Role of Artificial Intelligence in Supplier Relationship Management Decision Making: A Systematic Literature Review

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ABSTRACT

This review examines the role of Artificial Intelligence in enhancing decision-making in Supplier Relationship Management and identifies the main role. This function is under examined in the broader AI and supply chain management Literature. The researchers apply PRISMA flow models to mine 35 articles published between 2016 and 2026, identifying seven discrete AI-enabled roles: real-time supplier performance monitoring, data-driven decision-making, predictive risk assessment, procurement cost optimisation, buyer-supplier collaboration, supplier selection and segmentation, and contract management and optimisation. Empirical evidence across manufacturing, construction, banking, and enterprise procurement contexts confirms that AI improves supply chain performance by 49%, amplifies resilience by 66%, achieves 85% accuracy in supply chain risk detection, and reduces procurement-processing times by 85%. The Technology Acceptance Model is applied as the analytical framework, revealing a critical asymmetry: while all seven roles generate measurable Perceived Usefulness outcomes, Perceived Ease of Use barriers, including legacy system incompatibility, data quality deficits and workforce digital literacy gaps suppress adoption of the highest-impact roles. The review contributes a cross-sectoral validated typology of AI's SRM functions, a TAM-grounded adoption framework, and a research agenda addressing algorithmic bias, longitudinal deployment dynamics, developing economy contexts, and AI-ESG compliance integration.

Keywords: Artificial intelligence, decision-making, supplier relationship management, supply chain management, Technology Acceptance Model

INTRODUCTION

The evolution of procurement from a fundamentally transactional function to a strategic driver of organizational performance provides the essential backdrop for understanding the growing role of Artificial Intelligence (AI) in SRM. Esan et al. (2022) traces this transformation across decades, noting that traditional procurement focuses on cost minimization through manual processes and paper-based documentation, an approach that proved inadequate amid dynamic supply chain disruptions and rapidly shifting market conditions. Tatini (2025) similarly observes that conventional procurement processes follow manual interventions, relationship-based supplier selections and reactive approaches to market change. These methods, while foundational, struggle to adapt to the increasingly complex global marketplace birthed in data fragmentation. In addition, complex supplier relationships and the need for real-time decision-making creates new demands that human-led processes cannot efficiently meet. AI and machine learning technologies mark a pivotal departure from this paradigm, requiring a proactive strategic focus.

Empirical evidence confirms that AI's contribution to supply chain performance extends beyond individual procurement decisions to systemic resilience outcomes. Liu et al. (2024), using structural equation modelling across a multi-firm dataset, demonstrates that AI significantly improves supply chain performance, delivering a 49% boost in key performance metrics, including service-level agreement adherence and on-time delivery. Crucially, AI's effect on supply chain resilience amplified further by adaptive capabilities, resulting in a 66% increase in resilience. In contrast, AI-mediated supply chain collaboration further strengthens resilience.

Attaran (2020), examining the broader landscape of digital technology enablers in supply chain management documents that digital technologies, including Big Data, cloud computing, advanced analytics aided by machine learning, and IoT, are transforming traditional supply chain structures into intelligent digital models that enable better visibility, broader collaboration, and shorter response times. This transformation is therefore a paradigm shift positioning AI as a foundational capability for supply chain organizations seeking to compete in volatile, data-intensive global markets.

With such rapid evolution, Supplier Relationship Management (SRM) has undergone a significant structural transformation. SRM encompasses the systematic processes by which organizations identify, evaluate, develop, and maintain productive partnerships with suppliers, with the dual objective of minimizing supply chain risk and maximizing strategic value (Vaka, 2024; Emon et al., 2024). Conventional SRM models that relied mainly on periodic manual assessments, static scorecards, and subjective evaluation models can no longer keep pace with the dynamic supply chain environment (Esan et al., 2022; Adesola et al., 2025).

AI technologies, encompassing machine learning (ML), natural language processing (NLP), predictive analytics, robotic process automation (RPA) and generative AI, present new opportunities for SRM. These technologies help organizations process vast volumes of structured and unstructured data in real time, detect risks before they occur, automate procurement workflows, and support complex multi-criteria decision-making (Mhaskey, 2026; Veershetty, 2026; Richey et al., 2023). Supply disruptions stemming from ineffective supplier management cost businesses approximately $184 million annually (Adesola et al., 2025), underscoring the strategic imperative to deploy intelligent solutions at the buyer-supplier interfaces.

Despite such underlying urgency, scholarly work on AI and SRM remains fragmented. Prior studies have examined AI broadly across Supply Chain Management (Richey et al., 2023; Attaran, 2020; Culot et al., 2024) or narrowly within specific domains such as block chain or ERP analytics (Esan et al., 2022; Mehta, 2025). As such, limited empirical discussions have focused specifically on the decision-making roles of AI within SRM as a distinct SCM function, forming the gap basis of the current paper.

