



Explainable Artificial Intelligence for Supplier Cost-Risk Assessment and Margin Optimization in Global Manufacturing Supply Chains

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Abstract

This study has addressed the problem of limited transparency in artificial intelligence-supported supplier assessment, where complex predictive models may identify cost risks and recommend sourcing actions without sufficiently explaining the factors responsible for those outputs. The purpose of the study has been to quantitatively examine how Explainable Artificial Intelligence capabilities are associated with Supplier Cost-Risk and Margin Optimization Performance in global manufacturing supply chains. A quantitative, cross-sectional, case-study-based research design has been employed across selected manufacturing and enterprise supply-chain environments using procurement analytics, supplier evaluation systems, AI-supported decision tools, and advanced digital sourcing platforms. Using purposive sampling, 320 questionnaires have been distributed to procurement, sourcing, supply-chain, purchasing, supplier relationship, financial, operations, and AI or analytics professionals, of which 301 have been returned and 289 have been retained as valid responses, producing a 90.3% usable response rate. The study has examined Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics as predictors of Supplier Cost-Risk and Margin Optimization Performance. Data have been analyzed using descriptive statistics, Cronbach's alpha, construct-validity tests, Pearson correlation, and multiple regression. Reliability coefficients have ranged from .84 to .91, with KMO = .89 and Bartlett's Test significant at $p < .001$. Supplier Cost-Risk and Margin Optimization Performance has recorded $M = 4.18$, $SD = 0.53$. All four predictors have demonstrated significant positive correlations with performance, led by Explainable Supplier Cost-Risk Identification, $r = .75$, followed by AI-Enabled Cost Driver Transparency, $r = .72$, Explainable Supplier Risk Prioritization and Decision Support, $r = .69$, and Explainable Margin Scenario Analytics, $r = .66$, all $p < .001$. The regression model has explained 71.2% of performance variance, $R^2 = .712$, adjusted $R^2 = .708$, $F(4, 284) = 175.50$, $p < .001$, with significant standardized effects of $\beta = .31, .28, .24$, and $.21$, respectively. These findings indicate that explainable AI can strengthen supplier cost visibility, risk prioritization, sourcing decision quality, and margin-oriented management by making AI-supported assessments more interpretable and managerially actionable.

Keywords

Explainable Artificial Intelligence; Supplier Cost-Risk; Cost Driver Transparency; Supplier Risk Prioritization; Margin Optimization

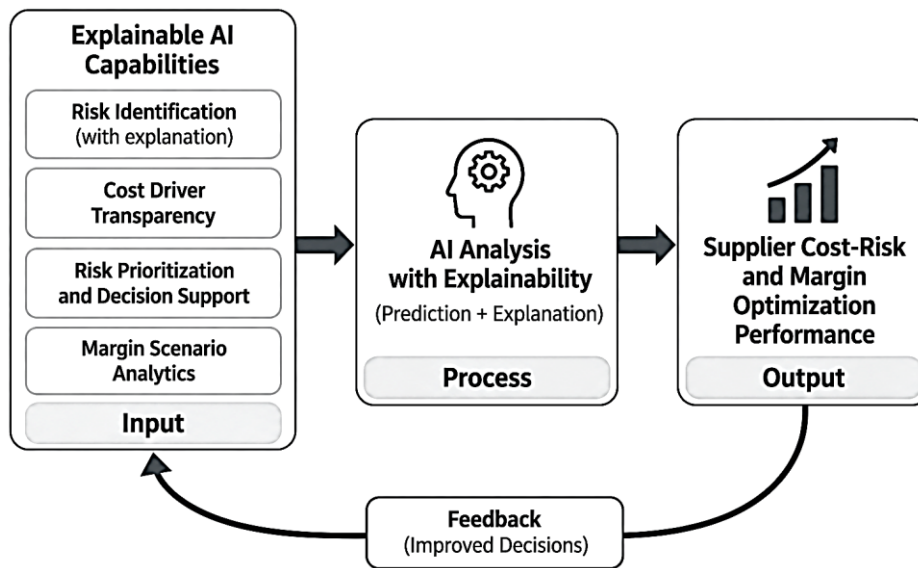
INTRODUCTION

Artificial intelligence (AI) refers to computational systems designed to perform tasks that ordinarily require human intelligence, including learning from data, identifying patterns, generating predictions, evaluating alternatives, and supporting complex decision-making. Within this broader domain, Explainable Artificial Intelligence (XAI) represents a set of techniques and design principles intended to make the reasoning, influential variables, and decision processes of AI systems understandable to human users. The need for explainability has become increasingly important as advanced machine-learning algorithms have grown more complex and their internal decision processes have become less transparent. Researchers have distinguished between inherently interpretable models and post hoc explanation techniques that provide human-understandable accounts of predictions generated by complex models (Adadi & Berrada, 2018; Guidotti et al., 2018). Explainability extends beyond technical model transparency because explanations must also enable users to understand why a particular prediction or recommendation has been generated and which factors have contributed most strongly to that result (Miller, 2019; Murdoch et al., 2019). This requirement becomes especially significant when artificial intelligence supports economically consequential organizational decisions involving supplier selection, procurement expenditure, sourcing alternatives, contractual negotiations, cost exposure, and profitability. Responsible AI research has therefore associated explainability with transparency, accountability, interpretability, and the capacity of decision makers to critically evaluate algorithmic recommendations rather than accepting them without adequate understanding (Arrieta et al., 2020; Rai, 2020). Human-centered investigations have similarly demonstrated that understandable AI explanations can influence user trust, perceived fairness, acceptance, and willingness to rely on algorithm-supported decisions (Langer et al., 2021; Shin, 2021). Within global manufacturing supply chains, XAI can consequently be understood as an analytical capability through which supplier-related predictions, cost-risk assessments, sourcing recommendations, and margin scenarios are accompanied by understandable explanations concerning the factors and relationships responsible for the generated outputs.

