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RESEARCH PAPER

Evaluating machine learning models compared to traditional supplier qualification process techniques in Supply Chain Management: a systematic literature review

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ABSTRACT

Goal: This study systematically reviews the literature on the application of machine learning algorithms in the selection, evaluation, and prediction of supplier performance in the context of supply chain management, identifying trends and opportunities for future research.

Design/methodology/approach: A systematic literature review was conducted, conducted, following the PRISMA protocol. The search was conducted in Scopus, ScienceDirect, Web of Science, and Engineering Village databases, considering articles published between 2015 and 2025. After applying the inclusion and exclusion criteria, 27 studies were selected and analyzed regarding the type of learning, performance metrics, application sectors, and methodological characteristics.

Results: The results indicate a predominance of supervised models (89.7%), with emphasis on algorithms based on decision trees and neural networks. The reported accuracies range from 46% to 99%, with an overall average of 91.97%, highlighting advances in the use of data-driven models for supplier classification and ranking.

Limitations: The main limitations relate to the heterogeneity of the databases, the lack of standardization of evaluation metrics, and the incomplete methodological description in some of the analyzed studies.

Practical implications: The study demonstrates that machine learning can support strategic decisions in purchasing and supply, increasing the accuracy in supplier selection and evaluation.

Originality/Value: The study offers a systematic and structured synthesis of recent literature, organizing evidence by algorithmic families, performance metrics, and application sectors, in addition to identifying relevant gaps for future research.

Keyword: Machine Learning; Supplier Qualification; Supply Chain Management; Supplier Selection.

1 INTRODUCTION

Supply chain management faces persistent structural challenges in optimizing time, cost, and quality across logistics processes. These challenges are particularly pronounced in environments characterized by high complexity, volatile demand, and increasing interdependence among stakeholders across the network. In industrial sectors, purchasing and supply activities may account for 50% to 70% of total production costs, directly impacting both operational and financial outcomes (Monczka *et al.*, 2020). As a result, supplier selection and qualification assume strategic importance, as poor decision-making in these areas can lead to increased costs, compromised input quality, and reduced delivery reliability throughout the supply chain (Ho *et al.*, 2010).

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Inadequate supplier selection can lead to rework, decreased productivity, and compromised service levels, quality, and delivery reliability, affecting operational stability and customer service capacity (Ho *et al.,* 2010; Monczka *et al.,* 2020). Therefore, supplier selection is not a one-time event but a recurring process connected to qualification, integration, and ongoing performance monitoring, requiring the simultaneous consideration of multiple criteria.

In the literature on purchasing and Supply Chain Management, supplier qualification is often presented as a sequential process, in which the organization progresses through stages until a supplier is consolidated as part of its active base. Figure 1 illustrates this process, which includes identification of potential suppliers, pre-qualification, audit assessments, selection and approval, integration, and continuous monitoring through key performance indicators (KPIs) (Monczka *et al.,* 2020).

Figure 1 – Supplier Qualification Process
Source: Designed from the Monczka *et al.* (2020).

In recent decades, the supplier selection and evaluation process has become more complex due to the need to consider multiple criteria beyond cost, such as quality, reliability, flexibility, serviceability, risk, and sustainability. This scenario is intensified by recurring disruptions and the use of heterogeneous data that are not always standardized or complete. Thus, although traditional methods remain relevant, there is a growing demand for analytical approaches capable of handling a greater volume and complexity of information (Mchopa; Kimario; Panga, 2025). Traditional multi-criteria decision-making approaches remain widely used in supplier selection, such as fuzzy AHP models applied in industrial contexts (De Santis; Felisberto, 2017).

In this context, digitalization has driven the use of artificial intelligence techniques in supply chain management. Machine learning algorithms have been employed to support supplier evaluation and selection by enabling the joint analysis of multiple criteria, identifying patterns in historical data, predicting non-conformities, and ranking suppliers according to performance indicators (Abdulla; Baryannis, 2024). These approaches tend to increase the consistency of analyses and reduce the exclusive reliance on expert judgment.

The adoption of these practices can be interpreted from the perspective of Dynamic Capabilities, according to which organizations in volatile environments need to integrate and reconfigure resources to sustain performance over time (Teece; Pisano; Shuen, 1997; Teece, 2007). In supplier management, machine learning can be understood as an organizational resource that enhances the capacity for adaptation and response to change (Beske, 2012).

Additionally, institutional theory suggests that organizations tend to adopt similar practices in response to pressures for legitimacy and conformity, a process known as institutional isomorphism (DiMaggio; Powell, 1983). In this sense, the incorporation of AI-based analytical technologies in purchasing processes can reflect both a functional response to challenges of complexity and a convergence of practices in competitive environments, where technological modernization assumes an institutional value. This combination of pressures helps explain why hybrid approaches between traditional MCDM models and interpretable models have attracted attention.

Practical applications of machine learning have been applied to support supplier-related decisions in supply chains, including enhanced delivery scheduling planning (Palakshappa *et al.*, 2025). Given this scenario, the present study aims to systematically review the applications of methods in supplier selection and evaluation, with an emphasis on the use of machine learning algorithms. The selected studies are analyzed according to algorithm families, application sectors, and performance metrics to identify research trends and opportunities for future studies.

Although previous research has applied multi-criteria methods and, more recently, machine learning algorithms to supplier selection and evaluation, a structured synthesis that integrates approaches, metrics, and applications comparably across different industries has yet to be developed. Many studies analyze isolated techniques, leaving gaps in the standardization of results. Thus, this study conducts a systematic review to consolidate evidence and identify trends and opportunities for future research. If these gaps persist, organizations may continue to make decisions based on manual processes, reducing the strategic efficiency of supply chain management.

2. LITERATURE REVIEW

The study was guided by the following research question: How have machine learning techniques been applied in the selection and evaluation of suppliers in the context of the supply chain? Based on this research question, Table 1 summarizes the propositions guiding the analysis.

Table 1 – Research hypotheses

Type of Hypothesis	Description
General	Machine learning models show superior performance compared to traditional methods for selecting the best supplier.
Specific	1. Machine learning models perform better when applied to large datasets. 2. Combining machine learning models with traditional supplier selection methods yields improved results. 3. Machine learning techniques require adequate computational capacity for supplier selection.

Source: The authors themselves.

Supply chain management literature highlights the use of Multi-Criteria Decision Making (MCDM) methods to support complex decisions involving multiple criteria, such as cost, quality, delivery time, and logistics performance. Unlike machine learning approaches, MCDM methods do not learn from historical data, as the criteria, their respective weights, and activation functions are defined a priori, based on expert knowledge or procedures (Saaty, 1980; Brans; Vincke, 1985).

Figure 2 illustrates the typical implementation flow of an MCDM framework, highlighting its sequential nature and direct focus on decision support. In this type of approach, the process begins by defining the criteria, followed by assigning weights, applying the chosen method, and analyzing the results to select the best alternative.

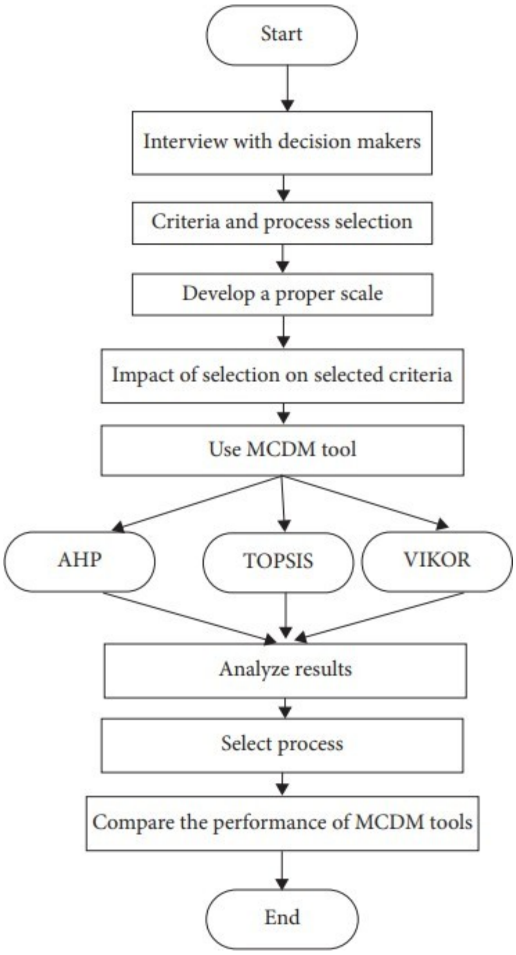

Figure 2 – MCDM Framework Implementation Flowchart
Source: Ghaleb *et al.* (2020).

In the context of supplier selection, methods such as AHP, TOPSIS, ELECTRE, PROMETHEE, VIKOR, and MARCOS are widely used due to their transparency, traceability of decisions, and ease of interpretation by managers (Ho; Xu; Dey, 2010; Govindan; Rajendran; Sarkis, 2015). Therefore, MCDM is characterized as an approach marked by the explicit definition of criteria and weights, the absence of statistical learning, and a direct focus on multi-criteria decision making.

Despite their widespread adoption, MCDM methods have significant limitations. A critical aspect concerns the definition of criterion weights, which often depends on the subjective judgments of experts or stakeholders. While this procedure is consistent with organizational decision-making logic, it can introduce human biases that may not adequately reflect the factors that actually impact supplier performance over time. For example, an organization might assign greater importance to the cost criterion when, in practice, delivery time or logistical reliability are more decisive for operational performance.

