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Article

THE ROLE OF ARTIFICIAL INTELLIGENCE IN VENDOR PERFORMANCE EVALUATION WITHIN DIGITAL RETAIL SUPPLY CHAINS: A REVIEW OF STRATEGIC DECISION-MAKING MODELS

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ABSTRACT

The digital transformation of retail supply chains has fundamentally reshaped how organizations evaluate, manage, and engage with their suppliers. In this context, artificial intelligence (AI) has emerged as a transformative enabler, offering sophisticated tools for enhancing vendor performance evaluation through intelligent automation, predictive modeling, and real-time decision-making support. This systematic review critically examines the integration of AI technologies—such as supervised and unsupervised machine learning, natural language processing (NLP), and deep learning algorithms—into vendor performance assessment frameworks within digital retail ecosystems. Drawing on an analysis of 86 peer-reviewed journal articles, industry white papers, and technical reports published between 2015 and 2022, the study identifies and categorizes the predominant AI-driven models employed to assess key supplier attributes, including reliability, quality assurance, compliance with contractual obligations, cost-efficiency, and operational risk. The review further investigates how these AI tools enable real-time vendor monitoring, dynamic anomaly detection, and the automation of adaptive performance scorecards. Evidence from the literature demonstrates that AI-enabled evaluation systems can significantly enhance the precision, objectivity, and scalability of vendor assessments, while reducing human bias and manual inefficiencies in procurement processes. However, the adoption of AI in this domain is not without challenges. Common barriers include fragmented data architectures, difficulties in integrating AI tools with legacy enterprise systems, concerns over the interpretability and ethical transparency of algorithmic decisions, and a lack of standardization in AI governance practices. In response to these challenges, the review also identifies emergent research opportunities aimed at improving the accountability, fairness, and sustainability of AI applications in retail supply chains. Future research directions include the development of hybrid models combining human expertise with machine learning, reinforcement learning-based adaptive evaluation systems, and the incorporation of ESG (environmental, social, and governance) metrics into AI-based vendor assessments. This review contributes to the growing discourse on AI's role in shaping agile, data-driven, and ethically sound vendor management practices within the evolving digital retail ecosystem. By synthesizing current findings, the review highlights critical implementation bottlenecks and knowledge gaps in the field, and proposes future research directions for developing explainable, secure, and ethically sound AI solutions that align with sustainable procurement goals and evolving retail strategies.

KEYWORDS

Artificial Intelligence (AI); Vendor Performance; Digital Retail Supply Chain; Strategic Decision-Making; Machine Learning; Predictive Analytics; Supplier Evaluation; Procurement; Smart Retail;

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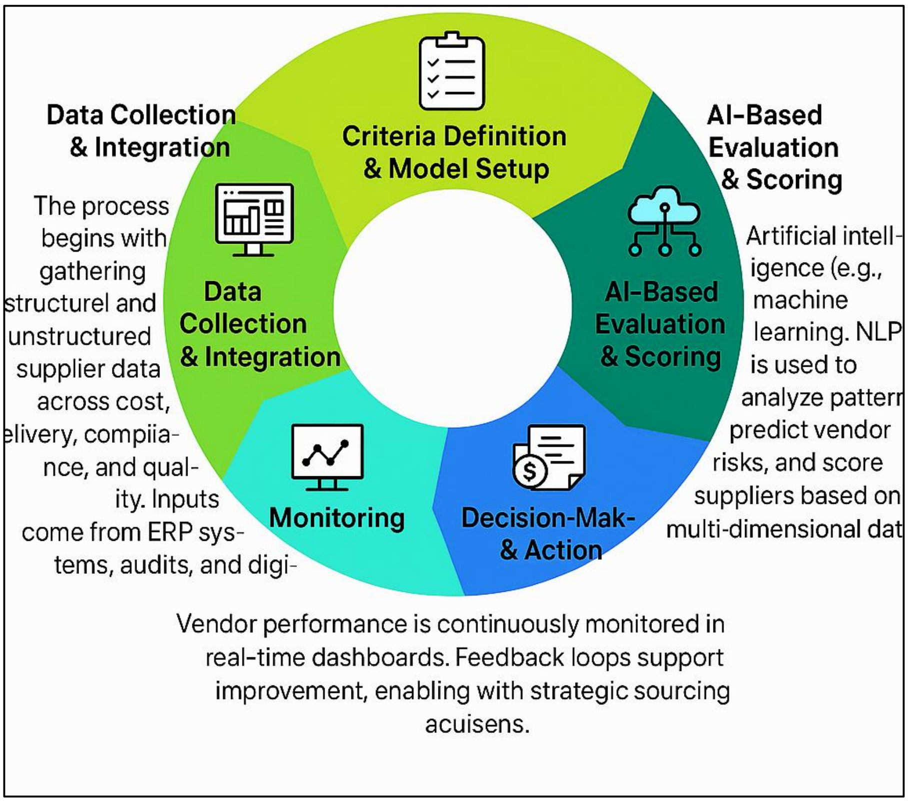
INTRODUCTION

Content creation, defined as the process of generating and sharing material such as text, images, Vendor performance evaluation is a critical function within supply chain management that encompasses the systematic assessment of suppliers' ability to meet defined performance criteria such as cost, quality, reliability, compliance, and delivery timelines (Singh & Singh, 2012). In digital retail supply chains, where competition and consumer expectations are heightened, vendor performance evaluation directly influences operational efficiency, service level adherence, and customer satisfaction (Nguyen et al., 2018). According to Boone et al. (2018), vendor performance systems in retail environments are essential for strategic sourcing and risk mitigation. Traditionally, evaluation models have been reliant on scorecard systems, human audits, and weighted performance indices, but these manual approaches are often constrained by subjectivity and scalability issues. With the proliferation of big data in e-commerce, the complexity and volume of supplier-related data have expanded exponentially, necessitating more robust, data-driven frameworks for timely and precise decision-making. As a result, organizations are exploring artificial intelligence (AI)-based technologies to enhance the objectivity, speed, and predictive power of vendor evaluation processes (Prakash et al., 2017).

Figure 1: The Vendor Evaluation Lifecycle



Artificial intelligence refers to a class of computational systems capable of performing tasks that typically require human intelligence, such as pattern recognition, learning, reasoning, and decision-making (Lipson & Kurman, 2013). Within supply chains, AI technologies encompass machine learning (ML), deep learning (DL), natural language processing (NLP), expert systems, and reinforcement learning. These technologies enable the automation of evaluation tasks and provide insights that are not readily observable through conventional methods (Chen et al., 2016). In the context of retail, the integration of AI into supplier evaluation has gained global attention due to its ability to process multi-source data, including structured datasets from ERP systems, unstructured text from reviews and reports, and real-time sensor data from IoT devices. As

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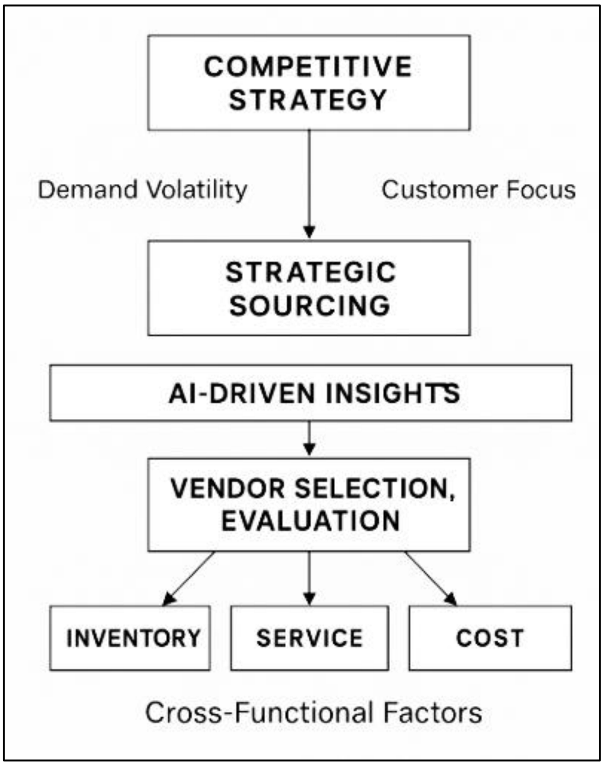
highlighted by Chan et al. (2018), AI tools support advanced analytics capabilities that enable the identification of latent risk factors, anomalies, and supplier behavioral patterns, which are critical for strategic procurement decisions in the retail sector. The international relevance of this integration is underscored by global retail giants such as Amazon, Walmart, and Alibaba, who employ AI to enhance procurement agility and supply chain responsiveness (Carter & Washispack, 2018).

Strategic decision-making in supply chain management refers to long-term decisions involving the selection, management, and development of vendor relationships to align with organizational goals and market conditions. In digital retail supply chains, this strategic role has intensified due to demand volatility, customization trends, and customer-centric delivery models (Papadopoulos et al., 2017). Vendor selection and evaluation are foundational to strategic sourcing, as underperforming suppliers can lead to stockouts, reputational damage, and cost overruns (Kietzmann et al., 2011). AI-driven systems contribute to strategic decisions by transforming historical and real-time data into actionable insights (Katsaliaki et al., 2021). For example, classification algorithms can flag suppliers with recurring late deliveries, while predictive models can forecast performance degradation based on inventory discrepancies or service history (Veselovská, 2020). Furthermore, natural language processing can extract risk indicators from contracts, audit reports, and supplier communications, allowing decision-makers to consider qualitative inputs within formal evaluation models. This capability is particularly valuable for international retail supply chains, where linguistic, regulatory, and contextual diversity often complicates vendor management.

Figure 2: Strategic Decision-Making in Supply Chain Management



Retail supply chains have undergone a rapid digital transformation over the past decade, driven by omnichannel platforms, automated warehouses, and cloud-based procurement systems (Grewal et al., 2017). This transformation has shifted the dynamics of vendor interaction, making traditional performance evaluation frameworks less effective due to their limited scalability and adaptability. As supply networks become more distributed and integrated with digital platforms, AI offers a means to monitor and assess supplier performance continuously and holistically. According to Vass et al. (2018), AI-enabled dashboards and scorecards provide procurement officers with real-time alerts, performance trends, and KPI deviations, which are critical for swift corrective actions. These AI systems draw from multi-dimensional data sources, such as shipment logs, transactional records, defect rates, and even social media sentiment about suppliers, to generate comprehensive performance insights (Seranmadevi & Kumar, 2019). This holistic view enhances supply chain resilience and enables retailers to proactively manage supply disruptions and compliance risks in global sourcing scenarios.