Supplier cost-risk constitutes an important dimension of global supply-chain management because manufacturing organizations frequently depend on geographically dispersed suppliers whose prices, production capacities, financial conditions, logistical performance, and operational reliability can directly affect manufacturing costs. Supply-chain risk management generally encompasses the identification, assessment, treatment, and monitoring of uncertain conditions capable of influencing material, information, financial, and operational flows across interconnected organizations (Jüttner, 2005; Tang, 2006). International manufacturing networks have become structurally dependent on suppliers operating across different economic, regulatory, geographic, and commercial environments, which makes supplier-related uncertainty a multidimensional management problem. Risks arising from supply availability, transportation disruption, demand fluctuation, financial instability, supplier capacity, quality variation, and market conditions can interact and influence organizational performance simultaneously (Tang & Musa, 2011; Thun & Hoenig, 2011). Supplier cost-risk can therefore be defined as the potential exposure of a manufacturing organization to unfavorable changes in supplier prices, procurement costs, input expenses, transportation charges, currency-related costs, production constraints, and other supplier-related conditions capable of increasing the effective cost of acquiring goods or services. Research has emphasized that supply-chain risk should not be treated as a single homogeneous phenomenon because its measurement and managerial relevance depend substantially on the specific decision environment under investigation (Heckmann et al., 2015; Sodhi et al., 2012). Supplier evaluation similarly requires decision makers to consider several interdependent criteria, including cost, quality, capacity, delivery reliability, operational capability, and uncertainty surrounding supplier performance (Ferreira & Borenstein, 2012). Comprehensive reviews of supply-chain risk management have demonstrated that supplier-risk identification, assessment, mitigation, monitoring, and decision support remain central components of organizational attempts to manage uncertainty across extended supply networks (Fan & Stevenson, 2018; Ho et al., 2015). For global manufacturing companies, supplier cost-risk is therefore closely connected with margin performance because unfavorable supplier cost movements can increase the cost of production, weaken purchasing efficiency, reduce pricing flexibility, and compress the economic margin generated from manufactured

products.

Figure 1: Explainable AI Framework for Supplier Cost-Risk Assessment and Margin Optimization Performance



The expansion of digital supply-chain systems has considerably increased the volume and diversity of information available for assessing suppliers, sourcing conditions, procurement expenditures, operational performance, and cost structures. Enterprise resource planning systems, procurement platforms, supplier-management systems, transactional databases, market information, logistics records, and production systems collectively generate extensive datasets that can support more sophisticated approaches to supply-chain decision-making. Predictive analytics and data science have been introduced into supply-chain management as mechanisms for transforming large and complex datasets into information that supports operational and strategic decisions, although the reliability of resulting insights depends strongly on the quality and suitability of the underlying data (Hazen et al., 2014). The organizational use of big-data analytics has been associated with improved information-processing capabilities and enhanced value creation within supply-chain operations (Chen et al., 2015). Digital information and analytics can also expand organizational visibility by integrating information across supply-chain functions and enabling managers to identify relationships that may remain difficult to observe through conventional analysis (Kache & Seuring, 2017; Rony & Md, 2026). Procurement represents a particularly data-intensive organizational function because purchasing professionals continuously evaluate supplier quotations, spending patterns, delivery records, quality measures, sourcing categories, contractual terms, and cost changes. Evidence from procurement research indicates that big-data applications can improve several purchasing activities by strengthening the informational foundation of procurement decisions (Moretto et al., 2017; Kanti, 2026). At a broader organizational level, the development of big-data analytics capabilities has been associated with firm performance through strengthened dynamic and process-oriented capabilities (Shamima, 2026; Wamba et al., 2017). Manufacturing research has also demonstrated relationships between big-data and predictive-analytics capabilities and manufacturing performance, indicating that analytical capabilities can contribute to improved management of complex production and operational environments (Dubey et al., 2019; Pervaz, 2026). Artificial intelligence has extended these analytical capabilities through machine learning, automated pattern recognition, predictive modeling, intelligent decision support, and optimization applications across supply-chain activities (Pournader et al., 2021; Toorajipour et al., 2021). Within procurement specifically, AI-based systems can affect supplier pricing interactions and support buyer decision processes involving quotations and sourcing choices (Cui et al., 2022; Kaium, 2026). Empirical evidence has additionally connected supply-chain analytics adoption with organizational performance and competitive advantage, strengthening the relevance of analytics

capabilities to manufacturing decision systems (Kalaitzi & Tsolakis, 2022; Khalid, 2026). Recent procurement research has identified supplier evaluation, spend analysis, sourcing, negotiation, risk assessment, and cost analysis as significant areas in which artificial intelligence and machine learning are being applied (Guida et al., 2023; Spreitzenbarth et al., 2024).

The use of artificial intelligence in supplier assessment does not automatically ensure that generated predictions or recommendations are sufficiently understandable for procurement, finance, and supply-chain professionals. Complex machine-learning algorithms can provide strong predictive performance while simultaneously functioning as black-box systems whose underlying decision mechanisms are difficult for users to interpret. Such opacity creates a significant concern in supplier cost-risk management because a numerical risk score alone may not explain why a supplier has been classified as costly or risky, which variables have contributed to the prediction, how strongly individual cost drivers have influenced the outcome, or why a particular sourcing option has been recommended. Interpretability research has emphasized that an effective explanation should help users establish meaningful relationships between model inputs, algorithmic behavior, and resulting outputs rather than simply expose technical model characteristics (Miller, 2019; Murdoch et al., 2019). This issue has direct relevance to supply-chain risk assessment. Research applying machine learning to multi-tier supply-chain risk prediction has identified a measurable relationship between predictive performance and interpretability, demonstrating that interpretable models can reveal decision-relevant relationships underlying predicted risk outcomes (Baryannis et al., 2019). A systematic examination of explainability in supply-chain operational risk management has similarly identified limited explainability across many AI applications used for risk identification, assessment, management, and optimization (Nimmy et al., 2022). Explainable AI offers a means of addressing this analytical limitation by providing information concerning important variables, feature contributions, decision rules, local explanations, global model behavior, or other understandable representations of the reasoning underlying AI-generated results (Arrieta et al., 2020; Guidotti et al., 2018). In supplier cost-risk assessment, such explainability can allow decision makers to identify whether predicted cost exposure originates from raw-material prices, transportation costs, supplier financial weakness, quality problems, capacity constraints, delivery uncertainty, exchange-rate movement, or other measurable conditions. Explainability can also support the interpretation of margin-related sourcing scenarios by showing how changes in supplier prices, order allocations, procurement conditions, and other cost assumptions contribute to different economic outcomes. User-oriented research has demonstrated that explainability can influence perceptions of transparency, trust, and acceptance when individuals interact with AI-supported decisions (Jannatul, 2026; Langer et al., 2021; Shin, 2021). These characteristics make XAI especially relevant in organizational environments where managers remain responsible for validating, justifying, and acting upon algorithmic recommendations.