In this context, machine learning algorithms emerge as a complementary alternative by offering a distinct evaluation logic. Unlike MCDM, machine learning models learn patterns from historical data, adjusting their parameters based on past observed performance, rather than by instruction. Figure 3 illustrates, in an abstract way, the machine learning process in a supervised classification model, in which input data is progressively transformed to identify patterns and generate predictions or classifications.

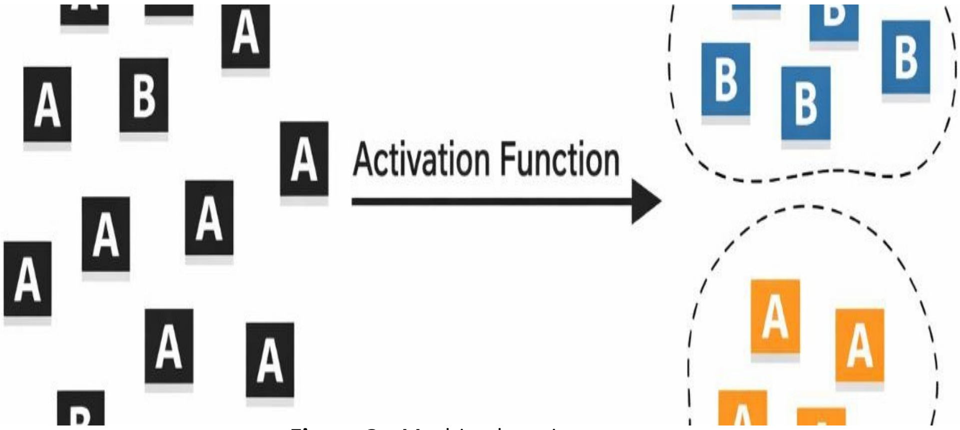

Figure 3 – Machine learning process
Source: Designed from the Goodfellow (2016).

Machine learning algorithms vary in their architecture and activation function, depending on the type of problem addressed (classification, regression, or clustering). In general, these models are based on parametric mathematical functions, in which the initial weights are iteratively adjusted by minimizing error, also incorporating bias terms. This process allows the model to refine its generalization capacity and increase its accuracy as it is exposed to different examples from the database.

From this perspective, a conceptual similarity can be observed between the logic of MCDM and the so-called computational neuron, a fundamental principle of machine learning models. Both operate from inputs (criteria or variables), associated weights, and an aggregation function. However, while in MCDM the weights remain fixed after their definition, in machine learning models these parameters are dynamically adjusted throughout the training process, considering the error and the activation function, as illustrated in Figures 4 and 5.

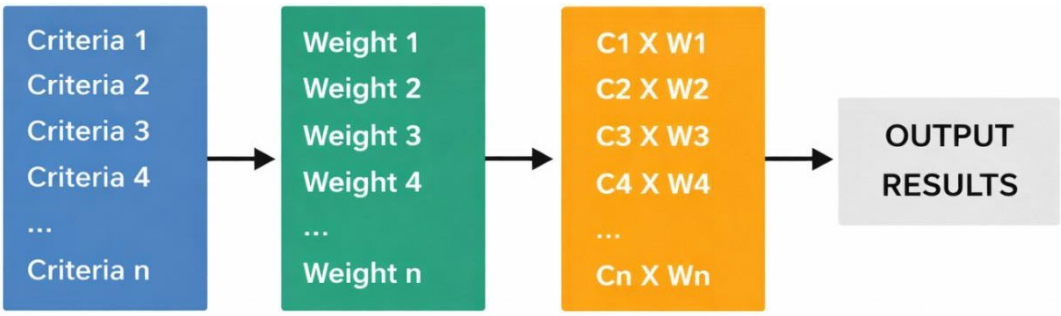

Figure 4 – Aggregation logic of Multi-Criteria Decision Making methods
Source: Designed from the Saaty (1980).

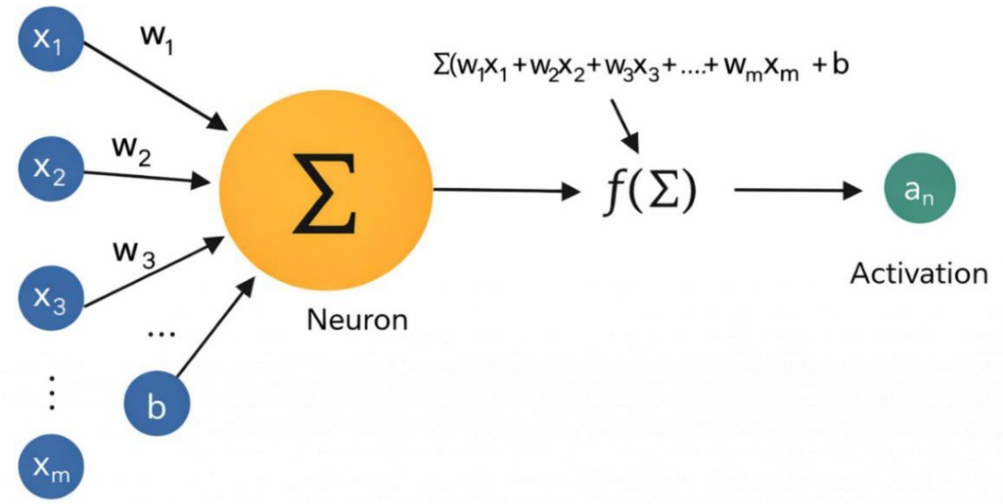

Figure 5 – Principle of machine learning: computational neuron and activation function
Source: Designed from the Goodfellow (2016).

This fundamental difference highlights the potential of machine learning models to handle environments characterized by higher data volumes, variability, and complexity, such as contemporary supply chains. For this reason, recent literature has explored hybrid approaches that combine traditional MCDM techniques with machine learning algorithms, seeking to integrate the transparency and interpretability of multi-criteria methods with the predictive and adaptive capabilities of data-driven models. It is within this context that the present literature review is situated, analyzing research that investigates the isolated and combined application of these techniques in supplier selection and evaluation.

3. METHODS

This study is characterized as an analytical and descriptive research, developed through a Systematic Literature Review (SLR), conducted according to the PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). PRISMA constitutes a protocol adopted to guarantee transparency, traceability, and methodological rigor in systematic reviews, allowing the structured synthesis of available evidence on a given topic (Liberati *et al.*, 2009).

To support the planning, execution, and documentation of the systematic review, the Parsifal tool (Protocol for Systematic Literature Reviews) was used. Parsifal was chosen because of its suitability for structuring review protocols, managing inclusion and exclusion criteria, recording decisions throughout the process, and ensuring methodological reproducibility. Unlike tools primarily focused on bibliometric analysis or network visualization, Parsifal offers direct support for the formal stages of the systematic literature review, aligning with the PRISMA method guidelines.

To structure the search strategy and ensure adherence to the research question, the PICO method was adopted. In this study, the population refers to industrial suppliers; the interest focuses on the application of machine learning algorithms for classification and evaluation of supplier performance; the comparison involves traditional supplier selection methods; and the results relate to performance metrics reported in the literature. The use of the PICO method contributed to increasing the precision of the search and reducing selection biases, as detailed in Table 2.

Table 2 – PICO method

PICO element	Description
Population	Industry suppliers
Interest	Application of machine learning algorithms for classification and prediction of supplier quality
Comparison	Comparison between correlated machine learning algorithms and traditional supply chain techniques.
Outcomes	Accuracy results and other statistical metrics between different algorithms

Source: The authors themselves.

The searches were conducted in the Scopus, ScienceDirect, Web of Science, and Engineering Village databases, selected based on their scope and relevance to studies in the areas of engineering, operations, and supply chain management (Harzing; Alakangas, 2016). The search strategy was structured to balance scope with accuracy, using keywords related to supplier selection and evaluation, machine learning, and supply chain management, applied to the title, abstract, and keyword fields of the databases: string=(("supplier selection" OR "supplier evaluation" OR "vendor selection" OR "supplier management") AND ("machine learning" OR "ML" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "decision support system") AND ("supply chain management" OR "supply chain")).

The time frame between 2015 and 2025 was intentionally defined to capture the period in which machine learning began to be systematically incorporated into decision-making in supplier selection processes. Studies prior to 2015 show the still incipient use of these techniques, while more recent works reflect the consolidation and maturation of applications, with greater data availability and computational capacity, which justifies the adopted time delimitation.

The inclusion and exclusion criteria were defined to ensure the selection of studies aligned with the research objectives, and were applied systematically across all databases considered, as shown in Figure 6.

During the application of the PRISMA protocol, 993 studies with the string were initially identified. The exclusion process involved the removal of duplicates, analysis of titles, abstracts, language, and publication period, as well as evaluation of the eligibility of full texts regarding their thematic relevance and accessibility. The numerical values for each step are described in the flowchart in Figure 6. The entire study selection and exclusion process was documented in the PARSIFAL tool, and at the end of the process, 27 studies met all inclusion criteria and comprised the final analysis base of the systematic review.