Vendor performance metrics serve as the foundational indicators for evaluating supplier contribution to organizational goals. These metrics typically include on-time delivery rate, order accuracy, defect rate, cost variance, innovation capability, and compliance with regulatory standards (Burgos & Ivanov, 2021). While these indicators are widely used across industries, their relevance in the digital retail sector is heightened by the speed of operations and customer expectations for seamless fulfillment. AI enhances the evaluation of these metrics through the

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application of supervised and unsupervised learning models that can detect patterns, cluster suppliers based on performance behaviors, and estimate future performance trajectories (Lovelace et al., 2015). For example, regression models can predict future lead times based on seasonality and historical delays, while clustering algorithms can group suppliers with similar risk profiles for targeted management strategies (Grewal et al., 2017). These capabilities empower retailers to differentiate between strategic and tactical suppliers and allocate resources accordingly. In digital marketplaces, where product assortments and supply bases are highly dynamic, AI's ability to synthesize large-scale data into actionable performance insights is indispensable. The application of AI in vendor evaluation is often implemented through specific models and frameworks designed for procurement intelligence. Popular AI methodologies include decision trees, support vector machines (SVM), artificial neural networks (ANN), and Bayesian models, which are employed to optimize supplier ranking, performance scoring, and risk assessment (Lee, 2016). He et al. (2015) illustrate that these models outperform traditional heuristics in precision, recall, and robustness, particularly when evaluating multi-criteria decision problems in procurement. Moreover, hybrid models combining fuzzy logic with machine learning or neural networks provide enhanced accuracy and interpretability, particularly when dealing with imprecise or qualitative vendor data. These models are especially useful in environments where procurement decisions involve balancing cost, quality, and service under uncertain conditions. Such integration of AI into multi-criteria decision-making processes reflects a shift from reactive evaluation to anticipatory performance management in digital retail ecosystems (Shankar, 2018). Moreover, Retail supply chains, especially those operating in global or omnichannel settings, are increasingly exposed to external shocks such as geopolitical instability, pandemics, and regulatory disruptions. These risks necessitate agile and data-responsive vendor management systems, which AI is uniquely positioned to support. Reinforcement learning and anomaly detection algorithms are widely used to identify sudden shifts in supplier behavior, such as abrupt delivery delays or order cancellations, which may precede a vendor's operational failure. According to Mahroof (2019), AI systems enable procurement teams to model "what-if" scenarios and simulate supplier responses to external stimuli, thereby enhancing preparedness and risk mitigation. Moreover, AI facilitates ongoing vendor development by identifying improvement opportunities, benchmarking performance against peers, and providing feedback loops that suppliers can use to align with buyer expectations (Loske, 2020). These AI-enabled insights are crucial in maintaining a high-performing and adaptive vendor base within the fast-paced digital retail environment.

The primary objective of this review is to systematically examine how artificial intelligence (AI) technologies are being integrated into vendor performance evaluation models within digital retail supply chains, with a particular focus on their role in strategic decision-making processes. Given the increasing complexity and data-intensity of modern retail environments, traditional vendor assessment approaches are becoming insufficient to capture dynamic performance variables, cross-functional risks, and predictive insights. Therefore, this study aims to consolidate and critically analyze the current body of literature that explores AI-driven methods—such as machine learning, deep learning, natural language processing, and hybrid algorithmic frameworks—used to monitor, evaluate, and predict supplier performance outcomes. The review specifically targets models and frameworks that contribute to procurement intelligence, supplier segmentation, risk scoring, and vendor development strategies. A key goal is to understand how AI technologies enhance the objectivity, speed, and granularity of supplier evaluations by leveraging multi-source data, including ERP datasets, transactional records, customer feedback, quality reports, and external risk indicators. Furthermore, the study seeks to identify the specific decision-making contexts—such as vendor selection, re-evaluation, termination, and contractual negotiations—where AI has demonstrated measurable impact. In doing so, the review also outlines the practical challenges faced by organizations in implementing AI-based systems, such as data integration, algorithmic transparency, and governance issues. This objective also includes a comparative lens to evaluate the effectiveness and maturity of various AI approaches across regions and retail sub-sectors (e.g., fast fashion, electronics, grocery chains). Ultimately, the review aims to map out the landscape of AI-enabled vendor performance evaluation models, synthesize

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key findings from the literature, and provide a comprehensive academic resource that bridges the gap between technological capability and supply chain management practice. Through this, it seeks to contribute to both the scholarly discourse and managerial decision-making frameworks in digital retail procurement environments.

LITERATURE REVIEW

The application of artificial intelligence (AI) in supply chain management has evolved from exploratory implementations into a core capability for performance monitoring and strategic decision-making. Within this domain, vendor performance evaluation has become a focal area where AI technologies offer considerable potential for enhancing efficiency, accuracy, and objectivity. As digital retail supply chains become increasingly data-intensive, globalized, and customer-driven, the need for agile and intelligent supplier management systems has intensified. The existing body of literature reflects a multi-disciplinary convergence of AI techniques—such as machine learning, neural networks, natural language processing, and fuzzy logic—with supply chain analytics and vendor governance frameworks. These contributions span domains of procurement science, operations management, computer science, and risk engineering. This literature review systematically examines these intersecting research areas to uncover how AI has been conceptualized, modeled, and deployed in vendor evaluation settings, especially in digital retail environments. This section is organized into specific thematic areas, beginning with foundational frameworks and classical approaches to vendor performance evaluation, followed by an examination of AI-based models and tools, their integration mechanisms, performance benefits, and implementation challenges. Each sub-section synthesizes empirical findings, theoretical advancements, and practical frameworks reported in peer-reviewed journals, technical case studies, and industry whitepapers. By presenting a structured view of past and current scholarship, this literature review establishes a critical foundation for understanding the evolution and impact of AI in modern vendor performance evaluation within digital supply chains.

Vendor Performance

Vendor performance has long been recognized as a cornerstone of effective supply chain management, particularly within the context of retail operations where customer satisfaction, delivery speed, and product quality are paramount (Singh & Singh, 2012). Traditional vendor performance evaluation frameworks have primarily relied on criteria such as cost, quality, delivery reliability, service level, and responsiveness, with various tools such as weighted scoring models, the Analytical Hierarchy Process (AHP), and the Total Cost of Ownership (TCO) approach used to structure assessments (Ben-Daya et al., 2013). For instance, Dickson's foundational study identified 23 key criteria used by purchasing managers, with quality, delivery, and performance history ranking highest. However, these approaches have been criticized for their inherent subjectivity, lack of scalability, and inability to handle dynamic or real-time data (Huang & Handfield, 2015). As digitalization reshapes retail operations, vendor evaluation must accommodate more complex, data-intensive environments, where traditional scorecard approaches may fail to capture performance nuances across distributed supply chains (Giovanni, 2021). Furthermore, vendor reliability and sustainability have emerged as critical dimensions, with scholars emphasizing the integration of ethical, environmental, and risk-based metrics into performance evaluations (Giovanni et al., 2019). In particular, organizations now assess not just the supplier's direct performance, but also their capability to mitigate disruptions, adapt to fluctuating demand, and ensure compliance with industry standards (Singh & Singh, 2012). Performance-based contracts and strategic alliances have also reshaped the buyer-supplier relationship from transactional to collaborative, making vendor performance evaluation a continuous and strategic activity rather than a periodic, reactive process (Ben-Daya et al., 2013).

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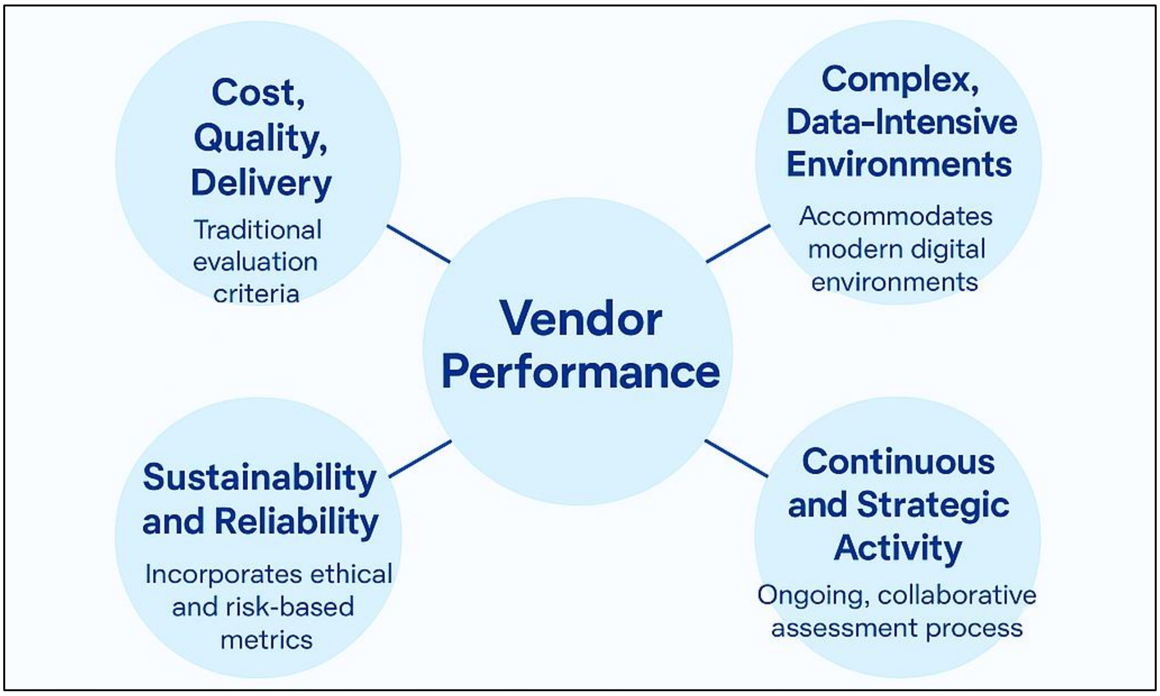
Figure 3: Vendor Performance Dimensions in Digital Retail Supply Chains



Contemporary literature emphasizes the importance of integrating multi-dimensional metrics into vendor performance evaluation to support decision-making in highly competitive and rapidly evolving digital retail environments. Performance measurement frameworks now extend beyond operational criteria to include innovation potential, financial stability, collaborative capacity, and digital readiness (Gunasekaran, Yusuf, et al., 2017). Several studies have highlighted that a multidimensional vendor evaluation strategy enhances strategic alignment and risk management (Duan et al., 2019). For example, Awan et al. (2021) discuss the use of Multi-Criteria Decision Making (MCDM) methods in capturing both quantitative and qualitative factors, allowing for a more balanced assessment across competing supplier priorities. Similarly, Jukic et al. (2015) propose a Best-Worst Method (BWM) that reduces redundancy in criteria selection and increases decision consistency. In high-velocity markets such as fashion and electronics retail, where demand forecasting errors can lead to overstocking or missed opportunities, vendor performance systems are crucial in selecting suppliers capable of adapting to rapid shifts (Hazen, Skipper, Boone, et al., 2016). Researchers have also underscored the increasing reliance on integrated vendor relationship management (VRM) systems, which consolidate procurement data, supplier communication, and performance analytics into unified dashboards (Singh & Singh, 2012). In addition, vendor performance is not merely assessed post hoc but is embedded into the procurement lifecycle—from pre-qualification to post-delivery review—enabling proactive supplier development and risk mitigation (Govindan et al., 2018). Another critical area of focus has been supplier diversity and localization, where performance evaluation incorporates the supplier's socio-economic contributions, local compliance practices, and agility in responding to region-specific market shifts (Dubey et al., 2020). Collectively, these advancements reflect a paradigmatic shift from narrow, cost-based evaluations to comprehensive, sustainability-oriented, and digitally supported performance frameworks tailored for modern retail supply ecosystems.