Despite the growing body of evidence documenting AI's impact on supply chain performance, the scholarly Literature has not systematically examined AI's roles specifically within SRM as a defined organizational function. Richey et al. (2023), in their roadmap for AI in logistics and Supply Chain Management (SCM), acknowledge that most AI research are been conducted at the broad SCM level, leaving supplier-specific relationship management functions under examined. Culot et al. (2024) similarly note that systematic reviews of AI in supply chains have tended to focus on operational and logistics applications, with limited attention to the relational and strategic dimensions of supplier management. Attaran (2020) identifies supplier relationship management as one of eight supply chain functions undergoing digital transformation. No systematic review has yet mapped AI's specific decision-making contributions within this function in isolation.

This gap is significant since SRM is the mechanism through which organizations govern supply risk, develop supplier capabilities, and build the relational foundations of supply chain resilience. A systematic review that precisely delineates how AI reshapes SRM decision-making provides both theoretical and practical value that broader SCM reviews cannot deliver. This review anchored on the Technology Acceptance Model (TAM) to address this gap.

Study Objective

The objective of this study is to investigate the roles of Artificial Intelligence in enhancing decision-making in Supplier Relationship Management and to identify the main role based on a systematic literature review.

THEORETICAL REVIEW

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), originally developed by Davis (1989), posits that users' adoption of new technologies primarily hinges on two cognitive constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is the belief that employing technology improves job performance, while PEOU is the degree to which a user believes the technology requires minimal cognitive effort to operate effectively (Brandon-Jones & Kauppi, 2017; Sharma et al., 2022). These constructs jointly determine user attitudes toward technology, which in turn, drive behavioural intention and actual usage behaviour.

When applied to AI in procurement and SRM contexts, TAM provides a rigorous analytical lens for interpreting adoption patterns documented across the reviewed Literature. PU is evidenced in findings showing that AI predictive analytics improves supplier selection accuracy (Vaka, 2024), machine learning detects early signals of supply disruption with greater precision than conventional methods (Najim et al., 2024; Ramanayake et al., 2025), and AI-powered monitoring reduces supplier underperformance incidents (Mehta, 2025; Liu et al., 2024). These Literature outcomes align directly with TAM's PU construct: procurement professionals who observe measurable gains in decision speed, accuracy, and risk reduction are more likely to sustain and expand AI adoption.

PEOU, the second TAM construct, reflected in the Literature through discussions of AI systems that feature user-friendly interfaces, integrate with existing ERP platforms, and minimize manual data entry requirements (Allal-Cherif et al., 2020; Helo & Hao, 2021). Where AI systems are perceived as technically demanding, incompatible with existing workflows, or inadequately supported by training programs, adoption resistance is consistently reported, precisely consistent with PEOU theory (Nitsche et al., 2021). Brandon-Jones and Kauppi (2017) specifically demonstrated, within the e-procurement context, that perceived ease of use significantly determines technology acceptance, underscoring TAM's continued relevance as digital procurement tools become more sophisticated.

TAM also acknowledges the moderating role of external factors, including organizational support structures, training programs, and prior technology experience, in shaping both PU and PEOU perceptions. The reviewed Literature directly reflects this dimension: Adesola et al. (2025) demonstrate that organizational capacity building initiatives significantly accelerate AI adoption in supply chains, while Faruquee et al. (2021) show that trust in digital transformation mediates the relationship between technology adoption and supply chain resilience. These findings indicate that effective AI integration in SRM requires simultaneous attention to technical functionality and human factors, precisely the analytical balance TAM provides.

RESEARCH METHODOLOGY

The paper employs a systematic Literature review (SLR) methodology guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework (Page et al., 2021). The PRISMA model is adopted since it provides a transparent, reproducible, and rigorous protocol for identifying, screening and synthesizing Literature, enabling findings to be independently verified and replicated. The SLR model is selected because it follows a predefined protocol that documents all stages of the search and selection process, thereby minimizing selection bias and enhancing the credibility of the conclusions.

A structured keyword search was conducted in Google Scholar, Semantic Scholar, and CORE in February 2025, given their comprehensive indexing of peer-reviewed journals across supply chain management, operations research, information systems, and engineering. Five search strings are developed based on the study's core theoretical and empirical constructs as shown in Fig. 1, along with the number of initial records identified per string.

Figure 1. PRISMA 2020 Flow Diagram

IDENTIFICATION Records identified via Databases (5 search strings) | n = 29,900
Duplicates removed (estimated 50% cross-string overlap) | n = 14,950 removed
SCREENING Records screened by title and abstract | n = 14,950 *Records excluded (not AI/SRM specific) | n = 14,817*