The relationship among explainable artificial intelligence, supplier cost-risk assessment, and margin optimization represents a specific analytical area within global manufacturing supply-chain management. Existing supply-chain risk literature has extensively examined risk identification, supplier evaluation, disruption management, mitigation practices, and organizational responses to uncertainty, while supply-chain analytics research has demonstrated the value of advanced data processing for improving operational and managerial decision-making (Fan & Stevenson, 2018; Ho et al., 2015). Procurement-focused studies have also established that artificial intelligence can support purchasing activities, supplier management, sourcing decisions, and interactions involving supplier pricing (Ahmed, 2026; Cui et al., 2022; Guida et al., 2023). At the same time, recent research on AI and machine learning in purchasing and supply management has identified continued scholarly attention to supplier assessment, purchasing decisions, and cost-related analytics (Spreitzenbarth et al., 2024). The explainability literature adds another dimension by demonstrating that predictive accuracy alone does not adequately address managerial requirements when users must understand and justify the reasoning underlying AI-generated decisions (Arrieta et al., 2020; Jahanara, 2026; Rai, 2020). Supply-chain-specific evidence similarly indicates that interpretability is particularly relevant when machine-learning models are employed to assess operational and supplier risks (Baryannis et al., 2019; Nimmy et al., 2022). Within the present study, these streams are integrated through four interrelated explainable AI capabilities. Explainable Supplier Cost-Risk Identification represents the capacity of AI-

supported systems to detect supplier-related cost exposure while providing understandable reasons for identified risks. AI-Enabled Cost Driver Transparency represents the capability to identify and clarify the supplier, market, operational, and financial variables that contribute to changes in procurement costs. Explainable Supplier Risk Prioritization and Decision Support represents the use of interpretable analytical information to rank suppliers, compare risk conditions, and support sourcing decisions. Explainable Margin Scenario Analytics refers to the ability of AI-supported systems to evaluate alternative sourcing and cost conditions while explaining how changes in relevant variables are associated with margin outcomes. These constructs are examined in relation to Supplier Cost-Risk and Margin Optimization Performance, representing the effectiveness with which manufacturing supply chains identify supplier-related cost exposure, improve cost visibility, support economically informed sourcing decisions, control procurement-related costs, and maintain stronger margin performance through explainable analytical information.

Background of the Study

Global manufacturing supply chains have become increasingly complex because manufacturers rely on extensive networks of suppliers, contract manufacturers, logistics providers, distributors, technology platforms, and geographically dispersed production facilities. Within these networks, supplier-related costs directly influence production expenses, procurement efficiency, product pricing, profitability, and overall margin stability. Supplier cost-risk refers to the possibility that changes in supplier prices, raw-material costs, transportation expenses, exchange rates, energy prices, labor costs, production capacity, quality performance, delivery reliability, financial condition, or other supplier-related factors may adversely affect the purchasing costs and financial performance of manufacturing organizations. Traditional supplier assessment methods have generally depended on historical records, predefined performance indicators, managerial judgment, and periodic supplier evaluations. Although these approaches remain important, they may be insufficient for processing the growing volume and complexity of data generated across modern global supply chains. Artificial intelligence has therefore become an increasingly relevant analytical mechanism for identifying hidden relationships within supplier, procurement, operational, financial, and market data. AI-supported systems can assist organizations in identifying cost-risk patterns, classifying suppliers, analyzing cost drivers, prioritizing risks, and evaluating alternative sourcing scenarios. However, the increasing complexity of machine-learning models has introduced another management challenge because decision makers may receive highly sophisticated predictions without fully understanding the reasons behind them. Explainable Artificial Intelligence addresses this issue by providing understandable information regarding the factors, relationships, and decision logic underlying AI-generated assessments. In supplier cost-risk management, explainability can enable procurement and supply-chain professionals to understand why a particular supplier has received a high-risk assessment, which variables have contributed to anticipated cost changes, and how different sourcing decisions may influence purchasing costs and manufacturing margins. Explainability is also important for margin optimization because cost reduction alone does not necessarily represent an economically appropriate sourcing decision when quality, continuity, reliability, capacity, and operational consequences are considered simultaneously. Therefore, integrating explainable AI with supplier cost-risk assessment creates a structured analytical environment in which organizations can combine predictive intelligence with transparent managerial interpretation. The present study has been developed within this context and focuses specifically on Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics as important capabilities associated with Supplier Cost-Risk and Margin Optimization Performance in global manufacturing supply chains.

Problem Statement

Global manufacturing organizations face substantial difficulty in controlling supplier-related costs because procurement decisions are influenced by multiple interconnected and continuously changing variables. Supplier pricing, material costs, logistics expenses, production capacity, quality performance, financial stability, geopolitical exposure, lead-time variability, currency movements, and market conditions can collectively affect the actual cost of sourcing products and components. Conventional procurement analysis may identify historical cost changes, but it can be less effective in