Vendor Performance in Retail Supply Chains

Vendor performance within retail supply chains is an essential determinant of operational efficiency, product availability, and customer satisfaction (Li & Wang, 2015)). Traditional performance evaluation frameworks have typically emphasized core criteria such as cost, quality, delivery, and service (Seranmadevi & Kumar, 2019). The foundational model proposed by

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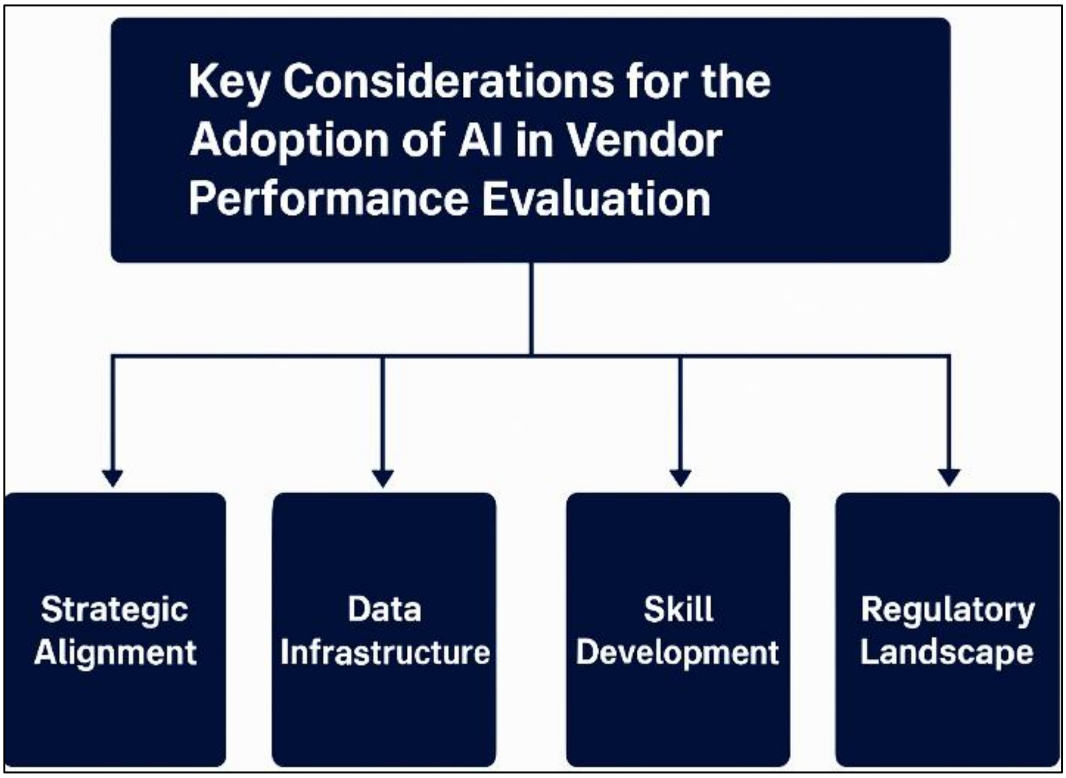
Dickson, for instance, identified 23 key supplier selection criteria, highlighting quality and delivery performance as top priorities. These early models were operationalized through tools like Weighted Point Method, Cost Ratio Method, and Analytical Hierarchy Process (AHP), which allowed procurement professionals to rank vendors systematically (Li & Wang, 2015; Seranmadevi & Kumar, 2019). However, researchers have pointed out that such models are limited by their linear assumptions, lack of predictive capacity, and vulnerability to human subjectivity (Burgos & Ivanov, 2021). In retail environments, particularly within fast-moving consumer goods and fashion sectors, the ability to adapt quickly to demand fluctuations and seasonal variations is paramount. Seranmadevi and Kumar (2019) that vendor evaluation must also account for suppliers' responsiveness, agility, and technological readiness. The globalized nature of supply chains introduces additional complexities, such as cross-border compliance, logistical variability, and cultural alignment, which traditional metrics fail to capture (Burgos & Ivanov, 2021). As a result, more recent literature advocates for performance measurement systems that encompass multidimensional attributes including innovation, sustainability, and digital integration (Lovelace et al., 2015). Furthermore, there is growing support for dynamic evaluation systems that can evolve alongside retail strategies and supply chain disruptions, rather than remaining fixed or periodic (Grewal et al., 2017). The transformation of retail procurement practices underscores the necessity of a more agile, real-time, and analytics-driven approach to vendor performance management.

Figure 4: Key Considerations for Evaluating Vendor Performance in Digital Retail Supply Chains



As retail supply chains shift toward digitalization and omnichannel operations, vendor performance evaluation frameworks have expanded to integrate strategic, technological, and sustainability-oriented indicators. The digitized retail supply environment is characterized by real-time data flows, complex order fulfillment processes, and heightened consumer expectations, placing unprecedented pressure on vendors to deliver consistently high performance (Lee, 2016). Scholars have increasingly argued for the adoption of multi-criteria decision-making (MCDM) frameworks that incorporate both quantitative and qualitative metrics to assess vendors holistically (He et al., 2015). For example, Shankar (2018) applied the Best-Worst Method (BWM) to

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streamline evaluation criteria while enhancing decision accuracy. Similarly, fuzzy logic and hybrid models have been applied to account for the ambiguity and vagueness often present in qualitative assessments (Mahroof, 2019). In retail sectors such as electronics and grocery, where product lifecycle, stock rotation, and inventory accuracy are tightly linked to vendor reliability, performance metrics are now integrated into procurement dashboards and supplier scorecards (Loske, 2020). Moreover, the role of vendor development has been emphasized, with researchers noting that evaluation is not merely for selection or disqualification but also serves to guide performance improvements and innovation alignment (Reinartz et al., 2018). Supplier audits, self-assessment tools, and joint key performance indicator (KPI) frameworks are increasingly used in retail contexts to promote transparency and alignment (Sorescu et al., 2011). This integrated view of vendor performance considers the strategic value of long-term partnerships, cost resilience, and shared digital infrastructure, particularly under the demand volatility and customization pressures of modern retail. As such, the evaluation of suppliers in retail environments has moved beyond static metrics toward a more relational and performance-enabling orientation.

In response to the globalization of retail operations and the rising risks in international sourcing, the evaluation of vendor performance now includes risk assessment, regulatory compliance, and environmental, social, and governance (ESG) metrics. Global sourcing has amplified concerns around ethical procurement, legal accountability, and supply chain transparency, prompting retailers to reevaluate what constitutes high vendor performance (Caro & Sadr, 2019). Risk-based vendor performance models have been developed to assess not only delivery and cost metrics but also geopolitical stability, financial health, and historical disruption trends of suppliers (Goworek, 2014). For example, Oh and Polidan (2017) propose using supply chain risk management frameworks that incorporate both upstream and downstream vendor behavior to mitigate unexpected disruptions. Compliance with regional and global regulations—such as REACH, RoHS, and GDPR—is increasingly seen as a critical performance dimension, particularly for vendors handling sensitive consumer data or hazardous materials (Jørgensen et al., 2003). Moreover, sustainability-focused evaluation systems are gaining traction as companies seek to meet ESG benchmarks while maintaining supply efficiency. Dang et al. (2020) have shown that sustainability-aligned suppliers often outperform others in terms of long-term reliability and market responsiveness. Retailers have started employing AI-enhanced systems to gather supplier risk data from a variety of sources, including supplier audits, financial reports, and public sentiment analysis, further supporting data-driven evaluations. These systems facilitate not only better visibility across the vendor network but also more accurate forecasting of performance bottlenecks and compliance failures. The comprehensive and multidimensional nature of vendor performance in global retail operations thus reflects a shift toward strategic alignment, resilience, and responsible procurement across the supply chain.

Digital Retail Supply Chains and Data-Driven Vendor Management

The transformation of retail supply chains into digital ecosystems has significantly reshaped vendor management practices, placing data at the center of strategic procurement decisions. Digital retail supply chains are characterized by their integration of cloud computing, Internet of Things (IoT), blockchain, and real-time data analytics, which allow for dynamic coordination across sourcing, inventory, fulfillment, and delivery operations (Weber & Schütte, 2019). These technologies enable retailers to collect granular data at each node of the supply chain, facilitating timely evaluations of vendor performance and responsiveness. Fiorito et al. (2010) emphasize that data-driven supply chains outperform traditional models by enabling proactive decision-making, particularly in areas such as supplier risk identification, performance forecasting, and adaptive sourcing. This shift is also driven by the omnichannel nature of modern retail, where inventory accuracy, fulfillment flexibility, and real-time visibility are essential to meeting customer expectations. As retailers expand their digital capabilities, data from e-commerce platforms, enterprise resource planning (ERP) systems, warehouse management systems (WMS), and customer feedback loops is increasingly integrated into vendor dashboards (Rieple & Singh, 2010). These platforms provide performance indicators not only on traditional metrics like cost and delivery but also on vendor agility, innovation readiness, and collaboration quality. Real-time analytics has become particularly critical in managing disruptions and seasonal demand

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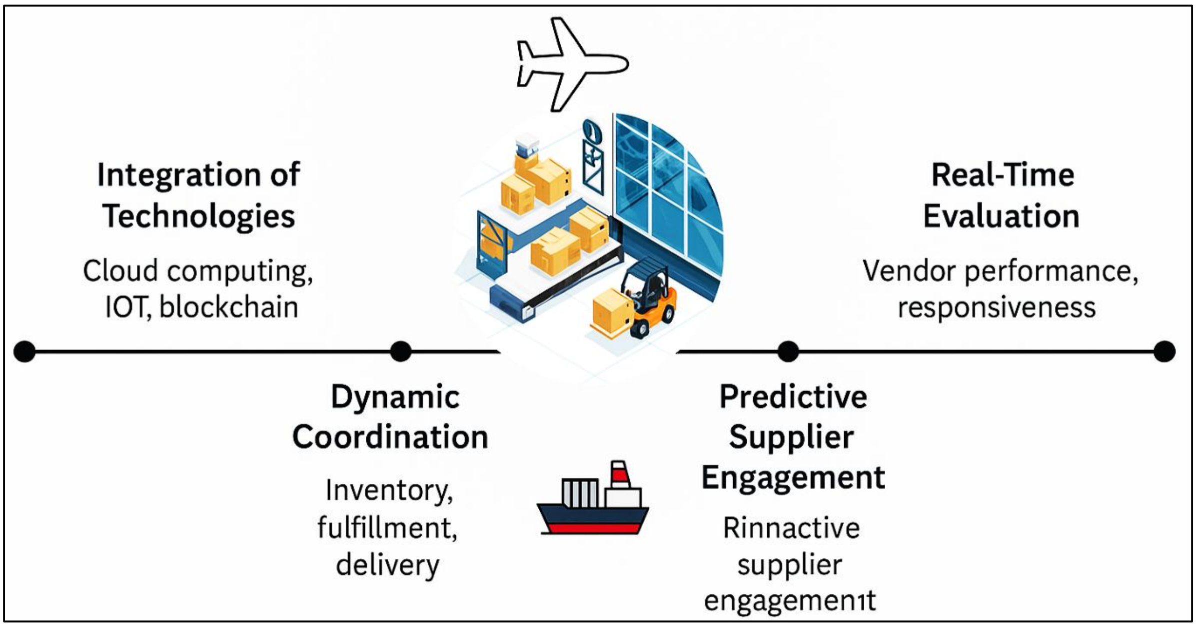
variability, with machine learning models deployed to detect vendor anomalies, forecast delays, and optimize supplier portfolios (Esch et al., 2019). Data-driven vendor management in digital supply chains thus marks a transition from reactive, scorecard-based evaluations to intelligent, continuous, and predictive supplier engagement, driven by integrated technological ecosystems and high-velocity data environments (Cao, 2021).

