63(16), 5987–6016. <https://doi.org/10.1080/00207543.2025.2466062>
- Vyhmeister, E., & Castañé, G. G. (2026). When industry meets trustworthy AI: A systematic review of AI for Industry 5.0. *AI and Ethics*, 6, 200. <https://doi.org/10.1007/s43681-026-01026-1>
- Walter, A., Ahsan, K., & Rahman, S. (2025). Application of artificial intelligence in demand planning for supply chains: A systematic literature review. *The International Journal of Logistics Management*,

36(3), 672–719. <https://doi.org/10.1108/IJLM-02-2024-0120>

Waubert de Puiseau, C., Ercan, F., Peters, J., Brune, M., Tercan, H., Prinz, C., Meisen, T., & Kuhlenkötter, B. (2026). A literature review on deep reinforcement learning for machine scheduling problems. *Journal of Manufacturing Systems*, 85, 96–126. <https://doi.org/10.1016/j.jmsy.2025.12.017>

Zhang, C., Xu, Q., Yu, Y., Zhou, G., Zeng, K., Chang, F., & Ding, K. (2025). A survey on potentials, pathways and challenges of large language models in new-generation intelligent manufacturing. *Robotics and Computer-Integrated Manufacturing*, 92, 102883. <https://doi.org/10.1016/j.rcim.2024.102883>

Zheng, T., Ardolino, M., Bacchetti, A., & Perona, M. (2021). The applications of Industry 4.0 technologies in manufacturing context: A systematic literature review. *International Journal of Production Research*, 59(6), 1922–1954. <https://doi.org/10.1080/00207543.2020.1824085>

Zhou, L., Jiang, Z., Geng, N., Niu, Y., Cui, F., Liu, K., & Qi, N. (2022). Production and operations management for intelligent manufacturing: A systematic literature review. *International Journal of Production Research*, 60(2), 808–846. <https://doi.org/10.1080/00207543.2021.2017055>