detecting complex relationships across large datasets or in explaining how multiple risk factors interact to create supplier cost exposure. Artificial intelligence offers advanced predictive and analytical capabilities for processing these conditions, yet many AI models operate with limited transparency. A procurement manager may receive a supplier-risk score, cost forecast, sourcing recommendation, or margin prediction without sufficient explanation of why the model produced that particular output. This creates an important managerial problem because supplier decisions often involve financial commitments, contractual consequences, production continuity, negotiation strategies, and profitability targets. A prediction that cannot be adequately interpreted may be difficult to validate, communicate, defend, or incorporate into sourcing decisions. There is therefore a practical and empirical need to determine whether explainable AI capabilities can strengthen supplier cost-risk assessment by making cost-risk drivers visible, prioritizing supplier risks in an understandable manner, and clarifying the relationship between sourcing scenarios and margin outcomes. Existing research has examined artificial intelligence, supply-chain risk, supplier evaluation, procurement analytics, and explainability, but these areas have often been studied separately. Limited quantitative research has integrated explainable supplier cost-risk identification, cost-driver transparency, supplier-risk prioritization, explainable decision support, and margin scenario analytics within a single empirical model focused on manufacturing supply chains. The central problem addressed in this study is therefore the insufficient understanding of how explainable AI capabilities are associated with supplier cost-risk and margin optimization performance. Without such understanding, manufacturing organizations may invest in advanced AI-based procurement systems while remaining uncertain about which explainability capabilities contribute most strongly to cost visibility, supplier-risk control, sourcing decision quality, and margin-oriented performance.

Purpose and Objectives of the Study

The purpose of this study is to quantitatively examine the relationship between Explainable Artificial Intelligence capabilities and Supplier Cost-Risk and Margin Optimization Performance within global manufacturing supply chains. The study specifically seeks to determine whether the ability of AI-supported systems to provide understandable supplier-risk assessments, transparent cost-driver information, interpretable supplier prioritization, and explainable margin scenarios is associated with stronger supplier cost management and margin-related performance. The first objective is to examine the relationship between Explainable Supplier Cost-Risk Identification and Supplier Cost-Risk and Margin Optimization Performance by determining whether understandable identification of supplier cost exposures is associated with improved control of procurement-related economic risks. The second objective is to assess the relationship between AI-Enabled Cost Driver Transparency and Supplier Cost-Risk and Margin Optimization Performance by evaluating whether clearer identification of the factors contributing to supplier costs supports stronger cost visibility and economic decision-making. The third objective is to examine the relationship between Explainable Supplier Risk Prioritization and Decision Support and Supplier Cost-Risk and Margin Optimization Performance, with particular attention to the extent to which transparent supplier ranking and understandable AI recommendations are associated with improved sourcing and risk-management decisions. The fourth objective is to evaluate the relationship between Explainable Margin Scenario Analytics and Supplier Cost-Risk and Margin Optimization Performance by determining whether explainable comparisons of sourcing, cost, and supplier scenarios are associated with stronger margin control. The final objective is to evaluate the combined predictive influence of these explainable AI capabilities on Supplier Cost-Risk and Margin Optimization Performance through a multiple regression model. Through these objectives, the study establishes a structured quantitative framework for examining the role of explainability within supplier cost-risk management rather than treating AI capability only in terms of predictive accuracy. The study therefore concentrates on the managerial usefulness of understandable AI-supported information and its statistical association with supplier-related cost control, sourcing effectiveness, risk visibility, and margin-oriented performance across global manufacturing environments.

Research Hypotheses

The research hypotheses have been developed to test the proposed relationships between the four explainable artificial intelligence capabilities and Supplier Cost-Risk and Margin Optimization Performance. The first hypothesis, H1, states that Explainable Supplier Cost-Risk Identification has a

significant positive relationship with Supplier Cost-Risk and Margin Optimization Performance. This hypothesis assumes that organizations are more capable of controlling supplier-related economic exposure when AI-supported systems not only identify risks but also explain the factors responsible for those risks. The second hypothesis, H2, states that AI-Enabled Cost Driver Transparency has a significant positive relationship with Supplier Cost-Risk and Margin Optimization Performance. This relationship is based on the expectation that transparent information concerning supplier prices, materials, transportation, quality, capacity, financial conditions, and other cost drivers can support more informed procurement and margin-related decisions. The third hypothesis, H3, states that Explainable Supplier Risk Prioritization and Decision Support has a significant positive relationship with Supplier Cost-Risk and Margin Optimization Performance. This hypothesis evaluates whether interpretable risk rankings and understandable AI-generated recommendations are associated with stronger supplier selection, sourcing, negotiation, and risk-response decisions. The fourth hypothesis, H4, states that Explainable Margin Scenario Analytics has a significant positive relationship with Supplier Cost-Risk and Margin Optimization Performance. This hypothesis examines whether clear explanations of alternative sourcing and cost scenarios are associated with improved understanding and management of margin outcomes. The fifth hypothesis, H5, states that Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics collectively have a significant positive influence on Supplier Cost-Risk and Margin Optimization Performance. These hypotheses will enable the study to evaluate both individual relationships and the combined explanatory power of the proposed XAI capabilities through correlation and multiple regression analysis.

Significance of the Research

i. Significance to Global Manufacturing Organizations: The study provides a structured basis for understanding how explainable AI capabilities are associated with supplier cost-risk management and margin-oriented performance. Manufacturing organizations can use the research framework to evaluate whether their AI-supported procurement systems provide sufficient transparency for economic and sourcing decisions.

ii. Significance to Procurement and Strategic Sourcing Managers: The study is significant for procurement professionals because it focuses on supplier cost-risk identification, cost-driver transparency, supplier prioritization, and sourcing decision support. These areas are directly connected with purchasing effectiveness, negotiation preparation, supplier evaluation, and cost control.

iii. Significance to Supply-Chain Managers: Supply-chain professionals can benefit from a clearer understanding of how explainable supplier intelligence is related to broader cost-risk and performance outcomes. The study connects supplier-level analysis with the management of global manufacturing networks.

iv. Significance to Finance and Cost-Control Professionals: The research directly links supplier-related analytical capabilities with margin optimization performance. Finance professionals can therefore use the proposed relationships to understand how explainable procurement intelligence may support cost visibility, budgeting, margin monitoring, and financially informed sourcing decisions.

v. Significance to AI and Analytics Professionals: The study emphasizes that predictive accuracy is not the only relevant characteristic of AI systems used in procurement. It highlights the importance of producing understandable explanations that business users can interpret, evaluate, and incorporate into managerial decisions.

vi. Significance to Suppliers and Supplier-Relationship Management: Transparent supplier-risk assessment can create clearer communication concerning cost drivers, operational weaknesses, and performance expectations. This can support more evidence-based interactions between manufacturers and strategic suppliers.

vii. Significance to Academic Research: The study brings together explainable AI, supplier cost-risk assessment, procurement analytics, and margin optimization within one quantitative framework. It also provides measurable constructs that can be tested through descriptive statistics, correlation analysis, reliability assessment, and multiple regression modeling.