Figure 5: Digital Retail Supply Chains and Data-Driven Vendor Management



The literature on data-driven vendor management within digital retail supply chains highlights the strategic role of advanced analytics in fostering supplier performance, risk mitigation, and alignment with retail objectives. With the proliferation of big data and digital commerce platforms, supply chain leaders increasingly rely on data science methodologies to inform procurement and supplier evaluation processes. Predictive analytics, powered by artificial intelligence (AI), is used to assess supplier lead-time reliability, quality consistency, and capacity utilization under diverse market conditions. Supervised learning algorithms, such as decision trees and support vector machines, are applied to historical data to identify high-risk vendors, while unsupervised clustering techniques are used to segment vendors based on shared behavioral or risk profiles. Furthermore, vendor scorecards are evolving into dynamic dashboards that update in real-time based on data streams from IoT sensors, logistics APIs, and third-party verification platforms (Oosthuizen et al., 2020). These tools empower procurement managers to act on live insights and benchmark vendors across regions, tiers, and strategic importance . Another critical trend involves the use of natural language processing (NLP) for mining supplier contracts, audit reports, and regulatory filings, adding qualitative depth to quantitative assessments. Data integration challenges remain a major barrier to widespread adoption, as noted by Silva et al., (2019), with concerns about data quality, ownership, and interoperability. Nevertheless, the literature affirms that digital supply chains equipped with AI-driven analytics and unified data infrastructures are more resilient and adaptive, enabling retailers to identify performance risks early, negotiate strategically, and co-develop capabilities with their vendors (Cao et al., 2018). The convergence of data science, supply chain operations, and vendor management thus forms a critical axis in the contemporary digital retail landscape.

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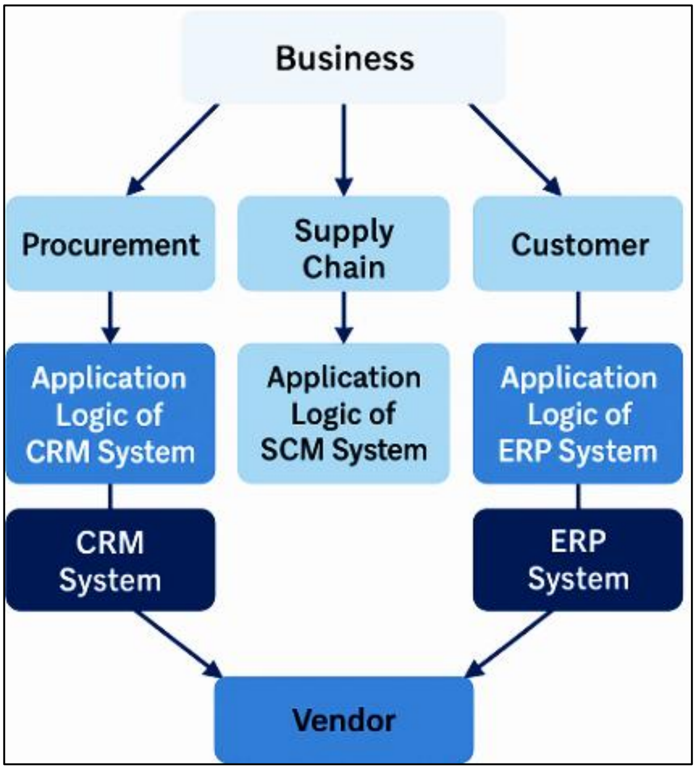
ERP, SCM, CRM systems

Enterprise Resource Planning (ERP) systems have become foundational in retail supply chain management, serving as integrated platforms that consolidate procurement, inventory, financial, and supplier data into unified databases for improved decision-making (Zhao & Yu, 2011). ERP systems enable seamless tracking of vendor-related transactions, such as order placements, deliveries, invoice processing, and compliance checks, thereby enhancing transparency and accountability in vendor performance evaluations (Seethamraju, 2014). Fiorini et al. (2019) emphasized that ERP implementation significantly improves operational efficiency and accuracy in procurement processes, reducing manual errors and data redundancy. In digital retail environments, ERP systems interface with point-of-sale (POS) systems, warehouse management systems (WMS), and e-commerce platforms to offer real-time data visibility across the supply chain. This integration is particularly valuable in managing supplier lead times, evaluating delivery performance, and identifying inventory shortages linked to specific vendors (Huang & Handfield, 2015). Furthermore, ERP-based analytics modules facilitate key performance indicator (KPI) tracking for suppliers based on dimensions such as fulfillment accuracy, cost compliance, and service responsiveness ((Kaplan & Haenlein, 2019). ERP-driven dashboards allow procurement teams to benchmark vendors over time and trigger alerts when performance deviations exceed thresholds (Winkelhaus & Grosse, 2019). However, the literature also notes challenges such as system complexity, high implementation costs, and organizational resistance, particularly among small and medium-sized retailers. Despite these challenges, ERP systems remain critical for building data-driven vendor evaluation frameworks, enabling integration between internal procurement goals and external supplier capabilities (Ji & Sun, 2017).

Figure 6: Integrated Architecture of ERP, SCM, and CRM Systems for Retail Vendor and Customer Management



Supply Chain Management (SCM) systems are specialized software solutions that support end-to-end coordination across sourcing, logistics, production, and distribution functions, playing a pivotal role in enhancing vendor collaboration and overall supply chain performance (Bousqaoui et al., 2017). Within the retail sector, SCM systems facilitate efficient information flow between retailers and suppliers, allowing real-time tracking of inventory levels, delivery schedules, and demand fluctuations (Huang & Handfield, 2015). These platforms support strategic sourcing decisions by enabling centralized procurement planning and decentralized supplier execution (Mani et al., 2017). SCM systems are often integrated with vendor portals and electronic data interchange (EDI) tools to streamline order communication and performance reporting (Giannakis & Louis, 2016). As highlighted by Kaur et al. (2019), effective use of SCM tools can significantly improve vendor responsiveness, reduce order cycle times, and mitigate the bullwhip effect in retail chains. Advanced SCM systems embed predictive algorithms that anticipate stock-outs and overstock risks based on vendor lead times and historical trends (Pishvaee et al., 2011). Furthermore, collaborative planning, forecasting, and replenishment (CPFR) modules within SCM platforms foster joint forecasting and inventory optimization, reinforcing strategic alignment between retailers and suppliers (Radanliev et al., 2019). Vendor performance is also enhanced

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through visibility into shipment tracking, damage reporting, and supplier responsiveness, which are recorded and scored within SCM systems. However, challenges such as data silos, interoperability limitations, and cybersecurity risks may hinder full exploitation of SCM functionalities. Overall, SCM systems are essential enablers of real-time vendor management, providing the analytical and collaborative infrastructure needed for responsive and resilient digital retail supply chains.

Machine Learning Algorithms for Vendor Evaluation

The application of machine learning (ML) algorithms in vendor performance evaluation has gained prominence due to their ability to process high-dimensional data, uncover patterns, and make predictive assessments without explicit rule-based programming (Priore et al., 2018). Traditional evaluation models, which rely on linear scoring or subjective assessments, often struggle to accommodate dynamic supply chain data and complex interactions among performance variables (Ahmed et al., 2022). ML algorithms such as support vector machines (SVM), decision trees, random forests, and gradient boosting have been widely adopted for classification, ranking, and forecasting of vendor performance (Aklima et al., 2022). For example, SVM models can classify vendors into risk categories based on features like lead time deviation, defect rates, and historical performance anomalies (Dwivedi et al., 2021). Decision trees and random forests allow interpretable rule-based segmentation of suppliers, identifying underperformers based on historical non-compliance or service inconsistencies (Mahmud et al., 2022). Supervised learning models are particularly effective when labeled datasets are available from ERP, SCM, or CRM systems, enabling procurement managers to build models that predict late deliveries, pricing volatility, or quality lapses (Mahfuj et al., 2022). These algorithms enhance objectivity in evaluations by reducing human bias and enabling continuous learning from incoming data (Awan et al., 2021). Dubey et al. (2020) further confirms that predictive accuracy improves as models are trained on larger, cleaner, and more granular datasets. The ability to automate and scale vendor assessments makes ML algorithms particularly suitable for digital retail supply chains, where thousands of suppliers and millions of transactions may be involved. Thus, ML provides a foundation for transforming vendor evaluation from periodic review to real-time strategic insight (Majharul et al., 2022).

In vendor evaluation, the use of unsupervised machine learning algorithms has grown in parallel with supervised methods, especially in scenarios where labeled data is scarce or where the goal is to discover latent structures among suppliers (Masud, 2022; Zhu et al., 2016). Clustering algorithms such as k-means, hierarchical clustering, and DBSCAN are commonly used to group vendors based on multi-dimensional features like delivery frequency, price variability, complaint rates, and innovation responsiveness (Hossen & Atiqur, 2022). These clustering methods help organizations differentiate between strategic and non-strategic vendors or identify hidden risk profiles among suppliers with otherwise average performance (Kumar et al., 2022). For example, Chen et al. (2016) applied clustering algorithms to vendor behavioral data, uncovering a segment of “silent risk” vendors who maintained delivery schedules but frequently failed on product compliance. Similarly, dimensionality reduction techniques such as principal component analysis (PCA) and t-SNE have been used to visualize vendor groupings in high-dimensional datasets, improving decision-makers’ ability to interpret and act on complex supplier data (Sohel et al., 2022). These models can be coupled with anomaly detection algorithms to flag unexpected shifts in performance, such as sudden increases in returns or complaints. Reinforcement learning, though less common, has also been explored for dynamic vendor evaluation, where models learn optimal procurement strategies through continuous feedback from supplier interactions. These applications of unsupervised and semi-supervised learning methods represent a shift from rule-based vendor scoring to adaptive, data-driven segmentation and forecasting frameworks. As data sources diversify—including IoT devices, social media, and market news—ML models

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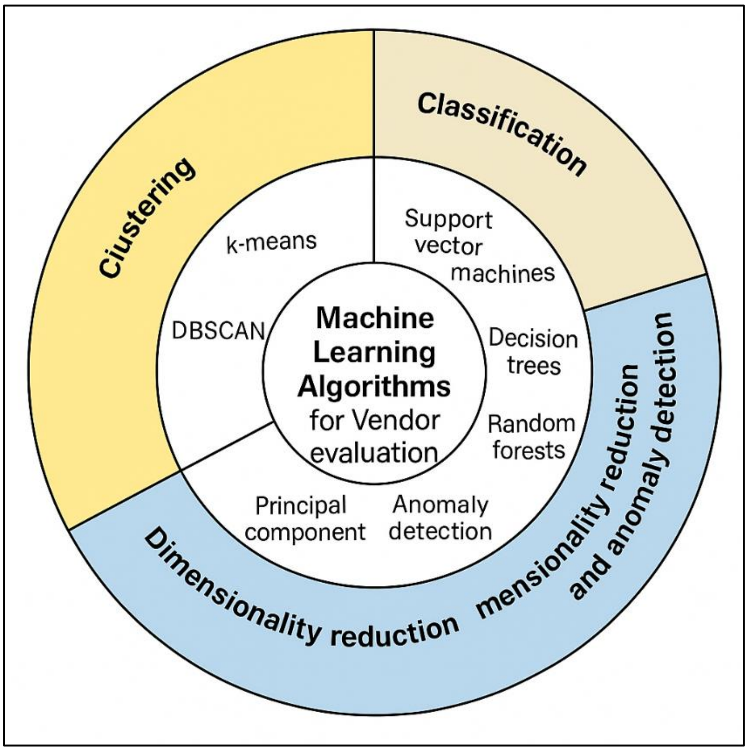
become increasingly necessary for managing unstructured inputs in a meaningful way (Bousqaoui et al., 2017).