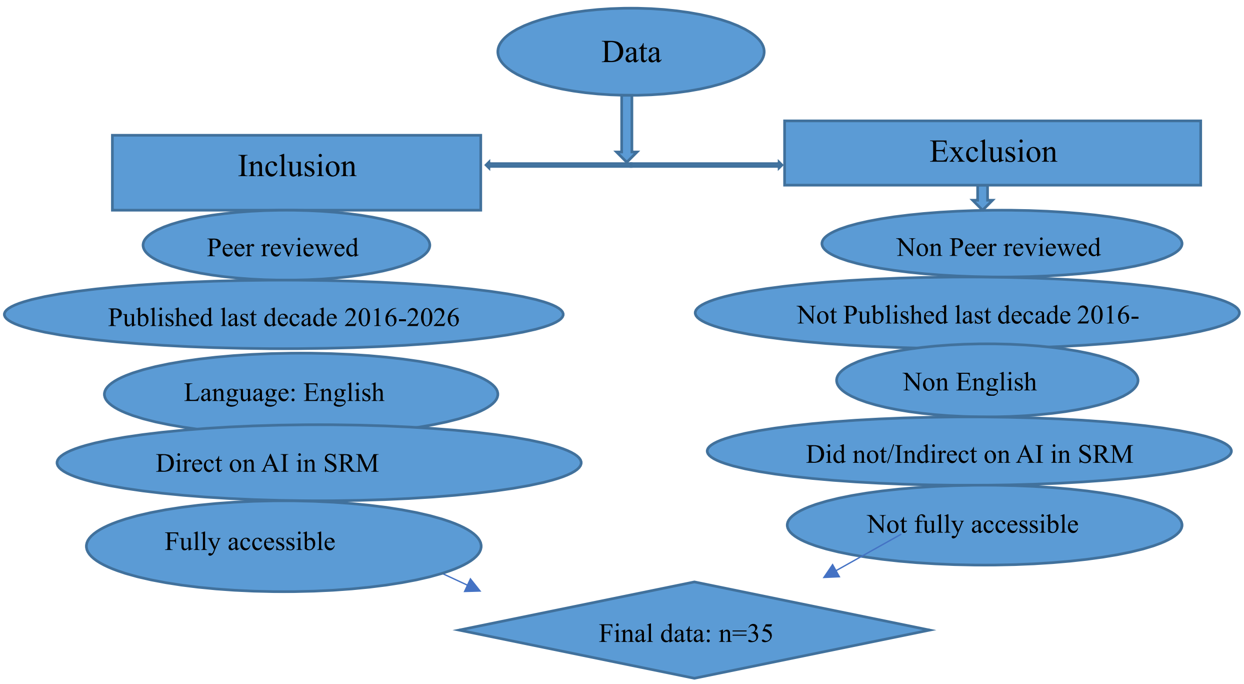
ELIGIBILITY Full-text articles assessed for eligibility | n = 133 *Full-text articles excluded (n = 98), with reasons:* Block chain-only focus (no AI component): n = 24 Insufficient AI specificity (general SCM): n = 31 Not peer-reviewed (preprints, student journals): n = 18 Predatory or unverifiable journals: n = 8 Duplicate content (different citation formats): n = 17
INCLUDED **Final review| n = 35**

Source: (Author's search, 2026*)*

Inclusion and Exclusion Criteria

Inclusion and exclusion criteria defined before the search to ensure systematic and consistent screening decisions throughout the review process. Articles were included if they: (i) were published in peer-reviewed journals or indexed conference proceedings; (ii) were published between 2016 and 2026; (iii) were written in English; (iv) directly addressed AI, machine learning, or related digital technologies within SRM, procurement, or supply chain management contexts; and (v) were accessible in full text. Articles were excluded if they: (i) addressed block chain or IoT without AI components; (ii) were published in predatory, hijacked, or non-indexed outlets; (iii) were conference abstracts, book chapters, or preprints without peer-review evidence; (iv) were duplicated across search strings; or (v) were published outside the 2016-2026 window. These criteria applied were consistently at each stage of the screening process.

Figure 2. The inclusion & Exclusion criteria



Source: (SLR, 2026)

Thematic Coding Protocol

Following inclusion, the researcher using a two-round thematic coding procedure adapted from Braun and Clarke (2006) coded each of the 35 articles. In the first round, open coding applied was to identify all AI related activities mentioned in relation to supplier management. In the second round, codes were grouped into themes based on conceptual similarity. Seven principal themes emerged from this process. An article was assigned to a theme if the AI-SRM role constituted a central focus of the study, not a peripheral mention. Where a single study addressed multiple themes, it was counted under each applicable theme.

FINDINGS

The systematic review identified seven primary roles of AI in Supplier Relationship Management decision making. These roles are grounded in evidence from the 35 included articles as discussed in the subsequent section.

Roles of AI in SRM decision making

Real-Time Supplier Performance Monitoring

The reviewed literature consistently establishes that AI enables a fundamental shift from periodic, manual supplier assessments to continuous, automated performance monitoring across multiple dimensions simultaneously. Where traditional SRM relied on static scorecards and reactive responses to supplier failures, AI-powered systems continuously evaluate Key Performance Indicators (KPIs), including quality scores, delivery reliability, financial stability, and compliance metrics in real time, enabling procurement teams to detect deteriorating supplier performance before it escalates into supply disruption (Esan et al., 2022; Mehta, 2025; Adesola et al., 2025; Veershetty, 2026). Supplier quality, compliance rates has shown to improve significantly following AI integration within ERP systems, rising from a baseline of approximately 70% to over 94% within twelve months of deployment (Mehta, 2025). Such evidence shows that continuous AI-driven monitoring strengthens supplier accountability and quality consistency in ways that periodic assessments cannot.