LITERATURE REVIEW

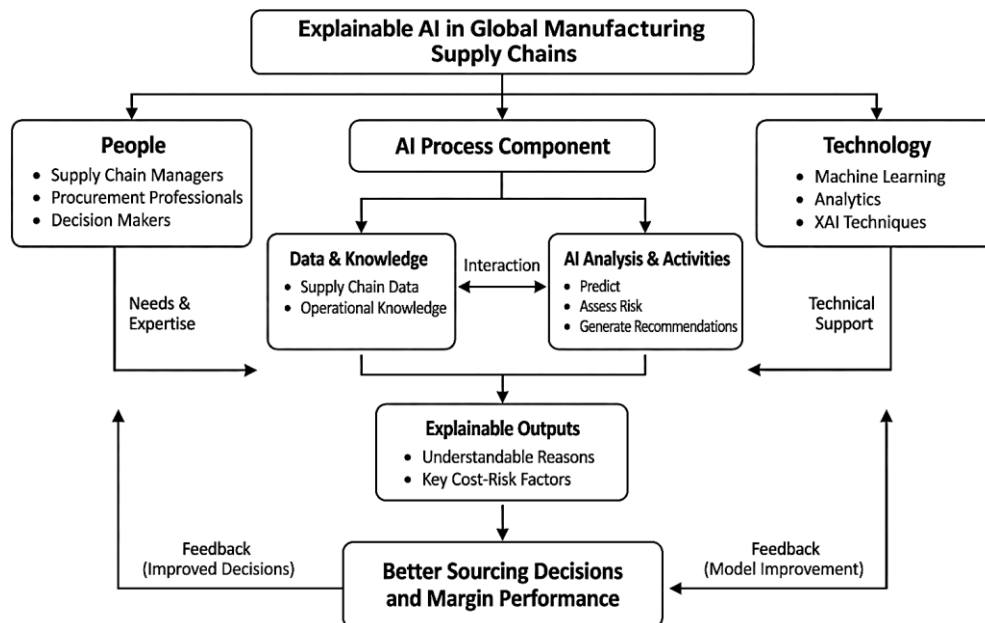
The literature on Explainable Artificial Intelligence for supplier cost-risk assessment and margin optimization is positioned at the intersection of artificial intelligence, supply-chain risk management, procurement analytics, supplier evaluation, decision transparency, and manufacturing performance. Global manufacturing supply chains generate extensive information concerning supplier quotations, purchasing transactions, quality performance, delivery records, production capacity, financial conditions, commodity prices, logistics costs, sourcing locations, contractual arrangements, and market movements. The increasing use of artificial intelligence and machine learning allows organizations to process these diverse datasets more rapidly and identify relationships that may not be evident through conventional supplier evaluation techniques. Within procurement and supply-chain management, AI can support supplier classification, cost prediction, risk identification, sourcing analysis, purchasing decisions, and scenario evaluation. However, the analytical complexity of advanced AI models creates an important concern regarding the interpretability of generated predictions and recommendations. Explainable Artificial Intelligence provides mechanisms through which procurement and supply-chain professionals can understand which factors have influenced an AI-generated supplier assessment and why a specific sourcing or risk-management recommendation has been produced. This capability becomes particularly important when supplier decisions directly affect manufacturing costs, production continuity, purchasing efficiency, and margin performance. Supplier cost-risk itself is multidimensional because it can arise from material prices, transportation expenses, currency movements, quality failures, capacity constraints, financial instability, lead-time variation, geopolitical exposure, and other conditions affecting the total economic cost of sourcing. Therefore, effective supplier cost-risk management requires more than identifying whether a supplier is risky; it requires understanding the sources of that risk and evaluating how alternative managerial responses affect economic outcomes. The literature review consequently examines Explainable Artificial Intelligence in global manufacturing supply chains, explainable supplier cost-risk identification, AI-enabled cost-driver transparency and supplier-risk prioritization, explainable margin scenario analytics, the theoretical basis of information processing in AI-supported supply-chain decisions, and the conceptual relationships linking these capabilities with Supplier Cost-Risk and Margin Optimization Performance.

Explainable Artificial Intelligence in Global Manufacturing Supply Chains

Explainable Artificial Intelligence has become increasingly relevant to global manufacturing supply chains because contemporary supply networks generate complex decisions that combine production, procurement, logistics, inventory, supplier, financial, and market information. Artificial intelligence in supply chain management broadly encompasses computational approaches capable of learning from data, recognizing patterns, supporting predictions, and assisting managers with decisions that are difficult to perform through conventional analytical techniques alone. Early research established that AI could contribute to supply chain activities through expert systems, neural networks, fuzzy logic, intelligent agents, and other knowledge-based approaches capable of supporting planning, forecasting, supplier management, logistics, and coordination decisions (Abdur & Iftikhar, 2021; Min, 2010). In global manufacturing environments, these capabilities are especially relevant because decisions made at one point in the supply network can influence purchasing cost, production continuity, inventory availability, delivery performance, and financial outcomes elsewhere in the system. The growth of machine learning has further strengthened the analytical capacity of manufacturing organizations by allowing systems to identify nonlinear relationships and operational patterns across large volumes of structured and unstructured data. Manufacturing applications have included quality analysis, predictive maintenance, process monitoring, production optimization, fault detection, and decision support, demonstrating the broader capacity of machine learning to convert manufacturing data into operationally useful knowledge (Hasan & Adnan, 2022; Wuest et al., 2016). However, greater predictive sophistication also increases the importance of understanding how AI-supported decisions are produced. A manufacturing supply chain manager who receives a supplier-risk classification, procurement recommendation, cost estimate, or sourcing priority requires more than an output value when the decision affects contracts, production schedules, supplier relationships, and margins. XAI therefore extends conventional AI by emphasizing the interpretability, traceability, and human comprehensibility of algorithmic outputs within operational decision environments. This requirement

becomes stronger when supplier networks span multiple countries because managers must reconcile algorithmic evidence with different commercial conditions, operational dependencies, and cost structures simultaneously.