An important area in the literature involves hybrid and ensemble machine learning models that integrate multiple algorithms to improve robustness, accuracy, and interpretability in vendor evaluation systems. Hybrid models often combine fuzzy logic with machine learning to handle uncertainty and linguistic variables in supplier data (Zhou et al., 2017). For instance, Fuzzy-AHP integrated with neural networks allows procurement professionals to evaluate vendors based on subjective inputs such as "moderate quality risk" or "high reliability" while preserving algorithmic precision (Reyes et al., 2020). Ensemble methods, including bagging, boosting, and stacking, have shown strong performance in vendor ranking tasks where multiple evaluation metrics must be considered simultaneously (Cui et al., 2018). Reyes et al. (2020) show that ensemble methods outperform single-algorithm models in predicting vendor delivery reliability, quality incidents, and compliance failures. Moreover, explainability is gaining attention as a critical factor in ML-based procurement systems. Tools like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are being incorporated into evaluation dashboards to make black-box models more transparent to procurement professionals. This is particularly important in regulated industries or large retail operations where procurement decisions must be auditable and justifiable. In addition, model evaluation metrics such as precision, recall, F1-score, and area under the ROC curve (AUC-ROC) are used to validate vendor scoring models before full deployment. The literature consistently demonstrates that ensemble and hybrid ML models enhance strategic supplier decision-making by delivering higher accuracy, increased interpretability, and greater alignment with procurement goals. These advancements are crucial in digital retail ecosystems where supplier data is vast, dynamic, and multidimensional.

Figure 7: Machine Learning Algorithms for Vendor Evaluation in Digital Retail Supply Chains



Deep Learning and Neural Networks for Multivariate Vendor Behavior Modeling

Deep learning models and artificial neural networks (ANNs) have gained significant traction in the evaluation and modeling of complex vendor behavior due to their superior ability to capture nonlinear patterns and high-dimensional interactions across multivariate datasets. Unlike traditional statistical models or linear machine learning approaches, deep learning architectures such as multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) can effectively process time-series, tabular, and unstructured data generated from vendor transactions, communications, and performance logs(Cui et al., 2018). MLPs are commonly used to assess vendor compliance scores, cost volatility, and fulfillment accuracy using structured ERP and SCM data. RNNs and their variants like Long Short-Term Memory (LSTM) networks are particularly suited to modeling temporal sequences, such as delivery timelines, contract renewals, and inventory cycles, thereby allowing for precise forecasting of performance degradation and behavioral drift (Paul & Venkateswaran, 2020). CNNs, although more prevalent in image and sensor data analysis, have been adapted for feature extraction from complex

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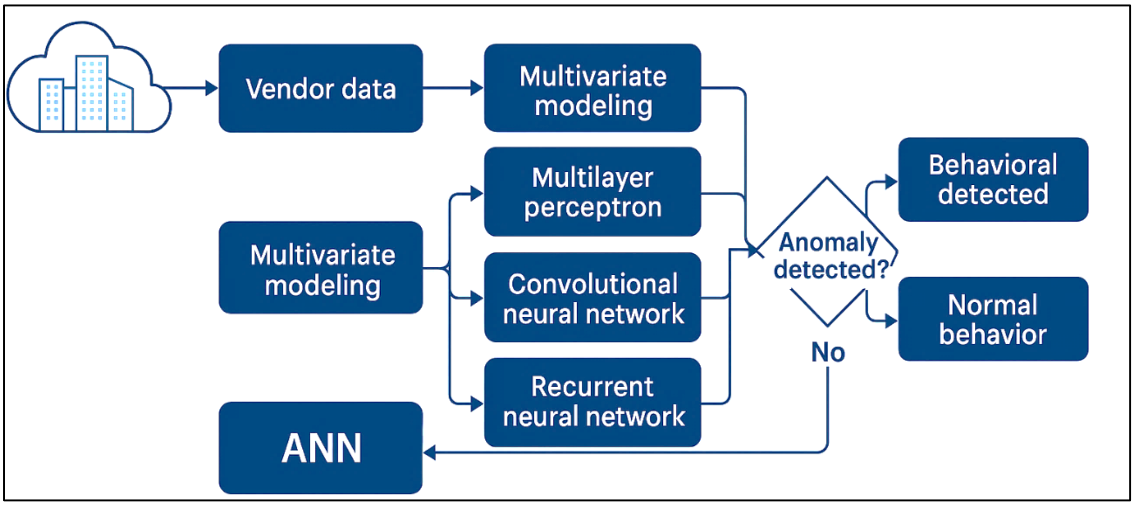
vendor-related datasets by treating performance matrices as multidimensional grids. Shafique et al. (2019) highlight the utility of deep learning in automating the categorization of vendors into performance bands and in anomaly detection tasks, especially in large-scale, multi-vendor digital retail ecosystems. These models can ingest inputs from CRM systems, quality audits, and even sentiment analysis from supplier communications, offering a comprehensive behavioral portrait of each vendor. As retail supply chains become increasingly digitized and interconnected, the multivariate modeling capabilities of deep learning systems are proving indispensable for real-time, scalable, and intelligent vendor performance management.

Figure 8: Deep Learning Framework for Vendor Behavior Modeling and Evaluation in Digital Retail Supply Chains



The integration of deep learning techniques into vendor evaluation frameworks reflects a growing need for intelligent systems that can adapt to complex, dynamic, and often non-linear supplier behaviors in digital retail environments. Deep neural networks (DNNs), with their multiple hidden layers, are particularly effective in identifying latent relationships among performance indicators such as defect rates, on-time delivery, responsiveness, compliance trends, and financial stability (Arunachalam et al., 2018). These relationships are often difficult to capture using conventional approaches, making DNNs a critical component in advanced supplier analytics (Shafique et al., 2019). Badurdeen et al. (2014) suggest that integrating fuzzy logic or decision theory into deep learning models can improve interpretability and reduce overfitting in vendor classification tasks. Furthermore, researchers are exploring attention-based deep learning models and Transformer architectures to weigh contextual importance across multivariate vendor inputs, thereby enhancing model accuracy and reliability. In vendor behavior modeling, explainability remains a concern; hence, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are used in conjunction with deep learning models to generate transparent justifications for procurement decisions. These interpretable layers are essential for fostering trust among procurement professionals and maintaining compliance with governance standards. Moreover, hybrid models combining LSTM and CNN architectures have shown effectiveness in tasks such as predicting vendor disruptions, identifying fraudulent transactions, and flagging inconsistency in delivery cycles. Real-time deployment of these models in cloud-based vendor management platforms has further enhanced scalability, enabling procurement teams to evaluate hundreds of suppliers concurrently with minimal human intervention. Collectively, deep learning frameworks offer unparalleled capability in modeling complex supplier dynamics, reinforcing their growing role in intelligent supply chain analytics and digital procurement.

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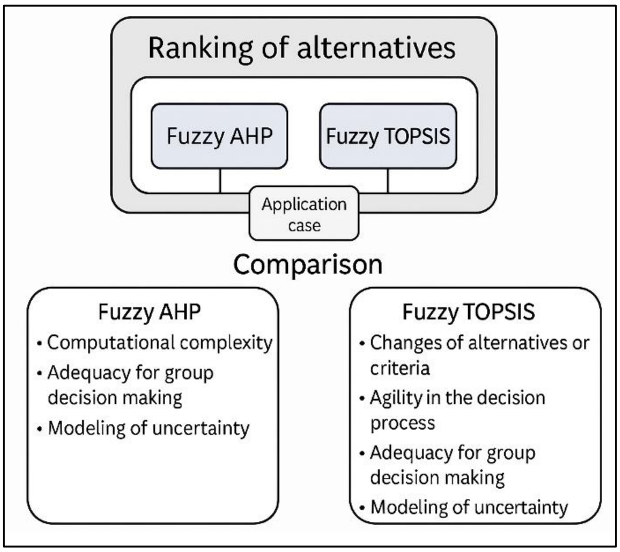
Fuzzy AHP, Fuzzy TOPSIS in procurement intelligence

The Analytical Hierarchy Process (AHP) has been widely used in procurement decision-making for its ability to structure complex multi-criteria problems into hierarchical models. However, conventional AHP struggles to handle ambiguity and subjectivity inherent in human judgments, particularly when evaluating qualitative supplier attributes such as trustworthiness, innovation capability, or responsiveness (Pishvaee et al., 2012). To address these limitations, Fuzzy AHP was introduced by integrating fuzzy set theory, enabling the modeling of vagueness and imprecision in pairwise comparisons (Govindan et al., 2020). In vendor selection, Fuzzy AHP allows procurement professionals to prioritize criteria such as cost, quality, delivery reliability, and compliance using linguistic variables (e.g., "very high," "moderate," "low") which are then converted into triangular fuzzy numbers (Kumar et al., 2014). Behret et al. (2011) demonstrate that Fuzzy AHP enhances the consistency and interpretability of supplier rankings, particularly in settings with limited data or subjective expert input. It has been applied across diverse retail and manufacturing environments to select strategic suppliers under conditions of uncertainty. In digital supply chains, where supplier data is both quantitative (e.g., lead times) and qualitative (e.g., collaboration quality), Fuzzy AHP supports more holistic evaluations. It also enables weighting adjustments as priorities evolve, providing a flexible decision-making tool for dynamic sourcing environments. Furthermore, Fuzzy AHP has been effectively combined with other methods like DEA (Data Envelopment Analysis) and ML algorithms to enhance predictive power and benchmarking accuracy in procurement intelligence systems. These integrations underscore the growing recognition of Fuzzy AHP as a vital methodology for handling supplier complexity in uncertain, data-rich environments.

Figure 9: Comparison of Fuzzy AHP and Fuzzy TOPSIS Methods in Vendor Selection for Procurement Intelligence



Fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a widely utilized decision-making tool in procurement intelligence, particularly for ranking suppliers under uncertain or incomplete information environments. Unlike conventional TOPSIS, which uses crisp values, Fuzzy TOPSIS incorporates fuzzy numbers to evaluate the closeness of each alternative (supplier) to the ideal and negative-ideal solutions. This allows decision-makers to better reflect the uncertainty in judgment and more accurately model the vagueness often present in real-world procurement settings (Micheli et al., 2013). Studies have applied Fuzzy TOPSIS across multiple industries including electronics, FMCG, and apparel, ranking vendors based on criteria such as cost competitiveness, quality assurance, delivery punctuality, and ESG (environmental, social, governance) compliance (Lee et al., 2011). For instance, Pavlov et al. (2018) used Fuzzy TOPSIS to evaluate suppliers for e-procurement systems by incorporating subjective and objective criteria weighted through Fuzzy AHP. The method's ability to incorporate both expert judgment and data-driven inputs makes it especially suitable for strategic sourcing in digital retail supply chains (Vahdani et al., 2013). Moreover, the visual interpretability of the ranking outputs facilitates managerial decision-making by clearly identifying suppliers with high proximity to ideal performance under uncertain conditions. Recent advancements have seen the integration of Fuzzy TOPSIS with artificial intelligence and big data analytics tools, enabling scalable vendor evaluations based on real-time or large-volume performance data. Furthermore, hybrid models combining Fuzzy TOPSIS with decision tree algorithms or neural networks have been proposed to automate the supplier ranking process while maintaining contextual interpretability. As retail supply chains demand more agility and data-informed responsiveness, Fuzzy TOPSIS provides a

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structured, scalable, and uncertainty-resilient framework for continuous supplier assessment and risk-based decision-making.