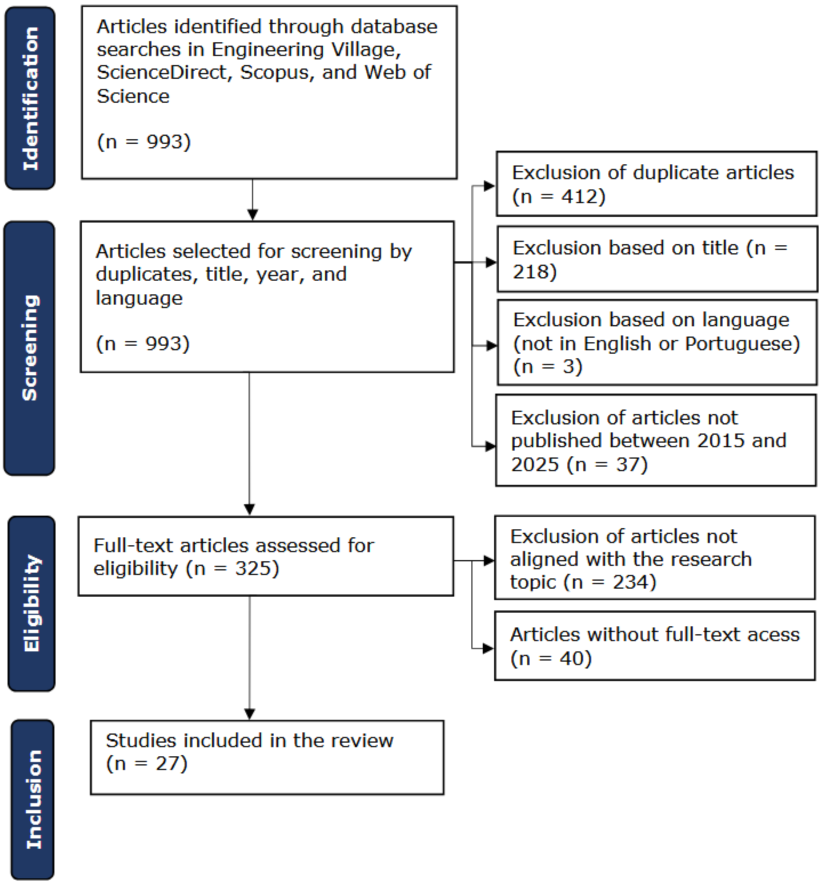

Figure 6 – Study selection process according to the PRISMA protocol
Source: The authors themselves.

4. RESULTS

The 27 articles selected after the exclusion process were organized in a Microsoft Excel spreadsheet and analyzed in detail. During the analysis, pertinent information was extracted to answer the research questions and hypotheses, including year of publication, predictive model used, performance metrics, implementation complexity, and industrial applicability.

In addition to the descriptive systematization of the studies, the analysis aimed to identify conceptual and methodological patterns that would allow us to interpret how machine learning is being incorporated into supplier selection in the context of supply chain management, as presented in Table 3.

The analysis of the 27 selected articles shows that approximately 89.7% of the studies employ supervised learning models, while about 10.3% use unsupervised approaches. This result provides evidence consistent with the study's general hypothesis, which posits that machine learning models outperform traditional supplier selection methods, particularly in contexts with labeled databases and structured performance histories.

Furthermore, the recurrence of consolidated supervised algorithms, such as k-Nearest Neighbours, logistic regression, and Support Vector Machines, is observed, frequently associated with multicriteria methods or used as reference models. These algorithms are widely adopted because they offer a balance between predictive performance and interpretability, a characteristic particularly relevant in organizational contexts that demand transparency and justification of decisions, as observed in Cavalcante *et al.* (2019), Azarakhsh; Ferrari (2025), and Khan *et al.* (2023).

Regarding Specific Hypothesis 1, which proposes that machine learning models perform better when large datasets are available, the results presented indicate that studies with higher accuracy levels are concentrated in sectors such as retail, pharmaceuticals, and automotive. These sectors are characterized by a greater volume, granularity, and availability of operational data, which favors the performance of algorithms such as Random Forest, Gradient Boosting, and artificial neural networks (Mahin *et al.*, 2025; Husna *et al.*, 2025; Kumaar; Maryam, 2025). These findings corroborate the hypothesis by highlighting the direct relationship between data quality and model performance.

Specific Hypothesis 2, which suggests that combining machine learning models with traditional supplier selection methods results in better outcomes, is also supported by the analyzed data. As indicated in Table 3, studies that adopted hybrid approaches, integrating predictive algorithms with multi-criteria methods such as AHP, TOPSIS, DEMATEL, and fuzzy techniques, demonstrated greater robustness in supplier evaluation (Ali *et al.,* 2020; Abdulla *et al.,* 2023; Giineri; Deveci, 2023). This evidence suggests the integration of methods reduces individual limitations and enhances the reliability of decisions, validating the proposed hypothesis.

Regarding Specific Hypothesis 3, it is observed that more complex models, such as deep learning, reinforcement learning, and graph-based architectures, were predominantly employed in studies conducted in environments with greater technological maturity and computational infrastructure (Huang *et al.,* 2024; Ravichandran *et al.,* 2025). This result suggests that computational and organizational constraints still represent significant barriers to the adoption of advanced models.

The temporal analysis of publications, presented in Figure 7, indicates progressive growth from 2020 onwards, reflecting the maturation of the field and the intensification of academic interest in the applying machine learning to supplier selection.

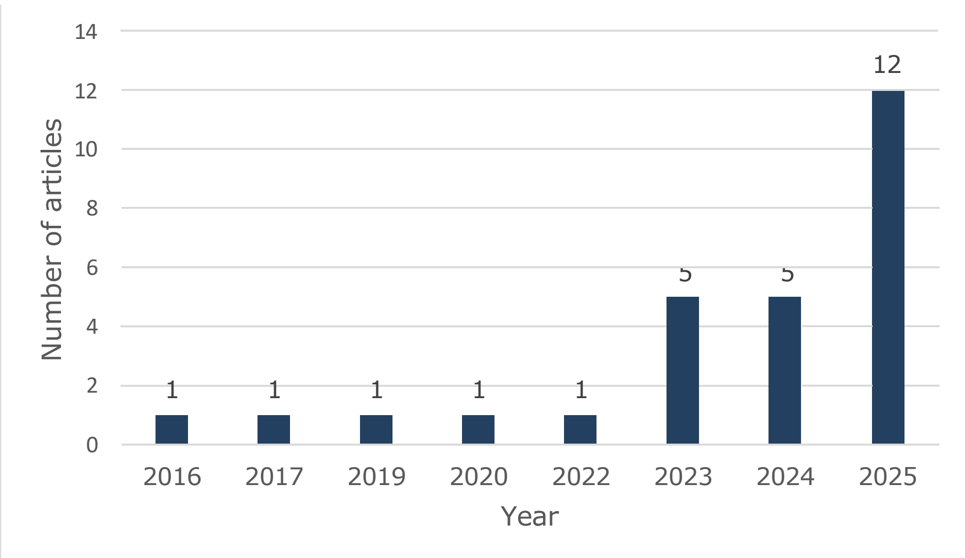

Figure 7 – Publication years of the selected articles
Source: The authors themselves.

Table 3 – Articles selected for analysis

Authors	Year	Application Sector	Algorithm(s)	Data Supervision	Accuracy (%)
Gupta *et al.*	2025	Automotive Industry	Decision Trees, Random Forest, Neural Networks, Logistic Regression, Naive Bayes, LIME, SHAP, Causal Forests, Structural Causal Models, Bayesian Networks	Yes	63,80%
Ali *et al.*	2023	Food Industry	Random Forest	Yes	81,54%
Ferreira *et al.*	2025	Aerospace Industry	K-Means, Hierarchical K-Means, AGNES, Fuzzy Clustering	No	80,00%
Abdulla; Baryannis	2024	Oil & Gas / Aerospace	Decision Trees, Random Forest (RF), K-Nearest Neighbours (KNN)	Yes	85,00%
Wei	2022	Financial Sector	Linear Regression (ML-LR)	Yes	NA
Zheng; Brintrup	2025	Automotive Industry	GCN, Federated Learning, GraphSAGE	Yes	NA
Shidpour *et al.*	2025	Multiple Industries	RF, SVM, DT, K-Means, MILP	Yes	97,19%
Vahdani *et al.*	2017	Cosmetics Industry	Enhanced SVM (GVNS)	Yes	99,61%
Cavalcante *et al.*	2019	Manufacturing	kNN, LR, Hybrid Models	Yes	46,16%
Hayati *et al.*	2025	Pharmaceutical Industry	ARIMA, Grey GM(1,1), BWM, ARAS, FPMOMILP	Yes	NA
Abdulla *et al.*	2023	Oil & Gas	Decision tree, Random forest, Extra trees e CatBoost	Yes	91,70%
Badakhshan *et al.*	2024	Healthcare Industry	Regression Analysis (RA), Support Vector Machine (SVM), AdaBoost (AB) and Artificial Neural Networks (ANN)	Yes	95,10%
Azarakhsh; Ferrari	2025	Multiple Industries	kNN, Bagging, SVM, GB, Stacking + BO	Yes	92,00%
Apriliani; Wibirama	2024	Power Sector	Random Forest + Feature Selection	Yes	98,34%
Mirasçı; Aksoy	2025	Automotive Industry	DT, RF, GB, ANN	Yes	83,60%

Dweiri *et al.*	**2016**	**Automotive Industry**	**AHP (Multicriteria DSS)**	**No**	**NA**
Kang; Bhawna	2025	Multiple Industries	RF, GB, SVM, LR, XGBoost	Yes	89,70%
Ravichandran *et al.*	2025	Multiple Industries	CNN + LSTM + GB + RL	Yes	96,20%
Mahin *et al.*	2025	Retail Industry	LR, Elastic Net, KNN, RF, Voting Regressor	Yes	99,99%
Giineri; Deveci	2023	Military Industry	DT, RF, SVM, LR + Q-ROF-DEMATEL	Yes	95,40%
Jebbor *et al.*	2024	Textile Industry	RF, XGBoost, LightGBM, DT, LR	Yes	94,80%
Ali *et al.*	2020	Textile Industry	Fuzzy-AHP-TOPSIS	No	NA
Asrol *et al.*	2023	Food Industry	GB, SVM, AdaBoost, RF, SGB	Yes	93,60%
Husna *et al.*	2025	Retail Industry	RF, GB Regression, ARIMA, LSTM	Yes	NA
Kumaar; Maryam	2025	Pharmaceutical Industry	Theory-Guided CNN + GOA	Yes	99,70%
Huang *et al.*	2024	Financial Market	VAE-GNN-DRL	Mixed	95,55%
Khan *et al.*	2023	Multiple Industries	SVM, Regression, Clustering, Classification	Yes	NA

Source: The authors themselves.