Figure 2: Explainable Artificial Intelligence Process Framework for Global Manufacturing Supply-Chain Decision-Making



The manufacturing context gives explainability particular importance because smart manufacturing systems increasingly connect physical operations with digital information, automated analysis, and distributed decision processes. Smart manufacturing is characterized by the integration of data, computational intelligence, automation, sensing, connectivity, and advanced analytical technologies across production systems, creating an environment in which operational decisions can be generated from continuously collected information (Kusiak, 2018; Mahbubul et al., 2022). When manufacturing is embedded within an international supply chain, the analytical environment expands beyond the factory to include suppliers, procurement categories, transport networks, external markets, customer requirements, and financial flows. AI-supported supply chain systems can therefore evaluate large combinations of variables when forecasting demand, scheduling operations, selecting suppliers, monitoring inventory, evaluating sourcing alternatives, or identifying risk conditions. Exploratory evidence from operations and supply chain settings shows that AI can support value creation through applications connected with planning, optimization, logistics, forecasting, and other business processes, while its organizational use depends on how effectively AI solutions are aligned with actual operational requirements (Helo & Hao, 2022; Mashfiqur & Md, 2022). For supplier cost-risk assessment, this alignment requires models to produce information that purchasing and supply chain professionals can interpret in relation to concrete business variables. A model may predict that a supplier presents elevated cost risk, yet the prediction becomes more decision-relevant when managers can determine whether the assessment is associated with material-price volatility, poor delivery reliability, capacity limitations, unfavorable quality performance, logistics exposure, financial weakness, or another measurable factor. Explainability consequently connects algorithmic prediction with managerial reasoning. Within global manufacturing supply chains, this connection is important because the same AI output may be interpreted differently according to product criticality, sourcing geography, contractual arrangements, substitution possibilities, supplier concentration, and the financial importance of the purchased category. XAI therefore functions as an interface between complex computational analysis and context-sensitive supply chain decision-making across functions and regions.

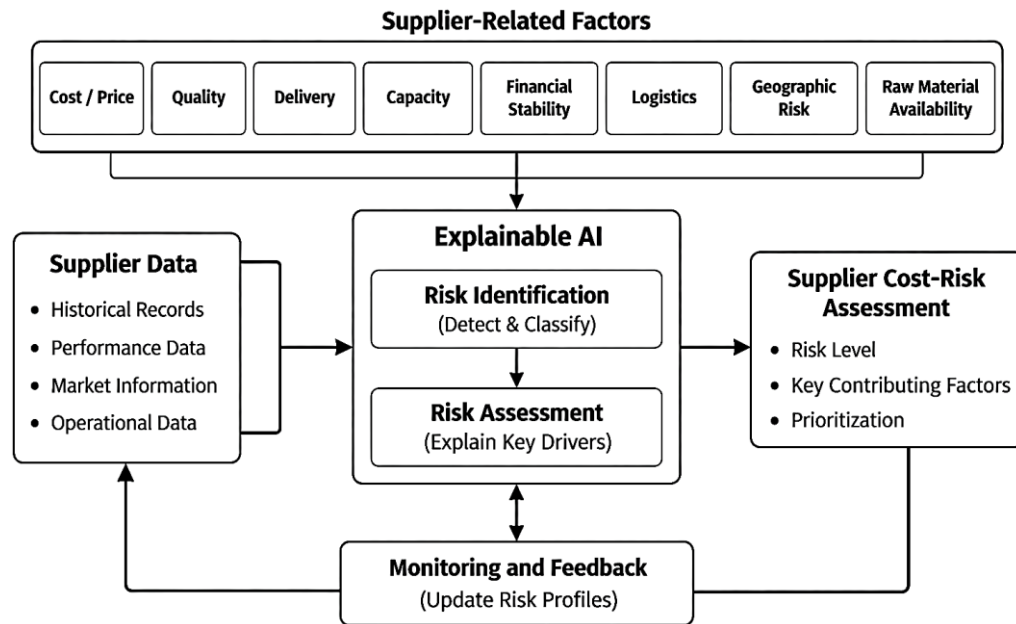
Explainability also changes the way artificial intelligence can be evaluated within manufacturing supply chains because a technically accurate prediction does not necessarily provide sufficient information for accountable managerial action. Interpretability in machine learning concerns the extent to which humans can understand the behavior of a model and the reasons underlying its predictions, while explanation methods attempt to present complex model behavior in forms that users can meaningfully examine (Carvalho et al., 2019; Ashfaq & Mohammad, 2022). This distinction is central to supplier cost-risk assessment because procurement decisions frequently require managers to justify supplier rankings, sourcing adjustments, negotiation positions, and cost-control measures to other organizational stakeholders. In such settings, XAI can support several levels of understanding. Global explanations can reveal the variables that generally influence a model across the full supplier dataset, whereas local explanations can clarify why a particular supplier, transaction, or sourcing scenario has received a specific prediction. Feature-level explanations can indicate the relative contribution of cost, quality, delivery, capacity, logistics, or financial variables, while rule-based or example-based explanations can provide more intuitive representations of algorithmic reasoning. These forms of transparency are closely aligned with the information requirements of manufacturing procurement because supplier decisions combine quantitative evidence with managerial judgment, contractual knowledge, operational constraints, and strategic considerations. For the present study, Explainable Artificial Intelligence in global manufacturing supply chains is therefore treated as more than the technical use of machine learning. It represents an organizationally usable form of AI-supported intelligence in which supplier-related predictions and recommendations can be understood, evaluated, and connected with identifiable cost and risk factors. This perspective provides the analytical foundation for examining Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics as distinct but related capabilities within manufacturing supply chain decision environments during consequential sourcing and margin decisions.