The transition from reactive to proactive supplier management being identified across the Literature as AI's most structurally significant contribution to SRM, with organizations gaining the capacity to anticipate supplier financial distress, production delays, and compliance violations rather than responding to them after they occur (Adesola et al., 2025; Esan et al., 2022; Liu et al., 2024). ML-based monitoring models consistently outperform conventional evaluation methods in classifying supplier reliability across construction, manufacturing, and technology sectors, identifying performance determinants that human evaluation routinely overlooks (Zvirgzdins et al., 2025; Ramanayake et al., 2025).

Digital procurement platforms further extend monitoring capabilities by providing suppliers with real-time access to performance feedback, compliance expectations, and procurement requirements. This creates a shared visibility architecture that supports both accountability and corrective action (Esan et al., 2022; Veershetty, 2026). The real-time monitoring power of AI pronounced more across Literature.

Data-Driven Decision-Making

Across the reviewed Literature, AI identified consistently as transforming procurement decision-making from experience-based intuition to data-validated intelligence. Organizations can now process and synthesize volumes, speeds, and varieties of supplier data that exceed human cognitive capacity (Allal-Cherif et al., 2021; Richey et al., 2023; Attaran, 2020). AI systems act as "information decoders," converting complex financial and non-financial supplier data into predictive models, visualization tools, and actionable insights that reduce cognitive barriers and enhance the quality of sourcing and supplier development decisions (Deng & Zhang, 2025).

Empirical evidence confirms that AI technology application significantly enhances corporate information transparency, which in turn enables more comprehensive supplier risk assessment and more diversified supplier portfolio decisions, reducing over-dependence on dominant suppliers and strengthening supply chain resilience (Deng & Zhang, 2025; Liu et al., 2024). AI integration into ERP and procurement platforms enables demand forecasting; spend analytics, root-cause analysis of supplier underperformance, and strategic monitoring (Mehta, 2025; Paul et al., 2024; Allal-Cherif et al., 2021). These capabilities collectively elevate the quality and speed of procurement decisions at operational and strategic levels

The Literature further establishes that AI-powered matching systems, decision support tools, and collaborative ideation platforms shift procurement professionals from operational transaction processors to strategic decision architects. Professionals can anticipate market trends, proactively manage supplier portfolios, and create competitive advantage through data-driven sourcing strategies (Allal-Cherif et al., 2021; Tatini, 2025; Gaddala, 2023). AI significantly improves supply chain performance, with a 49% increase in key metrics, including service-level agreement adherence and on-time delivery, attributable to AI-enabled data processing and predictive insight generation (Liu et al., 2024). Bid data is no longer an analytical bottleneck in the face of AI.

Predictive Risk Assessment and Mitigation

The Literature establishes that AI-powered predictive risk modelling represents a qualitative advancement over conventional periodic risk reviews. The result is a dynamic, continuously updated risk profiles that integrate financial health indicators, geopolitical stability assessments, historical performance metrics, and real-time market signals simultaneously (Adesola et al., 2025; Mhaskey, 2026; Joel et al., 2024). Supply chain disruptions attributable to inadequate supplier risk management cost organizations an average of $184 million annually, establishing the strategic imperative for intelligent, forward-looking risk assessment at the supplier interface (Adesola et al., 2025). Such costs underscore SRM's strategic importance in overall supply chain performance.

AI-enabled risk detection systems achieve 85% accuracy in early warning of supply chain disruptions, compared to the limited detection capabilities of traditional approaches. In comparison, the accuracy of supplier financial distress prediction reaches 88% up to 8 months in advance (Tatini, 2025). Such performance levels enable genuinely proactive rather than reactive risk management. Federated learning approaches further extend AI risk capabilities in distributed supply chain networks by enabling multiple supply chain partners to collaboratively train risk models without sharing sensitive proprietary data (Adesola et al., 2025). Both data privacy concerns and the need for collective supply chain intelligence remain non-issues.

Also, the reviewed Literature consistently shows that AI risk models identify not only financial risks but also operational, compliance, and ESG-related supplier risks, enabling procurement teams to conduct comprehensive multi-dimensional risk assessments that traditional scorecard approaches structurally cannot replicate (Veershetty, 2026; Mhaskey, 2026; Esan et al., 2022). Generative AI further enhances risk assessment by synthesizing unstructured data from news feeds, regulatory databases, and supplier communications into coherent risk narratives and scenario models, extending the scope of risk intelligence beyond what structured data alone provides (Mhaskey, 2026; Gaddala, 2023). Traditional SRM approaches remain incapable of processing such tremendous volumes of unstructured data.