The diversity of journals and the geographical distribution of publications, illustrated in Figures 8 and 9, highlight the multidisciplinary and global nature of the field. Brazil, Indonesia, and the United Kingdom concentrate the largest number of publications, followed by countries such as India, Iran, and Italy, indicating that the topic is relevant in both emerging economies and industrialized countries.

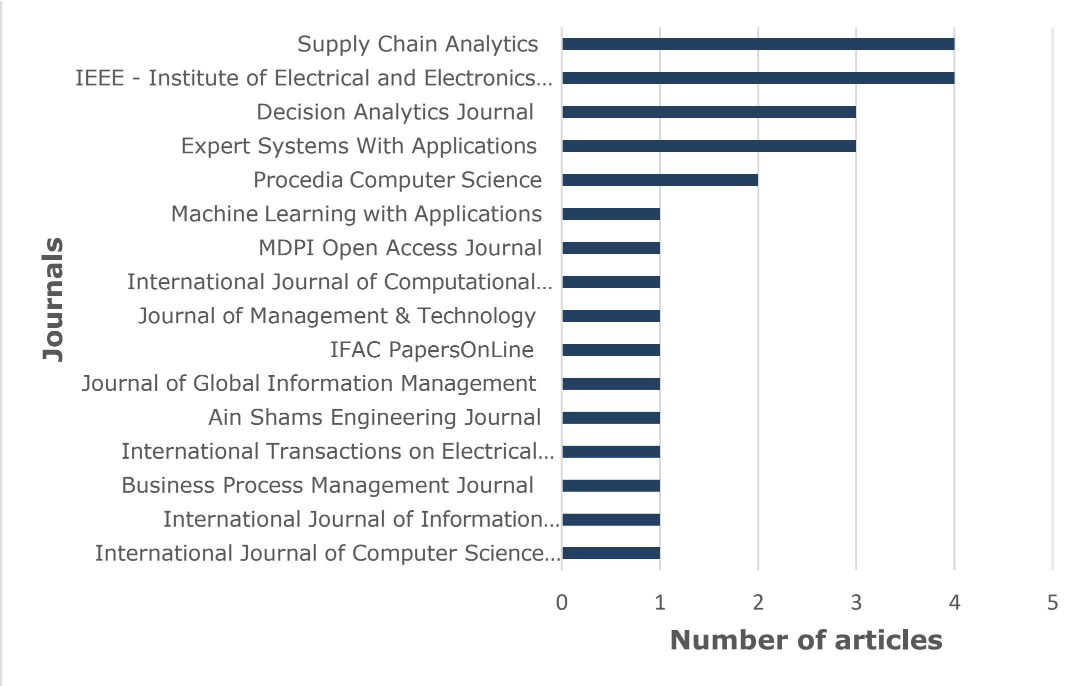

Figure 8 – Sources of the included articles
Source: The authors themselves.

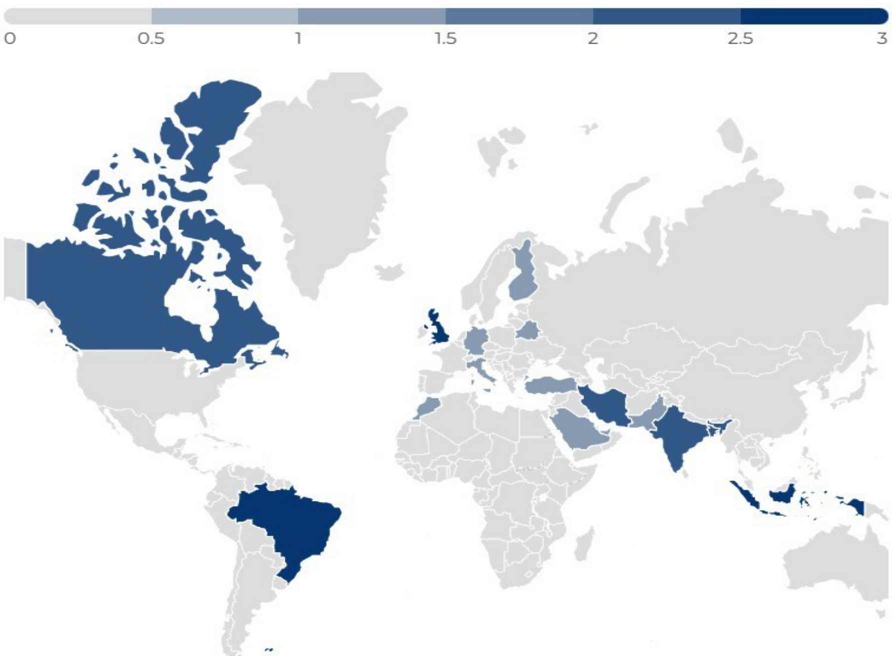

Figure 9 – Geographic distribution of publications by country
Source: The authors themselves.

The distribution of articles by application sector, presented in Figure 10, highlights the predominance of studies involving multiple industries, suggesting the use of integrated databases and models with greater potential for generalization. This pattern suggests a search for more flexible and transferable models across different sectoral contexts, as observed in Ravichandran *et al.* (2025), Kang and Bhawna (2025), Azarakhsh; Ferrari (2025) and Khan *et al.* (2023).

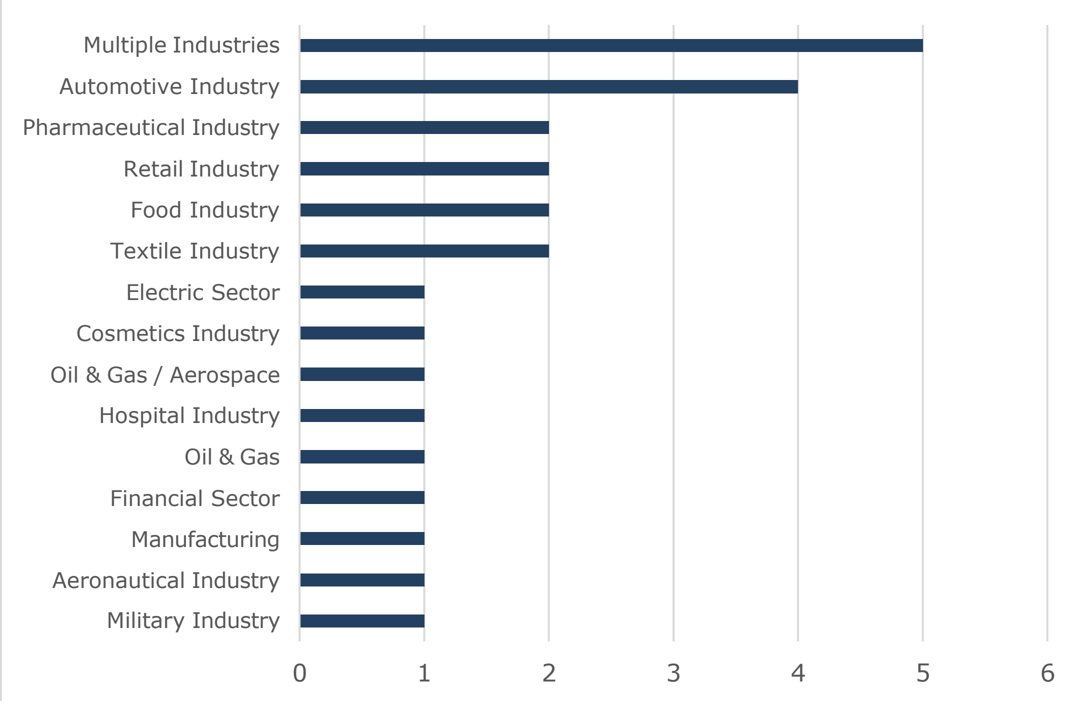

Figure 10 – Distribution of articles by application sector
Source: The authors themselves.

The pharmaceutical and food sectors follow, reflecting the high need for traceability, quality control, and logistical reliability. These operational requirements tend to favor the adoption of more advanced forecasting and classification models, as demonstrated by Hayati *et al.* (2025), Kumaar; Maryam (2025), and Asrol *et al.* (2023). The electricity, oil, and gas sectors have an intermediate share, while manufacturing and the military industry represent niches that are still little explored but have potential for expansion.

Figure 11 presents the distribution of the main groups of machine learning algorithms identified in the systematic review, based on their family or type of application.