Explainable Supplier Cost-Risk Identification and Assessment

Supplier cost-risk identification represents the systematic process through which manufacturing organizations recognize, classify, and evaluate supplier-related conditions that can increase procurement costs, disturb production economics, or weaken expected margins. In global manufacturing supply chains, cost exposure rarely originates from purchase price alone because supplier performance is influenced by quality consistency, delivery reliability, capacity utilization, raw-material availability, transportation conditions, financial stability, lead-time variability, geographic concentration, and dependence on critical components. These factors can interact and create cost consequences that are difficult to detect through conventional supplier scorecards based on isolated performance indicators. Effective supplier-risk identification therefore requires an analytical structure capable of linking observable supplier characteristics with their potential economic consequences. Research conducted within the automotive industry demonstrated that supplier and part-specific risks can be evaluated through multicriteria risk indices and monitored over time, allowing organizations to identify movement toward higher levels of supply-base exposure rather than relying exclusively on static evaluations (Blackhurst et al., 2008; Sadia & Mostari, 2022). This perspective is highly relevant to cost-risk assessment because an adverse change in supplier reliability, quality, capacity, or delivery performance can generate additional costs through production interruptions, emergency transportation, inventory adjustments, rework, substitute sourcing, or contractual renegotiation. Supplier assessment should consequently incorporate both direct economic factors and operational risk factors that may eventually translate into financial consequences. Multicriteria supplier-selection research has similarly demonstrated that minimizing purchasing cost without adequately accounting for supplier risk can create a sourcing structure that is economically vulnerable to disruption. Risk-adjusted supplier-selection models have therefore incorporated price, lead time, quality-related risk, and disruption exposure simultaneously when evaluating global suppliers and allocating orders among them (Ravindran et al., 2010; Shaiful et al., 2022). From an explainable AI perspective, these findings establish an important foundation because supplier cost-risk identification requires AI systems to reveal which supplier characteristics generate elevated risk assessments. An explainable assessment should allow managers to distinguish whether a supplier's risk level is primarily driven by

price volatility, delivery performance, quality deficiencies, capacity constraints, financial weakness, logistics exposure, or combinations of these factors, thereby connecting algorithmic risk scores with identifiable business conditions.

Figure 3: Explainable AI Framework for Supplier Cost-Risk Identification, Assessment, and Monitoring



The assessment of supplier cost-risk also requires methods capable of representing multiple risk dimensions without concealing the factors responsible for the final supplier classification. Supplier evaluation is inherently a multicriteria problem because procurement professionals must compare organizations whose strengths and weaknesses occur across different performance dimensions, and the relative importance of those dimensions may vary according to product criticality, sourcing strategy, manufacturing requirements, and financial exposure. Failure Mode and Effects Analysis provides one structured approach for identifying potential sources of supplier failure, although conventional applications can become limited when the severity, occurrence, and detectability of risk are difficult to prioritize consistently. An integrated supplier-selection model using modified Failure Mode and Effects Analysis and the Analytic Hierarchy Process demonstrated how supplier risk criteria could be organized and weighted to distinguish suppliers according to different dimensions of supply-chain exposure within an industrial case environment (Chen & Wu, 2013; Chandra, 2025). Such structured assessment is conceptually compatible with XAI because both approaches emphasize decomposition of an overall result into understandable contributing factors. Explainable Supplier Cost-Risk Identification extends this principle by allowing sophisticated AI models to analyze broader datasets while retaining visibility into the drivers underlying each prediction. Instead of presenting procurement managers with an unexplained probability of supplier failure or a single composite risk score, an explainable system can indicate the relative contribution of variables such as historical price increases, late delivery frequency, quality rejection rates, supplier utilization, transportation distance, financial indicators, geopolitical exposure, or commodity dependency. Risk assessment also needs to accommodate uncertainty because supplier conditions cannot always be expressed through precise numerical values. An integrated fuzzy framework for supply-chain risk assessment demonstrated how expert knowledge, historical information, risk likelihood, impact, predictability, causal relationships, and fuzzy inference could be combined to generate structured risk scores within a high-end server manufacturing environment (Mohammad, 2023; Aqlan & Lam, 2015). This type of assessment illustrates the importance of retaining contextual information surrounding risk estimates. For XAI-supported supplier analysis, explainability therefore involves not only identifying a risk level but also clarifying the evidence, variables, interactions, and uncertainty responsible for that level so that

purchasing professionals can evaluate whether the generated assessment corresponds with operational knowledge.