Procurement Cost Optimization

The Literature documents AI's cost impact across multiple procurement sub-functions, collectively delivering measurable efficiency gains and financial savings that traditional procurement processes cannot achieve (Tatini, 2025; Mehta, 2025; Veershetty, 2026; Esan et al., 2022). AI-enabled procurement systems reduce processing times from an average of 14 days to 2–3 days, improve supplier selection accuracy by 42%, generate 15–20% cost reductions through spend analysis, reduce contract processing time by 60%, and reduce compliance-related issues by 30% (Tatini, 2025). Spend analytics powered by AI identifies cost-saving opportunities across complex procurement categories that manual analysis routinely misses. ML algorithms demonstrating particular effectiveness in detecting maverick spending and contract leakage (Tatini, 2025; Veershetty, 2026). These gaps expose significant value losses for firms.

The concept of "cost of buying" encompasses internal process costs, supply disruption risk premiums, compliance leakage, and working capital effects, providing a more complete framework than unit-price optimization alone. AI-powered SRM platforms operationalize this broader cost perspective by guiding buying, automating compliance tracking, and enabling risk-adjusted sourcing decisions (Veershetty, 2026). Automation through RPA streamlines repetitive procurement workflows, reducing administrative overhead and enabling procurement professionals to redirect effort toward higher-value strategic activities (Esan et al., 2022; Tatini, 2025). Furthermore, AI-powered demand forecasting achieves accuracy rates exceeding 90%, enabling inventory optimization and reducing carrying costs by up to 25% (Tatini, 2025).

Buyer-Supplier Collaboration Strengthening

The Literature identifies AI as reshaping the relational dimension of SRM, enabling organizations to move beyond transactional supplier interactions toward strategic partnerships (Alshurideh et al., 2024; Emon et al., 2024;

Mhaskey, 2026; Allal-Cherif et al., 2021). AI use positively and significantly influences all dimensions of the buyer-supplier relational interface, including interaction, communication, engagement, learning, experience, and feedback, establishing a statistically validated empirical basis for AI's relational impact across the supplier interface (Alshurideh et al., 2024). Supplier collaboration and long-term supplier relationships collectively account for 64.2% of the variance in supply chain cost efficiency, positioning relational depth as a primary driver of procurement performance outcomes rather than a secondary consideration (Emon et al., 2024).

Supply chain collaboration strengthened through AI further amplifies supply chain resilience, with a 71% increase in resilience attributable to AI-mediated collaboration (Liu et al., 2024). AI enables collaborative decision-making by providing suppliers with real-time access to procurement requirements, performance feedback, and compliance expectations (Esan et al., 2022; Veershetty, 2026). This shifts supplier relationships from periodic, often adversarial interactions to continuous, transparency-based partnerships. Moreover, Generative AI enhances collaboration by automating supplier communication, supporting real-time performance feedback generation, and enabling co-innovation through collaborative ideation platforms, extending the scope of buyer-supplier collaboration beyond operational compliance into joint strategic development (Mhaskey, 2026; Allal-Cherif et al., 2021).

Supplier Selection and Segmentation

The Literature establishes that AI addresses the inherent complexity of supplier selection with a precision and consistency that human-led evaluation processes structurally cannot achieve. AI continuously evaluates KPIs, including quality, delivery times, financial stability, and compliance across all candidate suppliers simultaneously (Vaka, 2024; Zvirgzdins et al., 2025). Procurement professionals can conduct data-driven supplier selection. AI replaces experience-based and relationship-driven approaches with objective, multi criteria analytical frameworks.

ML classification models consistently outperform conventional scorecard and heuristic methods in predicting supplier reliability and identifying performance determinants that human evaluation routinely underweights (Zvirgzdins et al., 2025; Ramanayake et al., 2025). Examples of these determinants include financial stability, the cost of order modifications, and supplier experience. AI-driven segmentation categorizes suppliers into strategic, preferred, and transactional tiers based on comprehensive performance and risk data, enabling tailored governance approaches that allocate procurement resources and management attention proportionally to each supplier's contribution and risk profile (Veershetty, 2026; Vaka, 2024). Still, AI reduces supplier concentration risk by improving information transparency (Deng & Zhang, 2025; Najim et al., 2024). Organizations can identify and evaluate a broader supplier base and overcome path dependency on dominant suppliers.

Contract Management and Optimization

The reviewed Literature identifies AI as transforming contract management into a dynamic, performance-linked procurement function that directly supports supplier relationship quality and cost efficiency (Mehta, 2025; Veershetty, 2026; Esan et al., 2022). AI-driven contract management systems reduce contract review time by 85%, increase clause accuracy by 92%, reduce contract-processing time by 60%, and reduce compliance-related issues by 30% (Tatini, 2025; Veershetty, 2026). These performance gains collectively transform contract administration from a bottleneck into a strategic procurement enabler.