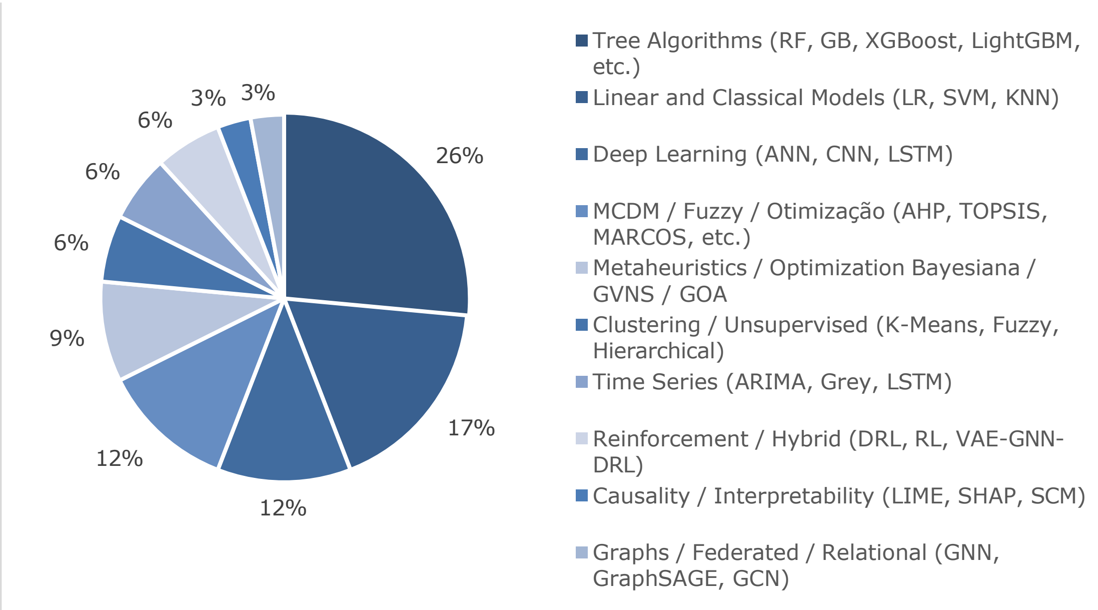

Figure 11 – Percentage distribution of machine learning algorithm families applied to supplier management
Source: The authors themselves.

The results indicate that ensembles based on decision trees, such as Random Forest, Gradient Boosting, XGBoost, and LightGBM, represent the largest share of studies (26%), highlighting the centrality of these supervised models in the literature on supplier selection. These algorithms stand out for combining high predictive performance with robustness on tabular data, in addition to offering relative ease of implementation and interpretation—characteristics valued in industrial contexts. This predominance is observed in research such as that of Ali *et al.* (2023), Abdulla; Baryannis (2024), and Mirasçı; Aksoy (2025), which employed these models for classification, ranking, and decision support in different industrial sectors.

Linear and classical models, representing 17% of applications, remain relevant mainly as comparative references (baselines), especially in studies that prioritize transparency, analytical simplicity, and lower computational cost. Algorithms such as Logistic Regression, Linear Regression, SVM, and kNN are widely used in contexts where the direct interpretation of coefficients and decision boundaries is considered essential, as evidenced in the works of Wei (2022), Cavalcante *et al.* (2019), and Badakhshan *et al.* (2024). These models enable direct analysis of risk, quality, and supplier performance, favoring their acceptance by managers and supply engineers.

Deep Learning models account for 12% of studies and are mainly applied to the identification of complex patterns and the modeling of temporal dependencies. Architectures such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) are recurrent in research focused on performance and operational risk forecasting, as in Mahin *et al.* (2025) and Ravichandran *et al.* (2025), who integrated deep neural networks with hybrid models for demand forecasting and anomaly detection in supply chains, especially in environments characterized by greater variability and uncertainty.

Clustering and unsupervised learning algorithms, such as K-Means, Hierarchical K-Means, AGNES, and Fuzzy Clustering, account for 6% of occurrences and are mainly used for exploratory supplier segmentation and identification of performance profiles in industrial databases. Studies such as those of Ferreira *et al.* (2025) explored these techniques to identify supplier clusters based on performance and efficiency, highlighting the role of unsupervised learning as a complementary step to predictive modeling in supply chain analysis. This distribution of approaches, which differentiates models focused on classification, regression, and exploratory segmentation, is shown in Figure 12.

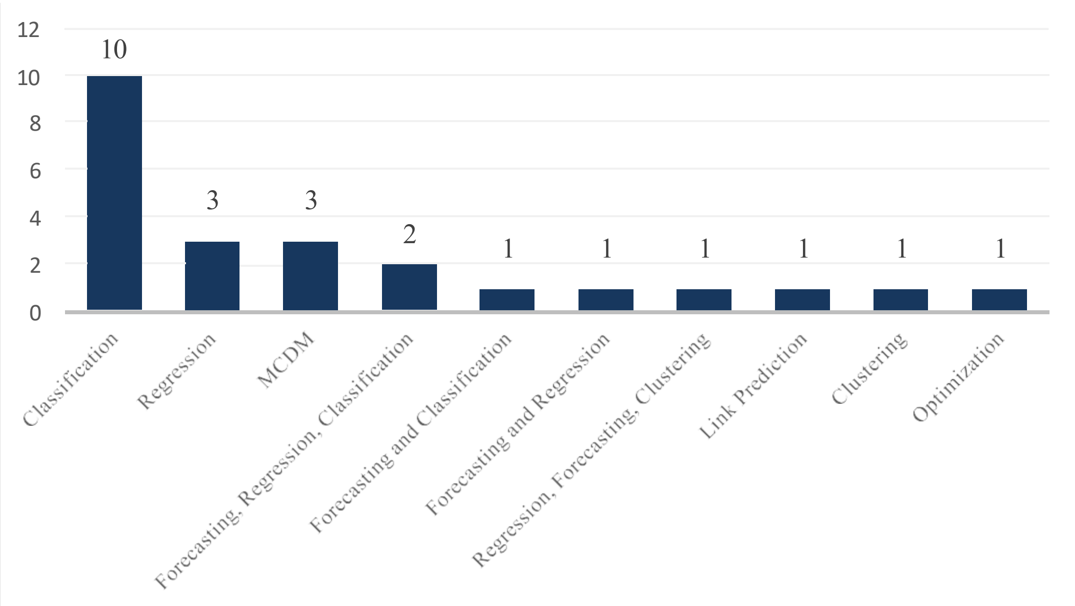

Figure 12 – Article typology based on its output
Source: The authors themselves.

The predominance of classification algorithms in the analyzed articles is consistent with the way the supplier selection problem is structured in industrial practice. In classification problems, the model predicts discrete labels or categories, such as approved or unapproved supplier, supplier classes A, B, and C, or different risk levels (Hastie; Tibshirani; Friedman, 2009; James *et al.,* 2013).

In contrast, regression models produce continuous values as output, such as total supplier cost, expected lead time, defect rate, emission level, or a numerical performance score (Bishop, 2006). These models aim to capture functional relationships between independent variables, such as price, quality, production capacity, delay history, and a quantitative dependent variable (Hastie; Tibshirani; Friedman, 2009).

Thus, regression is more frequently employed when the objective is to estimate future performance or quantify impacts, rather than classifying suppliers into discrete groups. This distinction aligns with the literature on supplier evaluation and qualification in supply chain management, which recognizes the coexistence of categorical and analytical decisions, depending on the stage of the decision-making process and the type of information required (Monczka *et al.,* 2016; De Boer; Labro; Morlacchi, 2001).

Regression algorithms and their combinations with classification and forecasting appear as the second most frequent approach, primarily employed to estimate quantitative indicators of future supplier performance, such as total cost, lead time, or defect levels (Carbonneau; Laframboise; Vahidov, 2008).

Among the selected articles, there are also 3 that utilize MCDM. Although numerically less representative, these works demonstrate that traditional approaches remain relevant in contexts where the explicit definition of criteria, weights, and decision rules is a priority. The use of MCDM proves suitable in scenarios with a scarcity of historical data, high dependence on expert judgment, or strong demands for transparency and auditability, as occurs in regulated environments or in strategic decision-making processes.

Although causality and interpretability methods represent only 3% of studies, they assume disproportionate relevance to their volume, as they offer mechanisms for explaining the results of learning models. Tools such as LIME, SHAP, and Structural Causal Models (SCM) enable us to understand the relationships between variables and identify the most relevant factors for decision-making, as demonstrated in Gupta *et al.* (2025), who associated causal learning and interpretable models with enhancing the resilience of the automotive supply chain.

Multicriteria and optimization models (MCDM/Fuzzy), such as AHP, TOPSIS, ARAS, and MARCOS, account for 6% of the studies and are used to integrate multiple decision criteria into supplier modeling, allowing for a balance of aspects such as cost, quality, sustainability, and risk. This approach is evidenced in the works of Ali *et al.* (2020) and Abdulla *et al.* (2023), who associated machine learning techniques with multicriteria methods to support strategic decision-making in complex environments.

Time series techniques, accounting for 6% of publications, are applied in contexts related to demand forecasting, risk and logistics performance. Models such as ARIMA and Grey GM(1,1) are used to estimate trends based on historical data, as reported by Hayati *et al.* (2025) and Husna *et al.* (2025), who combined time series forecasts with regression models and neural networks in pharmaceutical and retail supply chains.