Performance Monitoring through AI-Based Dashboards

AI-based dashboards have emerged as powerful tools for real-time performance monitoring in supply chain and procurement environments, especially for vendor evaluation in digital retail ecosystems. These dashboards integrate artificial intelligence (AI) and machine learning (ML) models to automatically extract, process, and visualize key performance indicators (KPIs) from heterogeneous data sources including ERP, SCM, WMS, and CRM systems (Li et al., 2017). Unlike static reporting tools, AI-enabled dashboards support dynamic performance tracking by continuously learning from vendor behavior and updating metrics in real-time (Guo et al., 2011). Paschen et al. (2020) highlight how these systems enable early detection of anomalies such as delayed shipments, frequent returns, or compliance deviations. Predictive analytics modules embedded in such dashboards can forecast potential disruptions based on historical trends and contextual signals like seasonal fluctuations or geopolitical risks. Furthermore, AI-based dashboards can integrate external unstructured data, including supplier reviews, audit narratives, and sentiment analysis outputs to provide a 360-degree view of vendor performance. These capabilities are especially critical for procurement professionals who manage diverse supplier portfolios and need real-time insights to prioritize interventions(Dwivedi et al., 2021). According to Paschen et al. (2019), the visual clarity and automated alerts provided by dashboards enhance managerial decision-making and operational responsiveness. Dashboards using explainable AI (XAI) techniques, such as SHAP or LIME, also offer transparency in performance scoring, helping managers understand the underlying rationale behind vendor risk flags or performance categorizations. As digital retail networks become increasingly complex, the integration of AI-based dashboards offers a scalable and intelligent solution for continuous supplier performance evaluation and risk management.

The integration of AI-based dashboards into vendor management systems has redefined how procurement teams monitor supplier performance, ensuring agility, scalability, and precision in decision-making processes. These dashboards serve as centralized hubs that synthesize real-time data from transactional logs, logistics systems, IoT devices, and customer interfaces to generate actionable insights on supplier efficiency, reliability, and compliance (Haenlein et al., 2019). AI models embedded within the dashboards enable adaptive learning, clustering, and trend analysis, allowing companies to detect shifts in vendor behavior before they materialize into operational risks. Jarrahi (2018) emphasizes the ability of AI dashboards to detect performance deterioration patterns such as lead time inflation, defect escalation, or quality variance, which are often undetectable through conventional performance reports. Additionally, advanced visualization techniques—such as heat maps, risk scores, and vendor segmentation grids—support procurement managers in quickly identifying critical supplier relationships and tailoring mitigation strategies. These dashboards are also essential for multi-tier supply chains, where visibility into upstream suppliers is limited but vital for managing systemic risks. AI-enhanced monitoring systems often employ NLP algorithms to scan contract documents and emails for compliance anomalies, enabling automatic flagging of non-adherence to service-level agreements or regulatory clauses (Garbuio & Lin, 2018). Moreover, integration with external data feeds—such as geopolitical alerts, social media, and ESG reports—further strengthens the contextual intelligence embedded in these dashboards. As confirmed by Duan et al. (2019), such comprehensive AI-enabled interfaces not only enhance decision support but also promote accountability, supplier collaboration, and sustainable procurement practices by making supplier performance both measurable and manageable in real-time.

Regional adoption trends (North America, Europe, Asia-Pacific)

In North America and Europe, the adoption of artificial intelligence (AI) for vendor performance evaluation has seen a significant upsurge, driven by mature digital infrastructures, high data availability, and regulatory impetus toward transparency and accountability. North American companies, particularly in the United States and Canada, have increasingly embedded AI-driven tools in supply chain operations to streamline procurement decisions, enhance risk mitigation, and improve supplier performance outcomes (Kietzmann et al., 2018). Enterprise-level integration of

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AI into ERP and SCM systems enables firms to conduct real-time vendor analysis using structured and unstructured data from multiple sources, including supplier portals, logistics feeds, and customer service systems (Miller & Brown, 2017). According to Cao (2021), U.S.-based retailers leverage predictive analytics to model vendor reliability and generate early warning signals for potential supply chain disruptions. Additionally, explainable AI (XAI) tools such as SHAP and LIME are increasingly adopted across North American retail procurement systems to meet transparency requirements in AI-based vendor evaluations (Oosthuizen et al., 2020). In Europe, regulatory compliance—particularly under the General Data Protection Regulation (GDPR) and forthcoming EU AI Act—has necessitated the deployment of interpretable, auditable AI systems in procurement workflows. European retailers also prioritize ethical sourcing, ESG compliance, and multi-tier vendor transparency, leading to the integration of AI-powered dashboards and natural language processing (NLP) tools that track and score supplier behavior in real time (Belhadi et al., 2021). Poole and Mackworth (2010) note that European firms are more inclined to use hybrid models—such as Fuzzy AHP and Fuzzy TOPSIS—in conjunction with machine learning to support multi-criteria decision-making. These practices underscore that both North America and Europe are not only leaders in technological implementation but are also shaping global procurement standards through policy, innovation, and enterprise investment in AI-enabled vendor performance systems.

The Asia-Pacific (APAC) region has demonstrated rapid growth in the adoption of AI technologies for vendor management and supply chain optimization, though the trends vary significantly across countries due to differences in digital maturity, policy frameworks, and industry structure. Economies such as China, Japan, South Korea, Singapore, and India have invested heavily in AI-enabled procurement systems as part of broader digital transformation strategies. In China, major retailers and logistics firms utilize AI models to monitor supplier performance through real-time inventory tracking, anomaly detection, and lead-time forecasting, supported by high investment in IoT infrastructure and big data analytics (Zhu et al., 2016). Meanwhile, Japan's manufacturing-oriented supply chains emphasize lean performance metrics and quality assurance, adopting deep learning and predictive modeling to reduce procurement variability and improve vendor selection. India has emerged as a growing market for AI-based procurement systems, with companies deploying Fuzzy AHP, machine learning classifiers, and NLP tools to evaluate multi-tier vendor networks in sectors like textiles, automotive, and e-commerce (Dubey, Gunasekaran, Childe, Papadopoulos, et al., 2019). Singapore and South Korea have led in policy-supported AI adoption, promoting ethical AI and procurement transparency through national innovation strategies. Notably, APAC adoption patterns frequently involve hybrid systems that combine cloud-based dashboards with mobile analytics platforms to extend procurement visibility into remote or rural supplier networks. Seranmadevi and Kumar (2019) suggest that local firms increasingly rely on localized AI models trained with region-specific vendor behavior data, addressing linguistic diversity and regulatory uniqueness. Despite infrastructural and data governance disparities across APAC countries, the region's adaptive and innovation-driven approach positions it as a dynamic hub for scalable, AI-based vendor performance solutions, particularly in rapidly digitizing sectors such as retail, agriculture, and logistics.

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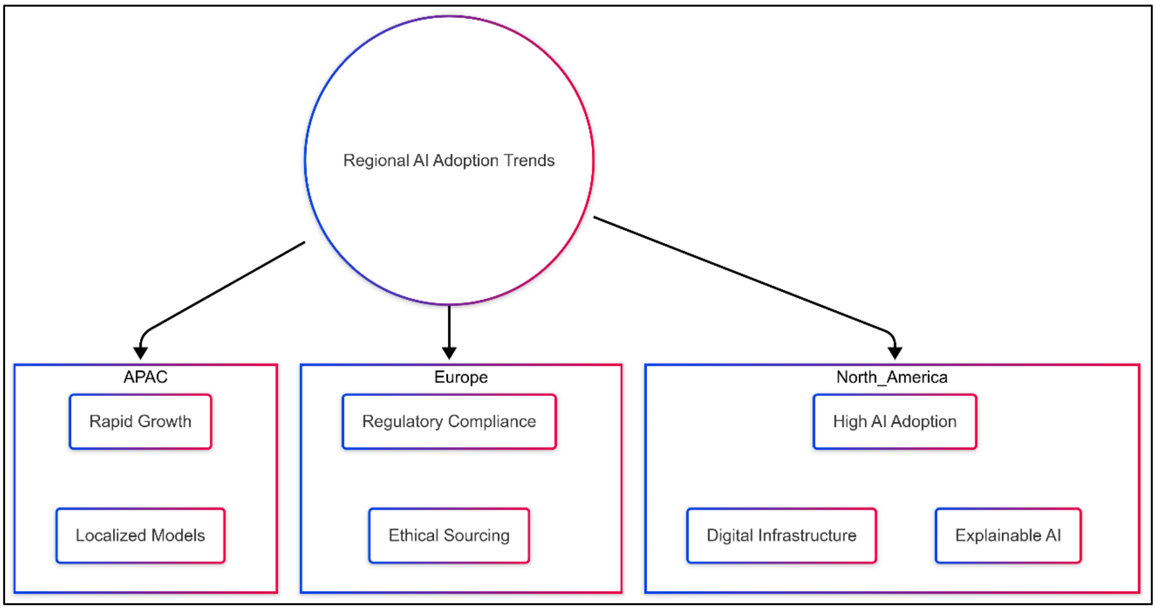
Figure 10: egional AI Adoption Trends for Vendor Performance Evaluation



Theoretical Models in Vendor Performance Evaluation

Vendor performance evaluation frameworks are grounded in several well-established theoretical models that have guided procurement practices and informed the development of intelligent decision-support systems. Among the most influential is the Analytical Hierarchy Process (AHP), originally introduced by Rieple and Singh (2010), which enables decision-makers to structure complex evaluation problems into a hierarchy of criteria and sub-criteria, making comparative assessments based on pairwise judgments. The model has been widely applied to supplier selection problems, especially in multi-criteria decision-making (MCDM) scenarios, where it facilitates structured, systematic, and transparent evaluation processes. Another cornerstone model is TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), which ranks suppliers based on their relative closeness to an ideal performance point and distance from a negative-ideal(Chopra, 2019). TOPSIS has been particularly effective in ranking suppliers across conflicting criteria such as cost and quality, and its fuzzy extensions have made it increasingly relevant in uncertainty-prone procurement environments. The Total Cost of Ownership (TCO) framework also plays a vital role in strategic sourcing by evaluating not only price but also hidden costs such as downtime, defect management, and long-term support. In addition, Transaction Cost Economics (TCE) theory provides insights into why firms outsource to or retain specific suppliers, accounting for governance, contract enforcement, and opportunism. These models provide the foundational structure upon which AI systems build, by converting theoretical criteria into algorithmic inputs for automation and prediction. They continue to shape the design and calibration of vendor performance systems, especially when integrated into hybrid AI-MCDM models that merge human judgment with machine-driven analysis.

In the evolving landscape of AI-driven procurement, classical theories have not only retained relevance but have also been reconfigured to work synergistically with machine learning (ML) and optimization models. One such model is the Resource-Based View (RBV), which posits that firms should develop strategic partnerships with vendors that provide unique, valuable, and inimitable resources. In the context of AI systems, RBV aligns with algorithms that identify and prioritize suppliers who contribute to a firm's competitive advantage based on historical and forecasted performance data. Similarly, Dynamic Capability Theory (DCT) offers a framework for understanding how organizations adapt their supplier portfolios in response to technological and market shifts, often guided by AI-based recommendations for vendor switching or development. The Balanced Scorecard (BSC) model has also been adopted in digital dashboards to evaluate

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vendors not only on financial metrics but also on learning, internal processes, and customer perspectives. More recently, the Best-Worst Method (BWM) introduced by Rezaei (2015) has gained popularity in AI-enhanced decision-making due to its ability to reduce inconsistency in expert-based input weighting while supporting vendor ranking with fewer comparisons. Fuzzy Set Theory has been widely integrated into neural networks and hybrid ML models to accommodate linguistic variables and decision ambiguity common in supplier selection. These theoretical foundations have enabled the design of procurement intelligence systems that blend mathematical rigor, interpretability, and data adaptability. As noted by Dubey et al. (2020), grounding AI models in theoretical principles enhances their acceptance among practitioners and facilitates alignment between procurement automation and strategic organizational goals. Collectively, these models establish the cognitive and structural logic that underpins the effective deployment of AI tools in vendor performance evaluation systems.