Generative AI further extends contract capabilities by automating the drafting of context-aware agreements that adapt to different jurisdictions and regulatory requirements. On the other hand, predictive analytics assess how proposed contract terms will affect future supplier performance and financial outcomes before agreements are executed (Mehta, 2025; Mhaskey, 2026). Automation through RPA and smart contract mechanisms ensures consistent enforcement of contractual terms, reduces maverick spend and contract leakage, and eliminates administrative burdens in approval workflows (Esan et al., 2022; Veershetty, 2026; Tatini, 2025). Automation directly reduces procurement value losses generated by contract non-compliance

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The Role of AI: Attention for Supply Chain Firms

Among the seven identified roles, real-time supplier performance monitoring emerges as the most frequently themes AI function in the reviewed Literature. This role is cited across the widest range of sectoral contexts, including manufacturing, construction, banking, and enterprise procurement, and is referenced by the highest number of included studies (Esan et al., 2022; Mehta, 2025; Adesola et al., 2025; Liu et al., 2024; Veershetty, 2026; Zvirgzdins et al., 2025; Ramanayake et al., 2025). Its prominence reflects a foundational logic that continuous, AI-driven monitoring is the enabling precondition upon which the other six depend for their effectiveness. Without reliable, real-time performance data, the downstream analytical and relational functions of AI in SRM meaningfully cannot operationalised. As such, supply chain firms need to consider leveraging on AI technologies to achieve real time performance monitoring

Table 1. Thematic Coding and Frequency Distribution: AI Roles in SRM

AI Role in SRM	Frequency (Articles)	% of Total	Source
Real-time supplier performance monitoring	20	57%	Adesola et al. (2025); Mehta (2025); Veershetty (2026); Zvirgzdins et al. (2025)
Data-driven decision-making	18	51%	Allal-Cherif et al. (2021); Deng & Zhang (2025); Richey et al. (2023); Paul et al. (2024)
Predictive risk assessment and mitigation	16	46%	Adesola et al. (2025); Mhaskey (2026); Ramanayake et al. (2025); Joel et al. (2024)
Procurement cost optimisation	13	37%	Tatini (2025); Mehta (2025); Esan et al. (2022); Veershetty (2026)
Buyer-supplier collaboration strengthening	11	31%	Alshurideh et al. (2024); Emon et al. (2024); Mhaskey (2026); Allal-Cherif et al. (2021)
Supplier selection and segmentation	9	26%	Vaka (2024); Najim et al. (2024); Zvirgzdins et al. (2025); Ramanayake et al. (2025)
Contract management and optimization	7	20%	Mehta (2025); Veershetty (2026); Esan et al. (2022)

Source: Author’s thematic coding of Literature, 2026.

DISCUSSION

The TAM Analytical Lens: Connecting Theory to Findings

The seven AI roles identified across the reviewed Literature map coherently onto the TAM framework, providing a theoretically grounded explanation of both the accelerating adoption of AI in SRM and the persistent barriers that constrain it. All seven roles represent direct and empirically documented manifestations of PU. For example, real-time monitoring, data-driven decision-making, predictive risk assessment, cost optimization, collaboration strengthening, supplier selection and segmentation, and contract management each correspond to improved job performance outcomes, which is the core definition of PU in TAM.

The evidence is not merely qualitative, but supported by quantitative measures. AI improves supply chain performance by 49% (Liu et al., 2024), reduces procurement costs by 15–20% (Tatini, 2025), and achieves 85% early warning accuracy in supply chain risk detection (Tatini, 2025). It also accounts for 64.2% of the variance in supply chain cost efficiency through collaboration and long-term relationships (Emon et al., 2024). It significantly reduces supplier concentration through enhanced information transparency (Deng & Zhang, 2025). Of the seven roles, real-time supplier performance monitoring is the most frequently discussed across the reviewed Literature, cited across the broadest range of sectoral contexts and serving as the foundational enabler upon which the remaining six AI-SRM roles depend. These are measurable PU outcomes across all seven roles, not theoretical claims. Allal-Cherif et al.'s (2021) multi-case evidence that AI adoption in purchasing accelerates precisely when platforms enable complex strategic decision-making in unpredictable environments directly reflects the PU core claim that organizations adopt AI when its usefulness is demonstrably felt at the decision making level, not merely proclaimed at the strategic level.

PEOU, by contrast, explains why adoption remains incomplete despite such compelling PU evidence. The reviewed Literature consistently documents PEOU barriers that moderate, and in some cases block, adoption even where PU is clearly perceived. Data privacy concerns affect 78% of organizations implementing AI procurement systems (Tatini, 2025). Approximately 65% of AI implementation projects exceed their initial timelines due to compatibility issues and data migration challenges with legacy ERP systems (Tatini, 2025). Workforce skill gaps remain a compounding barrier across sectors (Tatini, 2025; Esan et al., 2022; Mhaskey, 2026). These are not peripheral concerns that directly reflect the PEOU dimension: the effort required to deploy and operate AI systems reduces adoption intention even when the systems' usefulness is not in doubt.

Critically, the TAM analysis reveals an asymmetry across the seven roles. Roles with the lowest PEOU barriers, such as automated performance monitoring dashboards, spend analytics, and contract clause extraction via NLP, have the highest documented adoption rates. The roles with the highest PEOU demands, like federated learning for distributed risk modelling, generative AI for contract drafting, and ML-based supplier segmentation requiring clean, structured datasets, are the least widely adopted despite demonstrating the strongest PU evidence.