Graph-based and relational learning models, which include Graph Convolutional Networks (GCN) and GraphSAGE, represent 3% of the studies and reflect an emerging trend in structural analysis of supplier networks. Works such as that of Zheng and Brintrup (2025) explore these techniques to model interdependencies between entities in the chain, allowing the detection of vulnerabilities, critical dependencies, and structural bottlenecks.

Metaheuristics and advanced optimization techniques, such as Bayesian Optimization, GVNS, and GOA, account for 9% of occurrences and are widely applied for hyperparameter tuning and global search for optimal solutions. These approaches are reported in Vahdani *et al.* (2017), Azarakhsh; Ferrari (2025), and Kumaar; Maryam (2025), where the combination of machine learning and optimization resulted in gains in performance, stability, and computational efficiency.

Finally, hybrid and reinforcement learning models, such as DRL, RL, and VAE-GNN-DRL, comprise 6% of the studies and represent the most advanced frontier of machine learning applications in supplier management. These models are designed to learn adaptively, adjusting decisions based on continuous feedback and environmental simulations. Works such as that of Huang *et al.* (2024) demonstrate that this combination is particularly effective in complex contexts, such as risk management and dynamic resource allocation in global supply chains.

Figure 13 shows the percentage of accuracy obtained in the selected studies (blue line) and the overall average accuracy of the analyzed models (orange line), based on data extracted from the systematic literature review.

It is observed that the accuracy of the models varies significantly between studies, ranging from approximately 46% to 99%, with an average of 91.97%. This range highlights the heterogeneity of the approaches analyzed, reflecting not only the diversity of algorithms used but also differences in industrial contexts, the quality of the databases, and the validation procedures adopted.

Some studies showed accuracies below 60%, which may be associated with limitations in the volume or representativeness of the available data, as observed in studies that employed simpler linear or supervised models in the initial stages of application (Cavalcante *et al.,* 2019; Gupta *et al.,* 2025). However, the average trend presented (orange line) indicates a high overall level of performance, suggesting a progressive maturation of the methodological approaches throughout the analyzed period.

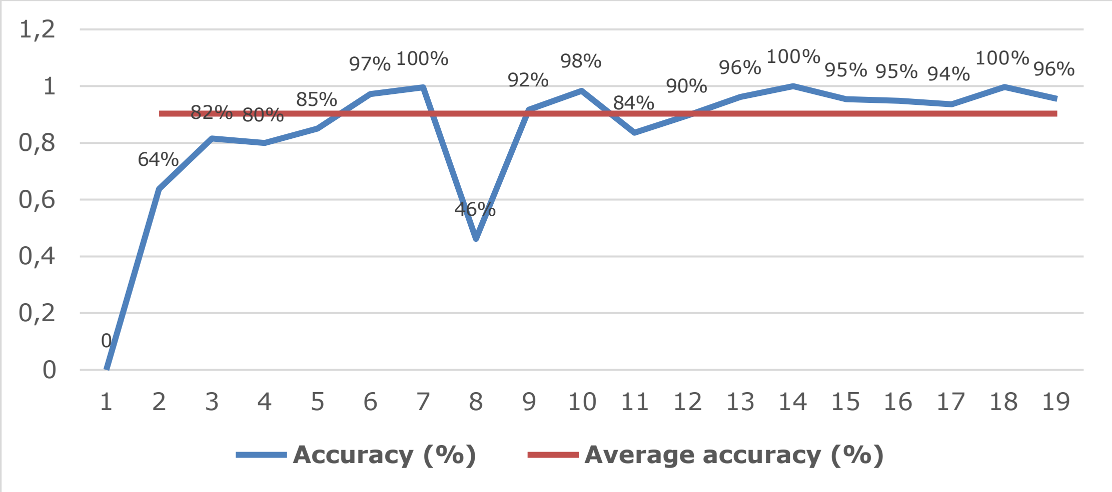

Figure 13 – Percentage of accuracy of the selected articles and overall average of the models
Source: The authors themselves.

It should be noted, however, that not all studies reported their validation metrics, such as accuracy, precision, recall, or F1-score, in a standardized manner. This lack of uniformity makes direct comparisons between studies difficult, although these studies remain relevant for their methodological contributions or innovative applications. This finding reinforces the need for greater standardization in performance evaluation in future research on supplier selection based on machine learning.

Table 4 presents a summary of the criteria considered in the analyzed articles for the evaluation and supplier selection. It can be observed that price, quality, and delivery performance are unanimously considered in the studies that explicitly state criteria, confirming their centrality in the decision-making process, regardless of the sector of application or the analytical technique employed.

Table 4 – Criteria considered among the articles for supplier analysis

Criteria considered	%
Price	100%
Quality	100%
Delivery Performance	100%
Flexibility	50%
Technical capability	33%
Reliability	17%
Risk	17%
Sustainability	50%
Service	17%
Relationship	17%
Capacity	17%

Source: The authors themselves.

Finally, it is observed that some of the articles do not clearly state the criteria used in selecting suppliers, despite presenting relevant results in their respective industrial contexts.

Nevertheless, the increasing adoption of machine learning in supplier evaluation needs to be aligned with international standards such as ISO 28000, ISO 20400, ISO 31000, and ISO 9001 (ISO, 2015; ISO, 2017; ISO, 2018a; ISO, 2018b), which emphasize governance, transparency, and risk management in supply chains. ISO 31000, in particular, as a structured risk management framework applicable to different organizational contexts, offers guidelines for integrating predictive models into decision-making processes. Furthermore, ISO 9001 stands out for being widely audited and recognized as an organizational quality certification, functioning as an important mechanism for institutional credibility, which reinforces the need for machine learning-based solutions to be compatible with audit requirements. Therefore, political implications related to the application of machine learning in supply chain management must be carefully analyzed by organizations considering real-world implementation contexts, as illustrated in Figure 14.

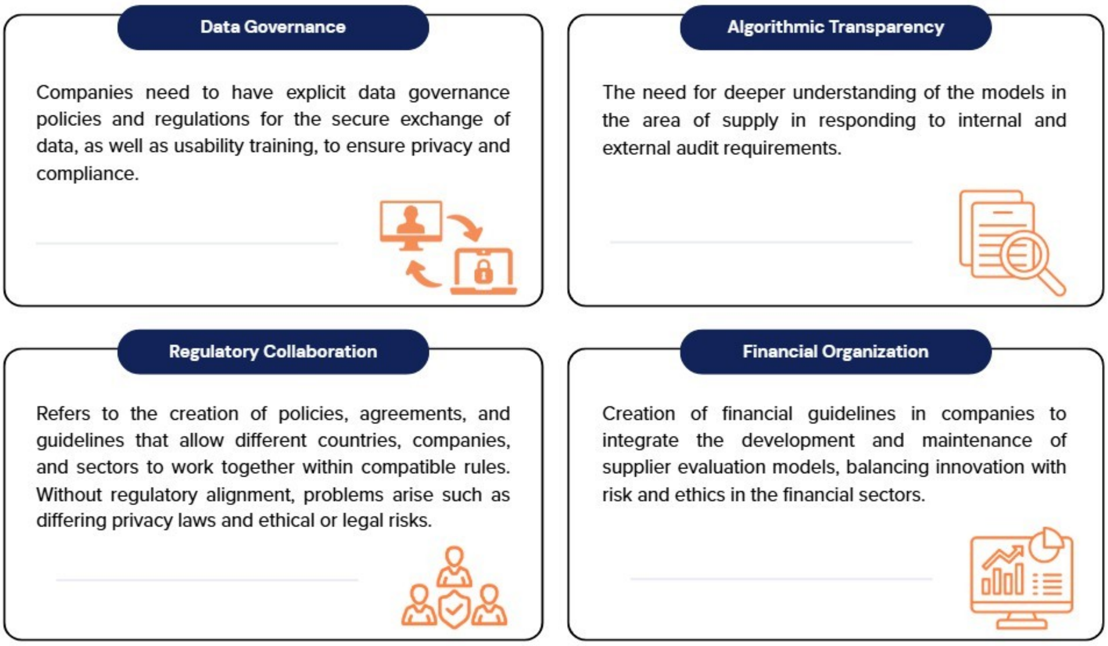

Figure 14 – Policies for Applying Machine Learning in Supply Chain Management
Source: The authors themselves.

The elements presented in Figure 14 demonstrate that the application of ML techniques depends on institutional mechanisms capable of supporting their implementation, indicating a convergence between analytical innovation and regulatory requirements in supply chains. Although the articles on the subject do not address the importance of ISOs in the real-world application of the models, the importance of risk management and its implications for company policies are discussed, as in Hayati *et al.* (2025) and Shidpour *et al.* (2025).

5. DISCUSSION

Despite the high accuracy reported by the analyzed studies, the adoption of machine learning (ML) in supplier selection and evaluation faces practical barriers. The first relates to the dependence on data quality and governance. Supervised models depend on labeled and consistent historical databases; however, in practice, purchasing and logistics performance data are often distributed across ERPs, spreadsheets, and legacy systems, with incomplete records, non-standardized criteria, and coding changes over time. This reduces the reliability of the training and makes the model susceptible to data collection biases. This point is particularly critical because the ML literature emphasizes that statistical performance depends on the representativeness and consistency of the data, while the supplier selection literature points to heterogeneity and multiplicity of criteria as central challenges in the decision-making process (Hastie; Tibshirani; Friedman, 2009; Ho; Xu; Dey, 2010).