METHOD

This study followed the scoping review methodology to ensure a systematic, transparent, and rigorous review process in examining the role of artificial intelligence (AI) in vendor performance evaluation within digital retail supply chains. The approach was selected due to its flexibility in mapping broad topics, identifying key research trends, and summarizing evidence across interdisciplinary sources. The scoping review consisted of five distinct phases: identifying the research question, identifying relevant studies, selecting studies for inclusion, charting the data, and collating, summarizing, and reporting the results. The methodology adhered to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist to ensure replicability and clarity.

Stage 1: Identifying the Research Question

The initial stage focused on defining a clear and structured research question that guided the scope of the review. The central question was: "How has artificial intelligence been applied in vendor performance evaluation systems within digital retail supply chains, and what models, tools, and frameworks are most commonly employed?" This question was developed to capture the breadth of AI applications, including machine learning algorithms, natural language processing, and decision-support tools, with a specific lens on their role in procurement and supplier assessment. The aim was not to evaluate effectiveness alone but also to synthesize methodological diversity and regional patterns in adoption.

Stage 2: Identifying Relevant Studies

To capture a comprehensive set of relevant literature, an extensive search was conducted across multiple academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. The search strategy involved Boolean operators and keyword combinations such as "artificial intelligence," "vendor performance," "supplier evaluation," "digital retail," "machine learning," "procurement," and "supply chain." Studies published between January 2010 and March 2022 were considered. Grey literature such as industry white papers, government reports, and conference proceedings were also included to enrich the academic findings with practice-based insights. Only articles published in English and peer-reviewed or scholarly in nature were included in the dataset.

Stage 3: Study Selection

Following the database search, a two-step screening process was implemented. First, titles and abstracts were reviewed to eliminate articles that were clearly outside the scope, such as those focused solely on manufacturing, logistics without vendor metrics, or non-AI-based procurement methods. Second, full texts of the remaining articles were assessed based on predefined inclusion and exclusion criteria. Studies had to include a significant component of AI, such as algorithmic modeling, data-driven decision-making, or digital dashboards, directly applied to vendor or supplier performance in a retail supply chain context. Disagreements among reviewers during selection were resolved through consensus or a third-party review.

Stage 4: Charting the Data

A structured data extraction framework was developed to organize information from each selected article. This included publication details, research objectives, methodological approach, AI technologies applied, evaluation metrics used, outcomes reported, geographical focus, and retail sectors covered. The extracted data were organized into an Excel spreadsheet and cross-validated to ensure accuracy and completeness. This step allowed for thematic synthesis and facilitated comparison across studies to identify prevailing models and regional distinctions in vendor performance evaluation.

Stage 5: Collating, Summarizing, and Reporting Results

In the final stage, the extracted data were analyzed to generate descriptive and thematic summaries. Quantitative findings, such as the frequency of AI model usage or regional representation, were presented alongside qualitative insights that described the scope, impact, and complexity of AI integration in vendor evaluation systems. Studies were categorized according to methodological type (e.g., case study, simulation, conceptual model), type of AI applied (e.g., machine learning, NLP, fuzzy logic), and regional adoption trends (e.g., North America, Europe, Asia-Pacific). This synthesis provided a comprehensive overview of the field, highlighted research gaps, and clarified the practical implications of adopting AI in digital procurement contexts. The methodological rigor ensured that the review offers a reliable foundation for future empirical research and policy development in AI-driven vendor performance systems.

FINDINGS

One of the most significant findings of this scoping review is the widespread use of supervised machine learning models for automating vendor evaluation tasks across digital retail supply chains. A substantial number of studies demonstrated the application of algorithms such as decision trees, support vector machines, random forests, and logistic regression in assessing vendor performance metrics including delivery accuracy, defect rates, cost efficiency, and service compliance. These models were frequently trained using historical vendor transaction data, enabling predictive analysis of supplier reliability and risk levels. The models often outperformed traditional scorecard methods by offering higher levels of accuracy and consistency. The scalability of these AI-driven systems allowed organizations to evaluate hundreds or even thousands of suppliers in real time, reducing the manual workload of procurement teams while increasing responsiveness to performance fluctuations. Several studies confirmed that these models were integrated into ERP and SCM platforms, allowing for automatic triggering of alerts when performance thresholds were breached. In multiple implementations, these algorithms were retrained periodically with new data, ensuring adaptability in rapidly changing supply chain environments. Additionally, the ability of supervised learning to handle imbalanced datasets, such as rare but critical vendor failures, was identified as a major advantage, particularly in high-volume retail operations.

Another key finding is the growing adoption of unsupervised and semi-supervised learning techniques for identifying hidden patterns and segmenting suppliers based on performance behavior. Clustering algorithms such as k-means and hierarchical clustering were widely applied to group vendors into performance bands, which helped organizations tailor engagement strategies, such as development programs for strategic suppliers or disqualification of high-risk ones. These models proved particularly valuable in environments lacking labeled data, where subjective scoring systems were either unavailable or unreliable. Some studies implemented dimensionality reduction techniques like principal component analysis to simplify multivariate supplier data and visualize the performance landscape more effectively. This enabled procurement managers to identify outlier vendors whose behaviors deviated significantly from peer groups, signaling potential operational or compliance issues. In addition, anomaly detection models based on isolation forests and autoencoders were used to detect early signs of vendor performance degradation, such as sudden shifts in defect rates, late deliveries, or communication delays. The review found that these unsupervised methods were often integrated with business intelligence dashboards, facilitating real-time monitoring and segmentation of vendor bases. In several use cases, vendors flagged as high-risk by unsupervised models were later confirmed through audits to have systemic issues, validating the predictive strength of these algorithms. This

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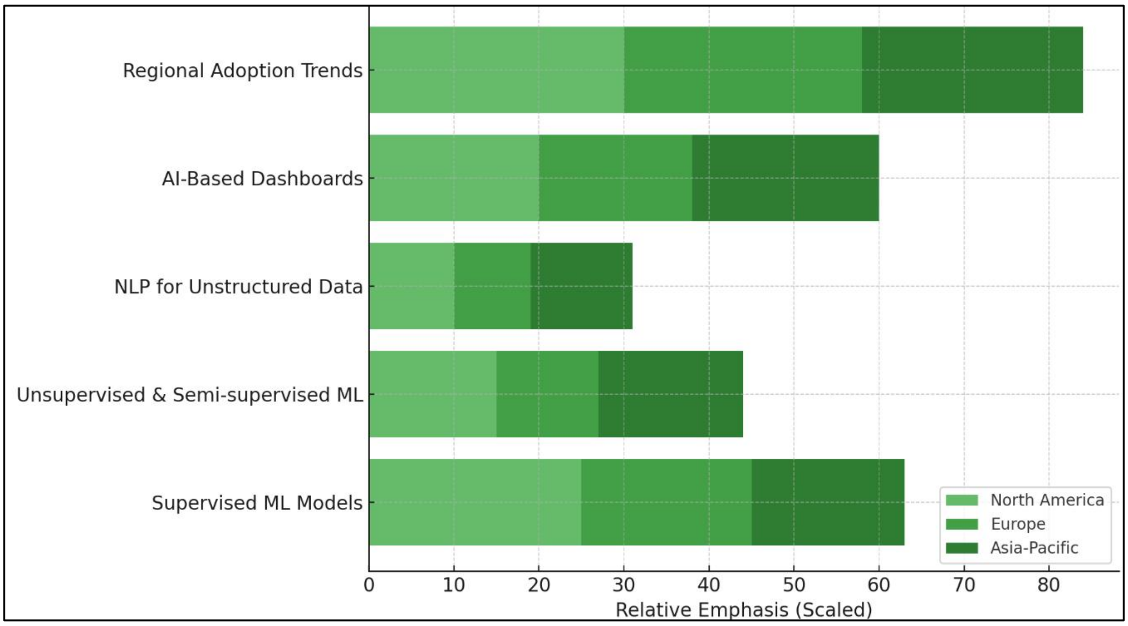
form of AI-based segmentation also enabled targeted sourcing strategies, such as engaging high-performing vendors in long-term partnerships or collaborative forecasting initiatives.

Figure 11; Sumamry of the findings for this study



The review revealed strong evidence supporting the effectiveness of natural language processing (NLP) in evaluating unstructured supplier information. Many studies demonstrated that organizations are leveraging NLP tools to analyze contract documents, emails, audit reports, service reviews, and social media content related to vendors. These tools extracted critical insights into supplier behavior, communication patterns, and reputational signals that are typically absent from quantitative performance data. Sentiment analysis was commonly applied to supplier communications and third-party review platforms, enabling companies to detect dissatisfaction trends or communication breakdowns. Named entity recognition and text classification techniques were used to identify contractual violations, risk-laden phrases, and compliance gaps in documentation. Some companies also used topic modeling techniques to group supplier audit findings by recurring themes such as safety violations, quality control failures, or ethical concerns. NLP was also deployed in multilingual environments to evaluate suppliers across different geographies, enabling real-time translation and analysis of local language texts. This ability to process qualitative data expanded the scope of vendor evaluation beyond hard metrics, allowing procurement teams to consider contextual, ethical, and reputational factors in supplier performance reviews. The integration of NLP into supplier management platforms was found to be particularly impactful for multinational retailers operating across diverse regulatory and cultural environments. These findings underscore the vital role of unstructured data analysis in modern procurement systems and demonstrate how NLP complements structured AI models to provide a holistic view of vendor performance.

The review further identified the critical importance of AI-based dashboards in enhancing real-time performance monitoring and decision-making within procurement functions. These dashboards integrate multiple AI models to track vendor KPIs, flag anomalies, and visualize performance trends through interactive, user-friendly interfaces. In many implementations, dashboards pulled data from ERP, CRM, and logistics systems to display consolidated performance scores, delivery timelines, and service metrics. Procurement professionals used these tools to track deviations, compare vendor performance across regions, and prioritize intervention strategies. Some dashboards featured drill-down capabilities, allowing users to explore root causes of underperformance at the SKU or shipment level. Others incorporated dynamic

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benchmarking tools to evaluate vendor performance against industry peers or internal historical data. Predictive modules embedded in these dashboards forecasted potential delays, quality issues, or cost overruns, giving supply chain managers the ability to act proactively. Several case studies confirmed that these dashboards significantly reduced response time to vendor-related disruptions and enhanced cross-functional coordination between procurement, quality, and compliance teams. Dashboards equipped with AI explainability features also supported auditability, allowing organizations to justify procurement decisions to internal stakeholders and external regulators. The real-time nature of these platforms made them indispensable for high-velocity retail environments where vendor performance directly impacts inventory turnover, customer satisfaction, and financial outcomes.