This asymmetry directly supports Jahani et al.'s (2021) finding that TAM is the appropriate theoretical model for procurement technology adoption, and Brandon-Jones and Kauppi's (2018) finding that organizational moderators, including training, digital infrastructure, and management commitment, are critical mediators between TAM constructs and actual adoption behaviour. The practical implication is that organizations should sequence AI deployments by PEOU, beginning with high-PEOU and low-PEOU applications and progressively building the digital infrastructure, data governance, and workforce competencies required for higher-PEOU deployments.

Geographical and Sectoral Patterns

The reviewed Literature spans diverse geographic and sectoral contexts. Adesola et al. (2025) examine automotive, technology, pharmaceutical, and agricultural sectors. Ramanayake et al. (2025) and Zvirgzdins et al. (2025) focus on the construction sector. Alshurideh et al. (2024) examine banking, while Emon et al. (2024) study Bangladesh's manufacturing and service sectors. Allal-Cherif et al. (2021) examine large European firms. This geographic breadth, which transcends developed and emerging economies, reinforces the generalisability of AI's documented SRM roles, while contextual implementation challenges vary by sector and regional digital infrastructure.

Implementation Challenges

A consistent thread across the reviewed Literature is the acknowledgement that AI's SRM potential faces structural implementation barriers. The first concerns legacy system incompatibility, particularly with established ERP platforms (Mehta, 2025; Veershetty, 2026; Esan et al., 2022). Secondly, there remain data quality deficits whereby AI systems require large volumes of clean, structured data for reliable performance (Mhaskey, 2026; Adesola et al., 2025). The third involves workforce digital literacy gaps, as procurement teams require new competencies in data analytics and AI-based decision tools (Esan et al., 2022; Tatini, 2025). Finally, algorithmic

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bias and ethical concerns in supplier evaluation persist, particularly where AI-driven assessments influence supplier selection and relationship continuity (Mhaskey, 2026).

Table 2: Database of Reviewed Literature (n = 35)

#	Author(s)	Year	Title
1	**Adesola, O. et al.**	2025	AI and Machine Learning in Global Supply Chain Management
2	**Allal-Cherif, O. et al.**	2021	Intelligent purchasing: How AI is changing procurement
3	**Alshurideh, M. et al.**	2024	AI and supplier relationship management in the banking sector
4	**Attaran, M.**	2020	Digital technology enablers and their implications for supply chain management
5	**Brandon-Jones, A. & Kauppi, K.**	2018	Examining the antecedents of the technology acceptance model within e-procurement
6	**Deng, Y. & Zhang, C.**	2025	The Impact of AI Technology Application on Supplier Concentration of Manufacturing Enterprises
7	**Dubey, R. et al.**	2019	Supplier relationship management for circular economy
8	**Ellaturu, S. & Awasthi, A.**	2024	AI-Driven Solutions for Supply Chain Management
9	**Emon, M.M.H. & Khan, T.**	2024	Quantifying the influence of SRM and supply chain performance: Bangladesh manufacturing and service sectors
10	**Esan, O.J. et al.**	2022	Procurement 4.0: Revolutionizing Supplier Relationships through Block chain, AI, and Automation
11	**Forkmann, S. et al.**	2016	Supplier relationship management capability: a qualification and extension
12	**Gaddala, J.**	2023	AI in Supply Chain Management
13	**Gaddala, J.**	2023	The Power of Generative AI in Supply Chain Management
14	**Helo, P. & Hao, Y.**	2022	Artificial intelligence in operations management and supply chain management: an exploratory case study
15	**Jahani, H. et al.**	2021	Industry 4.0 and supply chain sustainability: TAM in the procurement domain
16	**Joel, O.S. et al.**	2024	Leveraging Artificial Intelligence for Enhanced Supply Chain Optimization
17	**Liu, Z. et al.**	2024	Leveraging Data-Driven Insights to Enhance Supplier Performance and Supply Chain Resilience
18	**Mehta, A.K.**	2025	Supplier Performance Evaluation in ERP Systems Using Data Analytics and AI

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19	**Mhaskey, S.V.**	2026	Generative AI for Supplier Relationship Management: Applications, Challenges, and Future Directions
20	**Najim, A. et al.**	2024	Machine Learning Integration in Supplier Relationship Management for Stock Management
21	**Paul, P.O. et al.**	2024	The role of data analysis and reporting in modern procurement
22	**Ramanayake, S. et al.**	2025	Supplier Reliability Prediction in Construction with Artificial Intelligence and Adaptive Evaluation Metrics
23	**Richey, R.G. et al.**	2023	Artificial intelligence in logistics and supply chain management: A primer and roadmap for research
24	**Tatini, P.R.**	2025	Transforming Sourcing and Supply Chain Management: The Evolution of AI Agents in Modern Procurement
25	**Teller, C. et al.**	2016	Key supplier relationships and their management in retailing
26	**Vaka, D.K.**	2024	Enhancing Supplier Relationships: Critical Factors in Procurement Supplier Selection
27	**Veershetty, G.**	2026	AI-Driven Supplier Relationship Management in the Digital Enterprise: Quantifying Value and Resilience with SAP Ariba
28	**Veile, J.W. et al.**	2021	Lessons learned from Industry 4.0 implementation in the automotive industry
29	**Zvirgzdins, J. et al.**	2025	A Comparative Analysis of Machine Learning Model Utilization for the Optimization of Supplier Reliability Towards Sustainable Construction
30	**Culot, G. et al.**	2024	Artificial Intelligence in Supply Chain: A Comprehensive Analysis
31	**Brandon-Jones, E. et al.**	2014	The impact of supply base complexity on disruption recovery
32	**Fawcett, S.E. et al.**	2020	Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management
33	**Queiroz, M.M. & Wamba, S.F.**	2019	Block chain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA
34	**Choi, T.M. et al.**	2022	Artificial intelligence, block chain and smart supply chain operations
35	**Ivanov, D. & Dolgui, A.**	2021	A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0