The second refers to the interpretability and accountability of the decision. In procurement, decisions need to be justified to internal audits, regulatory bodies (especially in public procurement), and stakeholders. Models such as complex ensembles, deep learning, and graph-based architectures can improve performance, but they increase the cost of explanation, making it difficult to understand the "why" of the final ranking. Even with tools like LIME and SHAP, the challenge of translating technical explanations into replicable managerial justifications remains. This issue appears as a relevant limitation in recent studies on ML and decision-making in supply chains, reinforcing that predictive performance alone does not guarantee adoption (Bishop, 2006; Gupta *et al.*, 2025). Furthermore, traditional multi-criteria methods are often preferred for their structural transparency (explicit weights and criteria), which helps explain why MCDM still maintains a significant presence in supplier selection (Saaty, 1980; Brans; Vincke, 1985; Ho; Xu; Dey, 2010).

Finally, there are organizational barriers: analytical maturity, decision-making culture, and institutional isomorphism. Even with better models, organizations may maintain traditional practices to meet legitimacy, sectoral standardization, and audit expectations, not just immediate efficiency (DiMaggio; Powell, 1983). This helps explain the preference for hybrid approaches (ML + MCDM), which preserve decisional transparency while incorporating predictive capabilities (Ho; Xu; Dey, 2010; Ali *et al.*, 2020; Abdulla *et al.*, 2023). In more regulated sectors (pharmaceutical, defense, healthcare), the requirements for traceability and justification tend to increase the cost of adopting "black-box" models, reinforcing the need for interpretable models and decision governance (Beske, 2012; Gupta *et al.*, 2025).

6. CONCLUSION AND FUTURE RESEARCH

The findings of this systematic review indicate that the use of ML in supplier selection and evaluation has become established primarily in supervised applications, with emphasis on tree-based ensembles and, to a lesser extent, deep learning and emergent models (graphs and reinforcement). In practical terms, this suggests that, when structured historical data are available and labels are reliable, supervised models tend to be the most viable alternative for adoption, both for their performance and for the relative ease of implementation and maintenance in corporate tabular data (Hastie; Tibshirani; Friedman, 2009; James *et al.*, 2013).

6.1 Recommendations for the industrial setting

Industries with high transaction volumes and well-structured tabular data, such as retail, automotive, food: ensembles (Random Forest, Gradient Boosting, XGBoost/LightGBM) prove suitable due to their robustness and performance on tabular data, in addition to allowing explanations via variable importance and SHAP when necessary. They are good for classification (risk/level A–B–C) and for predicting performance metrics when the problem is regression (Hastie; Tibshirani; Friedman, 2009; James *et al.,* 2013; Chopra; Meindl, 2021).

Regulated and highly critical sectors (pharmaceutical, health/hospital, defense): prioritize models with explainability and governance. Simpler models (LR, trees, SVM with explanations) and/or hybrid models with MCDM can facilitate auditing and acceptance, as criteria and weights remain explicit and auditable, reducing organizational resistance (Saaty, 1980; Ho; Xu; Dey, 2010; Ali *et al.,* 2020).

Supply chains with strong interdependence between suppliers (complex networks, systemic risk, multi-tier): graph-based models (GCN, GraphSAGE) tend to be promising because they represent relationships and dependencies. However, they require data maturity (reliable network map) and MLOps infrastructure. For initial adoption, it may be advisable to combine a network layer (centrality/criticality indicators) with supervised tabular models or MCDM (Zheng; Brintrup, 2025; Ivanov; Dolgui, 2021).

Contexts with few labels or high uncertainty (new suppliers, emerging markets, incomplete data): clustering and unsupervised methods can support exploratory segmentation and initial screening, functioning as a step prior to formal qualification. In this case, the objective is to reduce uncertainty and support investigation, not to replace the final decision (Ho; Xu; Dey, 2010; Ferreira *et al.,* 2025).

Combined problems (order selection + allocation): hybrid approaches that integrate prediction (ML) with optimization and/or MCDM tend to be more aligned with the real process, as the final decision is not just "who is better," but "how much to buy from each" under multiple constraints (Hayati *et al.,* 2025; Ho; Xu; Dey, 2010).

6.2 Contribution of the research to professionals and researchers.

For professionals in the field (buyers, materials engineers, supply chain supervisors), a sequential framework based on the Monczka Framework for Supplier Qualification is recommended, adapted to the context of machine learning algorithms, regardless of whether it will be implemented on-site or using third-party software.

- Clearly define the type of output (classification vs. regression vs. optimization) and align the validation metric with the cost of error, avoiding relying solely on accuracy (Hastie; Tibshirani; Friedman, 2009; James *et al.*, 2013).
- Establish data and model governance: variable dictionary, standardization of criteria (e.g., "delay," "non-conformity"), traceability of labels, and model versioning (Monczka *et al.*, 2020).
- Incorporate explainability when the decision requires auditing: use LIME/SHAP and decision reports, or opt for hybrids with MCDM when transparency is a central requirement (Saaty, 1980; Ho; Xu; Dey, 2010; Gupta *et al.*, 2025).
- Plan the frequency of retraining and monitoring: suppliers and market conditions change; Therefore, drift and periodic updates should be planned for in the continuous qualification process (Monczka *et al.*, 2020; Teece, 2007).
- Validate with purchasing stakeholders (e.g., buyers, quality, logistics): without

alignment with the decision-making process and accepted criteria, the solution tends to remain "parallel" and not adopted (Chopra; Meindl, 2021; DiMaggio; Powell, 1983).

6.3 Study limitations and directions for further research

This study presents typical limitations of RSLs applied to an emerging field. First, the heterogeneity of reported metrics and the lack of validation standardization prevent robust direct comparisons between algorithms. Furthermore, some studies do not explicitly state selection criteria, which restricts the ability to compare "what" the models are learning or optimizing, suggesting the need for greater transparency regarding the variables and criteria used. Finally, the literature still lacks longitudinal evidence: few studies measure real organizational impact (total cost reduction, service improvement, risk reduction) after implementation, reinforcing the need for future agenda items such as evaluating the "value generated" in ML implementations in procurement (Chopra; Meindl, 2021; Ivanov; Dolgui, 2021).

REFERENCES

Abdulla, A.; Baryannis, G. (2024), “A hybrid multi-criteria decision-making and machine learning approach for explainable supplier selection”, *Supply Chain Analytics*, Vol. 7, p. 100074. https://doi.org/10.1016/j.sca.2024.100074

Abdulla, A.; Baryannis, G.; Badi, I. (2023), “An integrated machine learning and MARCOS method for supplier evaluation and selection”, *Decision Analytics Journal*, Vol. 9, pp. 100342. https://doi.org/10.1016/j.dajour.2023.100342

Ali, M. R.; Nipu, A.; Khan, S.A. (2023), “A decision support system for classifying supplier selection criteria using machine learning and random forest approach”, *Decision Analytics Journal*, Vol. 7, No. 2, 100238. https://doi.org/10.1016/j.dajour.2023.100238.

Ali, S.M.; Burney, S.M.A.; Khan, S.Y. (2020), “Fuzzy-AHP-TOPSIS: An integrated multi-criteria decision support system for supplier selection in Pakistan’s textile industry”, *International Journal of Computer Science and Network Security*, Vol. 20, No. 4, pp. 91–100.

Apriliani, R.; Wibirama, S. (2024), “Classification of vendor categories using machine learning in industrial decision support systems”, *IEEE*, pp. 888–893. https://doi.org/10.1109/ISRITI64779.2024.10963453.

Asrol, M.; Nipu, A.; Khan, S. A. (2023), “Improving supplier evaluation model using ensemble-method machine learning for food industry”, *Procedia Computer Science*, Vol. 227, pp. 307-315. https://doi.org/10.1016/j.procs.2023.10.529.

Azarakhsh, S.; Ferrari, S. (2025), “Bayesian Optimization in Hybrid Data Envelopment Analysis and Stacking Approach for Supplier Selection”, *IFAC-PapersOnLine*, Vol. 36, pp. 812-829. https://doi.org/10.1016/j.ifacol.2025.09.458.

Badakhshan, E.; Mustafee, N.; Bahadori, R. (2024), “Application of simulation and machine learning in supply chain management: A synthesis of the literature using the Sim-ML literature classification framework”, *Computers & Industrial Engineering*, Vol. 198, pp. 110649. https://doi.org/10.1016/j.cie.2024.110649.

Beske, P. (2012), “Dynamic capabilities and sustainable supply chain management”, International Journal of Physical Distribution & Logistics Management, Vol. 42, No. 4, pp. 372-387.

Bishop, C.M. (2006), Pattern Recognition and Machine Learning, Springer, New York.

Brans, J.P.; Vincke, P. (1985), “A preference ranking organisation method: The PROMETHEE method”, Management Science, Vol. 31, No. 6, pp. 647-656.

Cavalcante, I.M.; Frazzon, E.M.; Forcellini, F.A.; Ivanov, D. (2019), “A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing”, *International Journal of Information Management*, Vol. 49, pp. 86–97. https://doi.org/10.1016/j.ijinfomgt.2019.03.004.

Chopra, S.; Meindl, P. (2021), *Supply Chain Management: Strategy, Planning, and Operation*, 8th ed., Pearson, Boston.

De Boer, L.; Labro, E.; Morlacchi, P. (2001), “A review of methods supporting supplier selection”, *European Journal of Purchasing & Supply Management*, Vol. 7, No. 2, pp. 75–89.