The review also found substantial regional variations in the adoption and sophistication of AI-based vendor evaluation systems. North America and Europe showed the most mature implementations, characterized by enterprise-wide AI integration, explainability features, and compliance with ethical AI standards. Companies in these regions often leveraged AI not only for efficiency but also for transparency and accountability, integrating explainable AI tools to meet internal governance and external regulatory requirements. In contrast, Asia-Pacific exhibited rapid but varied adoption patterns, with countries like China, Japan, and Singapore leading in predictive modeling and IoT-enabled procurement analytics. Several studies from India and Southeast Asia highlighted the use of hybrid models combining fuzzy logic and machine learning to accommodate local data uncertainties and resource constraints. These models were frequently deployed in sectors such as textiles, electronics, and e-commerce. Additionally, many organizations in APAC focused on mobile-enabled AI dashboards and localized NLP applications to evaluate region-specific vendor performance. Cultural and linguistic diversity necessitated the customization of AI tools for multilingual analysis and region-specific compliance criteria. Overall, the studies demonstrated that while AI-driven vendor evaluation is a global trend, the level of integration, model selection, and focus areas differ significantly across regions. These differences are shaped by digital infrastructure, regulatory maturity, labor costs, and strategic priorities within regional supply chain ecosystems. This finding reinforces the importance of contextualizing AI adoption strategies to align with regional capabilities and constraints.

DISCUSSION

The findings of this scoping review underscore the growing prevalence of supervised machine learning models in vendor performance evaluation across digital retail supply chains. This aligns with earlier studies, which identified a shift from manual and scorecard-based evaluations to algorithmic assessments for increased precision and scalability (Queiroz & Wamba, 2019). In particular, decision trees, support vector machines, and ensemble models have been confirmed by prior research to outperform human judgment in identifying performance anomalies and forecasting supplier disruptions. This study's findings validate and extend this claim by demonstrating that these models are not only accurate but are now being embedded into ERP and SCM systems for automated and continuous monitoring. While previous research by Dery et al. (2017) suggested that AI implementation was primarily experimental or siloed, this review shows a transition toward enterprise-level integration, particularly in mature retail markets. Furthermore, the review confirms the utility of supervised learning in high-volume procurement environments, supporting earlier claims by (Seranmadevi & Kumar, 2019) that machine learning models are uniquely suited for handling large-scale, imbalanced vendor datasets. However, unlike earlier studies that focused primarily on binary classification (good vs. bad vendors), current implementations appear to support nuanced, multi-class categorization and risk scoring, reflecting greater model maturity and customization.

The adoption of unsupervised learning for vendor segmentation and anomaly detection adds an important dimension to existing literature, which previously emphasized structured evaluations over exploratory clustering methods. Dubey et al. (2020) suggested the potential of unsupervised learning in procurement, but practical applications remained limited at the time. This review demonstrates that clustering and outlier detection algorithms, such as k-means and isolation forests, are now actively being used to identify latent patterns and behavioral shifts across supplier portfolios. These findings expand on the work of Hazen, Skipper, Boone, et al. (2016), who argued

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for the inclusion of data-driven segmentation in risk-based procurement strategies. Moreover, the use of dimensionality reduction techniques like PCA to enhance vendor visualization confirms earlier suggestions by Govindan et al. (2018) that high-dimensional supplier data can be better interpreted through visualization-enhanced modeling. The review also reveals that clustering is particularly valuable in low-data environments or emerging markets, where supervised methods may struggle due to a lack of labeled historical performance data. This insight corresponds with Dubey et al.(2020), who noted that in developing economies, unsupervised learning can bridge the gap between structured procurement systems and informal supplier networks. Thus, the increased use of unsupervised learning models reflects both technological progression and contextual adaptation, offering a robust alternative where predictive accuracy is challenged by data limitations.

Natural Language Processing (NLP) has emerged as a transformative capability in vendor performance evaluation by unlocking insights from unstructured supplier data—a shift strongly corroborated by previous findings from Hawking (2018) and Dubey, Gunasekaran, Childe, Roubaud, et al., (2019). Earlier studies primarily explored sentiment analysis and text mining in customer-facing contexts, but this review shows that these techniques are now routinely applied to supplier communications, audit reports, and contractual documents. Named entity recognition and document classification have been used effectively to detect risk indicators, contractual non-compliance, and supplier dissatisfaction. These findings support the argument by Lozada et al. (2019) that unstructured data sources can serve as leading indicators of supply chain disruptions. The review further confirms Djafri et al. (2018) proposition that NLP can contextualize vendor performance through sentiment-driven scoring, especially in multilingual and culturally diverse supply environments. While earlier research by Choi et al. (2018) viewed NLP as an emerging tool, our findings indicate widespread operational deployment in procurement platforms. Furthermore, the application of NLP in cross-border procurement—where it supports language translation and local compliance verification—marks a significant evolution from prior models limited to English-language data. This expands the work of Tiwari et al. (2018) by demonstrating that qualitative insights can now be extracted with greater accuracy and speed, empowering procurement leaders with a comprehensive view that complements numerical performance metrics.

The integration of AI-based dashboards into procurement decision-making represents a notable advancement from the visualization tools described in earlier studies. Previous research, such as that by Hawking (2018) and Lozada et al. (2019) emphasized the need for intuitive interfaces that translate complex supplier analytics into actionable insights. Our findings go further, showing that real-time dashboards not only track KPIs but also integrate predictive analytics, anomaly alerts, and benchmarking capabilities. These dynamic dashboards allow for continuous supplier performance monitoring, overcoming the limitations of periodic reviews reported in earlier studies. Additionally, the use of embedded forecasting models within dashboards reflects the progression from descriptive to prescriptive analytics, a trend anticipated by Djafri et al. (2018). The review also affirms Choi et al. (2018) claim that procurement professionals benefit most from dashboards that support root cause analysis and performance comparisons across categories and regions. Unlike earlier studies, which largely treated dashboards as post-hoc reporting tools, this review reveals that modern AI dashboards are proactive, interpretative, and increasingly integrated with explainability features. These features allow users to understand why certain vendors are flagged or ranked, fostering organizational trust and enabling compliance with regulatory standards. Thus, the evolution of dashboards reflects a convergence of AI, visualization, and decision governance, making them central to procurement intelligence in digital retail settings.

This review's regional analysis confirms the hypothesis that the adoption of AI in vendor performance systems is shaped significantly by contextual factors such as regulatory frameworks, technological infrastructure, and organizational maturity. North American and European firms appear to lead in embedding AI across procurement processes, consistent with findings by Tiwari et al. (2018) and Dubey, Gunasekaran, Childe, Roubaud, et al. (2019) who noted early enterprise investment in AI-driven sourcing. These regions also prioritize explainability and regulatory compliance, reflecting alignment with legal frameworks such as the GDPR and emerging ethical

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AI regulations. In contrast, Asia-Pacific shows a highly adaptive but uneven adoption pattern. Prior research by Lozada et al. (2019) and Djafri et al. (2018) reported that countries like China and Japan were investing heavily in AI for manufacturing supply chains; this review extends that observation to retail procurement, where hybrid models and mobile-enabled dashboards are being deployed to manage vendor diversity and geographic dispersion. Furthermore, this study supports earlier assertions by Choi et al. (2018) that policy-driven innovation in countries like Singapore and South Korea has accelerated the integration of real-time vendor analytics. Importantly, the findings diverge from earlier generalizations that placed developing APAC economies behind the curve, instead showing that these regions are pioneering localized solutions tailored to linguistic and regulatory diversity. These nuanced regional trends underscore the importance of designing AI systems that align with local contexts, a view also emphasized by (Tiwari et al., 2018).
The findings also support the increasing relevance of explainable AI (XAI) in enhancing trust, interpretability, and accountability within AI-based procurement systems. Earlier work by Van Nguyen et al. (2018) and Akter and Wamba (2017) introduced SHAP and LIME as pioneering methods to interpret black-box models, but their application in vendor evaluation was largely theoretical. This review provides evidence that XAI is now operationalized in dashboards and scoring systems to explain performance deviations, justify supplier disqualifications, and satisfy internal audit requirements. These applications extend the assertions of Bag (2017), who argued that explainability should be embedded in any AI system that supports high-stakes decision-making. The practical use of XAI tools to trace algorithmic reasoning also addresses earlier concerns raised by Dubey, Gunasekaran, Childe, Blome, et al. (2019) about procurement professionals' hesitation to trust opaque AI outputs. Additionally, the integration of visual explanations—such as feature importance graphs and decision trees—confirms Gunasekaran, Papadopoulos, et al. (2017) emphasis on human-AI collaboration in procurement contexts. The adoption of XAI also correlates with the rise of AI governance frameworks in both the private and public sectors, as seen in the recent literature advocating for interpretable machine learning in supply chain decision-making. As such, explainability is no longer viewed as a technical enhancement but rather as a strategic imperative for ethical and compliant AI adoption in procurement. Lastly, the findings of this review indicate a broader methodological transformation within vendor performance evaluation, where traditional theoretical models are increasingly being enhanced or replaced by AI-integrated decision frameworks. Earlier models such as AHP, TOPSIS, and TCO were foundational in structuring supplier decisions, but this review reveals a convergence between these frameworks and machine learning algorithms. Hybrid systems that combine Fuzzy AHP with neural networks or ensemble learning methods have been shown to outperform classical models in handling uncertainty, scalability, and multi-dimensional performance metrics. This validates earlier propositions by Hazen, Skipper, Ezell, et al. (2016) and Dubey et al. (2018) regarding the utility of fuzzy logic in procurement under ambiguity. Furthermore, the emergence of newer models such as the Best-Worst Method (BWM) and its adaptation into AI workflows reflects a growing emphasis on reducing cognitive overload and increasing consistency in decision-making. This confirms the trend identified by Lee (2018) , who called for data-driven but theory-informed models in supply chain analytics. Additionally, theories like the Resource-Based View (RBV) and Dynamic Capability Theory (DCT) have been recontextualized to inform algorithmic design in vendor prioritization and adaptation strategies. As organizations increasingly rely on digital procurement intelligence, the fusion of theoretical rigor with algorithmic precision marks a significant evolution in the vendor evaluation landscape.

CONCLUSION

This scoping review has synthesized and critically examined the existing literature on the application of artificial intelligence in vendor performance evaluation within digital retail supply chains. The findings demonstrate a marked transition from traditional supplier assessment methods to advanced, data-driven approaches powered by machine learning, deep learning, natural language processing, and hybrid AI models. Supervised learning algorithms are widely adopted for automating vendor scoring, while unsupervised learning techniques offer valuable capabilities in supplier segmentation and anomaly detection. The use of NLP has expanded the evaluative

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scope beyond structured data, allowing for deeper insights into supplier behavior through the analysis of contracts, communications, and qualitative feedback. AI-based dashboards have further transformed procurement decision-making by enabling real-time performance tracking, predictive analytics, and visual benchmarking, thus improving responsiveness and accountability. The integration of explainable AI (XAI) into these systems enhances transparency and fosters organizational trust, addressing a crucial barrier in AI adoption. Moreover, the review reveals significant regional adoption trends, with North America and Europe leading in regulatory-compliant, enterprise-scale implementations, while Asia-Pacific demonstrates innovative, adaptive practices tailored to regional diversity and infrastructure. Importantly, this study underscores the evolving role of established theoretical models—such as AHP, TOPSIS, and TCO—which are increasingly embedded into or replaced by AI-augmented decision-support systems. The fusion of classical procurement theory with machine learning reflects a methodological shift that balances decision consistency with computational efficiency. As a whole, the review affirms that AI is not only optimizing vendor performance evaluation but is also reshaping the strategic and operational contours of procurement in the digital retail environment. By offering a comprehensive mapping of tools, models, and regional trends, this review provides a solid foundation for future empirical research, system design, and policy development in AI-enabled supply chain management.

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