Source: (Author’s systematic review, 2026)

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Model of AI led capabilities and SRM decision making

Based on the review findings, we developed a model linking AI led capabilities, the TAM model theory and outcomes of decision making in SRM to guide practitioners in Supply Chain Management keen to adopt AI in SRM, as well as providing an important body of knowledge in the wider business and management discipline. The figure 3 presents the model developed from the systematic review, mapping AI enablers through SRM decision domains to supply chain outcomes, with TAM constructs as the mediating layer governing adoption.

Figure 3: Model of AI Capabilities, TAM and SRM Decision Outcomes

AI CAPABILITIES	→	TAM MEDIATORS	→	SRM DECISION OUTCOMES
(Technology Inputs)		*(Adoption Mediators)*		*(Functional Roles)*
ML & Predictive Analytics	→	**Perceived Usefulness (PU)** *Measurable performance gains trigger adoption intent*	→	**Real-Time Supplier Monitoring**
Natural Language Processing (NLP)	→	**Perceived Ease of Use (PEOU)** *Integration complexity & data quality affect adoption*	→	**Data-Driven Decision-making**
Generative AI (Gen AI)	→	**Org. Moderators** *Digital infrastructure, training, and management commitment*	→	**Predictive Risk Assessment**
Computer Vision & IoT Sensing	→		→	**Procurement Cost Optimisation**
Robotic Process Automation (RPA)	→		→	**Buyer-Supplier Collaboration**
Federated Learning	→		→	**Supplier Selection & Segmentation**
			→	**Contract Management & Optimisation**

▼ SUPPLY CHAIN PERFORMANCE OUTCOMES ▼					
Supply Chain Resilience	**Cost Efficiency Gains**	**Supplier Diversification**	**Relationship Quality**	**Risk Mitigation**	**Strategic Procurement Value**

Source: (Author's model of AI led capabilities, TAM theory and SRM decision making)

CONCLUSION

The review identifies seven discrete AI-enabled roles: real-time supplier performance monitoring, data-driven decision-making, predictive risk assessment, procurement cost optimisation, buyer-supplier collaboration, supplier selection and segmentation, and contract management and optimisation. The empirical evidence across 35 sources is consistent and cross-sectoral convergent. AI improves supply chain performance by 49% in SLA adherence and on-time delivery metrics, amplifies resilience by 66% through adaptive capabilities, achieves 85% accuracy in supply chain risk detection, reduces processing times from 14 days to 2–3 days, and generates cost reductions of 15–20% through spend analytics. These outcomes documented are across manufacturing, construction, banking, and enterprise procurement contexts, establishing that AI's contribution to SRM not being theoretically anticipated but empirically grounded.

Theoretically, the review demonstrates that the Technology Acceptance Model (TAM) provides a coherent lens for explaining both AI's adoption momentum and its persistent incompleteness in SRM. All seven roles generate measurable Perceived Usefulness outcomes. Yet, adoption remains uneven because Perceived Ease of Use barriers operate at the organisational level and suppress deployment of the highest-impact roles precisely among organisations that need them most. This TAM asymmetry, in which roles with the strongest PU evidence face the highest PEOU barriers, is the central adoption dynamic documented in the review. The paper suggests an important conceptual model linking AI led capabilities, TAM model theory and decision making outcomes in SRM, providing important empirical thoughts as well as guiding stakeholders and practitioners in SCM.s

Future Research Lens

Four research gaps emerge that the current Literature does not adequately addressee: longitudinal studies tracking AI adoption trajectories in SRM over time; empirical audit studies measuring algorithmic bias in deployed AI supplier selection systems; comparative research on AI-SRM dynamics across developing economy contexts where relational governance mechanisms remain primary; and an investigation of how AI tools translate ESG compliance obligations into measurable supplier evaluation criteria as regulatory disclosure requirements intensify globally. Collectively, the evidence establishes that AI is not a peripheral efficiency tool for SRM but a foundational capability reshaping the strategic logic of the function. Supply Chain Firms that fail to develop systematic AI capability may face structurally inferior risk detection, supplier visibility and relational depth relative to those that do.

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