DiMaggio, P.J.; Powell, W.W. (1983), “The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields”, *American Sociological Review*, Vol. 48, No. 2, pp. 147–160.

Dweiri, F.; Kumar, S.; Khan, S. A.; Jain, V. (2016), "Designing an integrated AHP-based decision support system for supplier selection in automotive industry", *Expert Systems with Applications*, Vol. 62, pp. 273–283. https://doi.org/10.1016/j.eswa.2016.06.030.

Ferreira, A. C. A., de Pinho, A. F., Francisco, M. B., de Siqueira, L. A., Jr., & Vasconcelos, G. A. V. B. (2025), "A decision support system for classifying suppliers based on machine learning techniques: a case study in the aeronautics industry", *Computers*, Vol. 14, No. 7. DOI: 10.3390/computers14070271.

Ghaleb, A.M.; Kaid, H.; Alsamhan, A.; Mian, S.H.; Hidri, L. (2020), "Assessment and comparison of various MCDM approaches in the selection of manufacturing process", *Advances in Materials Science and Engineering*, Vol. 2020, Art. 4039253. https://doi.org/10.1155/2020/4039253

Goodfellow, I.; Bengio, Y.; Courville, A. (2016), *Deep Learning*, MIT Press, Cambridge, MA.

Govindan, K.; Rajendran, S.; Sarkis, J. (2015), "Multi criteria decision making approaches for green supplier evaluation and selection: A literature review", *Journal of Cleaner Production*, Vol. 98, pp. 66–83.

Guneri, B.; Deveci, M. (2023), "Evaluation of supplier selection in the defense industry using q-rung orthopair fuzzy set based EDAS approach", *Expert Systems with Applications*, Vol. 222, Art. 119846. https://doi.org/10.1016/j.eswa.2023.119846.

Gupta, I.; Martinez, A.; Correa, S.; & Wicaksono, H. (2025), "A comparative assessment of causal machine learning and traditional methods for enhancing supply chain resiliency", *Supply Chain Analytics*, Art. 100116. https://doi.org/10.1016/j.sca.2025.100116

Harzing, A.-W.; Alakangas, S. (2016), "Google Scholar, Scopus and the Web of Science: A longitudinal and cross-disciplinary comparison", *Scientometrics*, Vol. 106, No. 2, pp. 787–804. https://doi.org/10.1007/s11192-015-1798-9.

Hastie, T.; Tibshirani, R.; Friedman, J. (2009), *The Elements of Statistical Learning*, 2nd ed., Springer, New York.

Hayati, E.N.; Jauhari, W.A.; Damayanti, R.W. & Rosyidi, C.N. (2025), "An integrated analytics model for supplier selection and order allocation with machine learning and multi-criteria optimization", *Decision Analytics Journal*, Vol. 16, pp. 100599. https://doi.org/10.1016/j.dajour.2025.100599.

Ho, W.; Xu, X.; Dey, P. K. (2010), "A review of multi-criteria decision-making approaches for supplier evaluation and selection", *European Journal of Operational Research*, Vol. 202, No. 1, pp. 16–24. https://doi.org/10.1016/j.ejor.2009.05.009.

Huang, A.; Zhuang, J.; Ren, Y.; Rao, Y.; Tsai, S. (2024), "Supply chain management in the digital economy: Case studies of deep learning technology applications", *Journal of Global Information Management*, Vol. 32, No. 1. https://doi.org/10.4018/JGIM.361589.

Husna, A.; Amin, S.H.; Ghasempoor, A. (2025), "Machine learning techniques and multi-objective programming to select the best suppliers and determine the orders", *Machine Learning with Applications*, Vol. 19, Art. 100623. https://doi.org/10.1016/j.mlwa.2025.100623.

Ivanov, D.; Dolgui, A. (2021), "A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0", *Production Planning & Control*, Vol. 32, No. 9, pp. 775–788.https://doi.org/10.1080/09537287.2020.1768450.

International Organization for Standardization (2015), *ISO 9001:2015 – Quality management systems — Requirements*, ISO, Geneva.

International Organization for Standardization (2017), *ISO 20400:2017 – Sustainable procurement — Guidance*, ISO, Geneva.

International Organization for Standardization (2018a), *ISO 28000:2018 – Security and resilience — Security management systems — Requirements*, ISO, Geneva.

International Organization for Standardization (2018b), *ISO 31000:2018 – Risk management — Guidelines*, ISO, Geneva.

James, G.; Witten, D.; Hastie, T.; Tibshirani, R. (2013), *An Introduction to Statistical Learning*, Springer, New York.

Jebbor, I.; Benmamoun, Z.; Hachimi, H. (2024), "Forecasting supply chain disruptions in the textile industry using machine learning: A case study", Ain Shams Engineering Journal, Vol. 15, Issue 12, Art. 103116. DOI: 10.1016/j.asej.2024.103116.

Kang, P. S.; Bhawna, B. (2025), “Enhancing supply chain resilience through supervised machine learning: supplier performance analysis and risk profiling for a multi-class classification problem”, *Business Process Management Journal*, DOI: 10.1108/BPMJ-03-2024-0174.

Kumaar, S.J. & Maryam, Z. (2025), “Smart sustainability: A theory-guided convolutional neural network with gazelle optimization framework for supplier classification”, *Proceedings of the 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI-2025)*, IEEE, pp. 1–8. http://doi.org/10.1109/ICDICI66477.2025.11135188

Mahin, M.P.R.; Shahriar, M.; Das, R.R.; Roy, A. & Reza, A.W. (2025), “Enhancing sustainable supply chain forecasting using machine learning for sales prediction”, *Procedia Computer Science*, Vol. 252, pp. 470–479. https://doi.org/10.1016/j.procs.2025.01.006.

Mchopa, A. D.; Kimario, H. F.; Panga, F. P. (2025), “Green procurement practices and performance of small scale manufacturing firms in Dar es Salaam Region, Tanzania”, African Journal of Applied Social Sciences. https://www.ajol.info/index.php/ajasss/article/view/286049

Mirasçı, S.; Aksoy, A. (2025), “Data-Driven purchasing strategies: Price prediction models and strategy development”, *Expert Systems with Applications*, Vol. 266, Art. 125986. https://doi.org/10.1016/j.eswa.2024.125986.

Monczka, R.M.; Handfield, R.B.; Giunipero, L.C.; Patterson, J.L. (2020), *Purchasing and Supply Chain Management*, 7th ed., Cengage, Boston.

Palakshappa, A.; Maradithaya, S., & V, C. (2025). A Machine Learning Method to improve Supplier Delivery Appointments in Supply Chain Industries : A Case Study. *Brazilian Journal of Operations & Production Management*, 22(1), 2040. https://doi.org/10.14488/BJOPM.2040.2025

Ravichandran, I.; Sharma, S.; Rajendran, P.; Kumar, A.; Rahman, M. (2025), “Enhancing Supply Chain Transparency and Efficiency Through Hybrid Machine Learning Models”, *Proceedings of the 2025 Global Conference in Emerging Technology (GINOTECH)*, IEEE, pp. 1–6. https://doi.org/10.1109/GINOTECH63460.2025.11076956.

Saaty, T.L. (1980), *The Analytic Hierarchy Process*, McGraw-Hill, New York.

Santis, R. B. de, Golliat, L., & Aguiar, E. P. de. (2017). Multi-criteria supplier selection using fuzzy analytic hierarchy process: case study from a Brazilian railway operator. *Brazilian Journal of Operations & Production Management*, 14(3), 428–437. https://doi.org/10.14488/BJOPM.2017.v14.n3.a15

Shidpour, H.; Mousavi, S.; Ghadami, A.; Hashemi, A. (2025), “A multi-phase analytics framework for supply chain supplier selection and order allocation with delay risks and Industry 4.0 readiness”, *Supply Chain Analytics*, Vol. 3, Art. 100172. https://doi.org/10.1016/j.sca.2025.100172.

Tao, J.; Aamir, M.; Shoaib, M.; Yasir, N.; Babar, M. (2025), “Bridging the Gap Between Supply Chain Risk and Organizational Performance Conditioning to Demand Uncertainty”, *Sustainability*, Vol. 17, No. 6, Art. 2462. https://doi.org/10.3390/su17062462

Teece, D.J.; Pisano, G.; Shuen, A. (1997), “Dynamic capabilities and strategic management”, *Strategic Management Journal*, Vol. 18, No. 7, pp. 509–533.

Teece, D.J. (2007), “Explicating dynamic capabilities”, *Strategic Management Journal*, Vol. 28, No. 13, pp. 1319–1350.

Vahdani, B.; Mousavi, S. M.; Tavakkoli-Moghaddam, R.; Hashemi, H. (2017), “A new enhanced support vector model based on general variable neighborhood search algorithm for supplier performance evaluation: A case study”, *International Journal of Computational Intelligence Systems*, Vol. 10, No. 1, pp. 293–311. http://doi.org/10.2991/ijcis.2017.10.1.20.

Wei, Y. (2022), “A machine learning algorithm for supplier credit risk assessment based on supply chain management”, *International Transactions on Electrical Energy Systems*, Vol. 2022, No. 1, Art. 4766597. http://doi.org/10.1155/2022/4766597

Zheng, G., & Brintrup, A. (2025). A machine learning approach for enhancing supply chain visibility with graph-based learning. *Supply Chain Analytics*, 11, 100135. https://doi.org/10.1016/j.sca.2025.100135

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