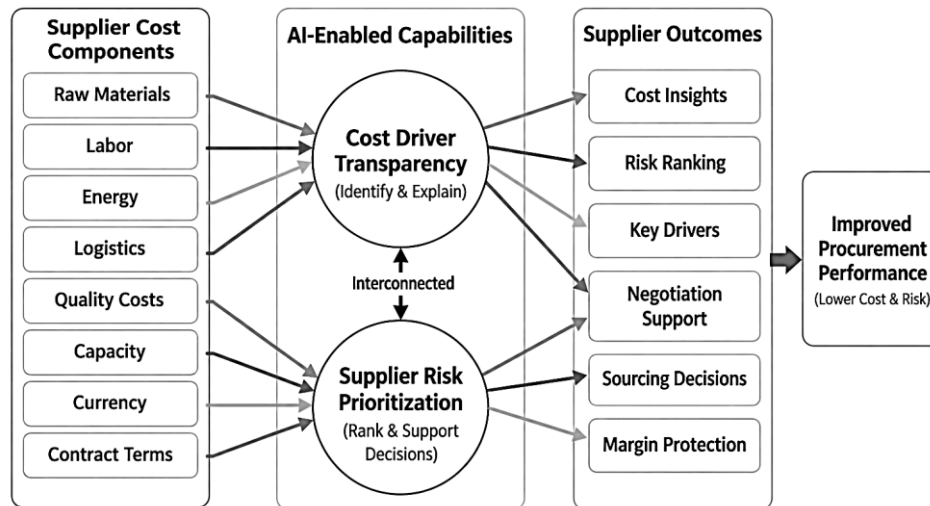
Explainable supplier cost-risk assessment becomes particularly valuable when manufacturing organizations manage large supplier portfolios in which risk patterns differ considerably among vendors, categories, locations, and purchased components. A supplier may exhibit strong cost competitiveness while carrying elevated financial or capacity risk, whereas another may provide stable delivery performance while remaining exposed to commodity-price fluctuations or geographic concentration. Treating such suppliers through a uniform risk score can hide economically meaningful differences and reduce the usefulness of analytical outputs for procurement decision-making. Supplier-risk assessment should therefore support both differentiation and prioritization by identifying groups of suppliers with similar exposure profiles and showing the criteria that distinguish one risk category from another. Empirical research in the heavy-machinery sector assessed suppliers across 17 qualitative and quantitative risk types, weighted the relevant criteria through the Best-Worst Method, extracted underlying risk factors, and subsequently applied K-means clustering to classify suppliers into groups characterized by different levels of risk exposure (Kara & Firat, 2018; Pervaz, 2025). The methodological logic of such classification is directly relevant to Explainable Supplier Cost-Risk Identification because AI-supported systems can perform similar differentiation across substantially larger and more complex supplier datasets. However, the practical informational value of those classifications depends on whether users can understand why individual suppliers occupy particular risk categories. In the context of the present research, Explainable Supplier Cost-Risk Identification therefore encompasses the ability of AI-supported systems to detect supplier-related cost exposure, separate important risks from less consequential signals, identify the variables associated with each assessment, and communicate those relationships in a form understandable to procurement and supply-chain professionals. Cost-risk assessment consequently includes direct supplier-price considerations as well as operational conditions capable of generating indirect economic consequences, including quality failures, delivery instability, capacity limitations, sourcing concentration, financial deterioration, and logistics uncertainty. This construct treats explainability as an integral characteristic of supplier-risk intelligence because purchasing decisions require managers to connect predicted risk with observable supplier conditions before determining sourcing priorities, negotiation positions, order allocations, or other cost-sensitive actions.

AI-Enabled Cost Driver Transparency and Supplier Risk Prioritization

AI-enabled cost driver transparency refers to the capacity of analytical systems to identify, separate, and communicate the underlying elements that determine supplier-related costs, while supplier risk prioritization refers to the systematic ranking of suppliers or risk conditions according to their relative economic and operational importance. These two capabilities are closely connected in global manufacturing because procurement managers cannot prioritize supplier risk effectively when the sources of cost exposure remain hidden within aggregated purchase prices. Supplier costs can reflect raw materials, labor, energy, logistics, tooling, quality losses, capacity constraints, currency movements, contractual conditions, and supplier margins, meaning that identical quoted prices can represent substantially different underlying risk structures. Evidence from international manufacturing operations has shown that cost management represents a major motive for supplier development and that manufacturers evaluate whether suppliers possess sufficient improvement potential before committing organizational resources to local sourcing and development initiatives (Adnan & Iftekhar, 2023; Wouters et al., 2007). This relationship indicates that supplier cost information becomes strategically valuable when it enables purchasing organizations to distinguish controllable supplier inefficiencies from structural or market-driven cost conditions. Open-book accounting research has similarly demonstrated that the nature and extent of cost-data disclosure vary according to the purchasing strategy adopted by the buying organization. In transactional purchasing relationships, disclosed supplier cost information is frequently directed toward purchase-price reduction, whereas more relational purchasing arrangements can employ broader cost information to facilitate collaborative cost reduction and joint product-development activities (Agndal & Nilsson, 2010; Sheak & Tahmedur, 2023). These findings establish an important basis for AI-enabled cost driver transparency because a sophisticated procurement system should extend beyond displaying a

predicted total cost, supplier score, or percentage of anticipated cost escalation. An explainable analytical system should identify which cost components have contributed to estimated supplier exposure, indicate their comparative importance, and differentiate temporary market movements from persistent structural cost conditions. Such transparency allows procurement professionals to interpret differences among suppliers, understand the sources of predicted cost movements, and connect analytical findings with negotiation, sourcing, budgeting, and supplier-management decisions.

Figure 4: AI-Enabled Cost Driver Transparency and Explainable Supplier Risk Prioritization Framework



Cost-driver transparency becomes particularly valuable when it is integrated with supplier evaluation because procurement decisions require trade-offs among price, quality, delivery, information sharing, transportation, capacity, and risk rather than the minimization of one isolated cost indicator. Transparent supplier-cost information can support evaluation and negotiation by clarifying which components of a supplier's price are economically justified and which components may indicate inefficiency, volatility, or avoidable exposure. Research concerning open-book accounting in buyer-supplier relationships has shown that the usefulness of disclosed cost information depends on sourcing strategy, the nature of the information exchanged, and the incentives provided to participating suppliers. Action research involving an Italian manufacturer and nineteen suppliers demonstrated that supplier selection for open-book collaboration should consider how shared cost data will be used and how suppliers can be motivated to disclose information without exposing themselves to inappropriate utilization of commercially sensitive information (Kaium, 2023; Romano & Formentini, 2012). This evidence highlights an important requirement for AI-enabled cost transparency because information should not merely be available but should be organized according to the procurement decision it is intended to support. Machine-learning techniques can strengthen this analytical process by determining which supplier attributes possess the greatest discriminatory value across large and heterogeneous datasets. A Random Forest-based decision-support model developed for supplier-selection criteria identified quality, on-time delivery, material price, and information sharing among the most critical factors, while transportation cost was also identified as an important consideration in supplier evaluation (Ali et al., 2023; Pervaz, 2023). These findings are closely aligned with supplier cost-risk prioritization because supplier-related economic exposure is distributed across financial and operational variables rather than being captured completely by quoted purchase price. Within an explainable AI system, feature-importance measures and similar transparent indicators can demonstrate why particular criteria receive greater analytical weight, how supplier rankings are established, and which cost drivers contribute most strongly to differences among suppliers. This produces a traceable progression from supplier data to cost interpretation and from cost interpretation to risk prioritization, enabling decision makers to compare suppliers through economically meaningful

and operationally defensible criteria.

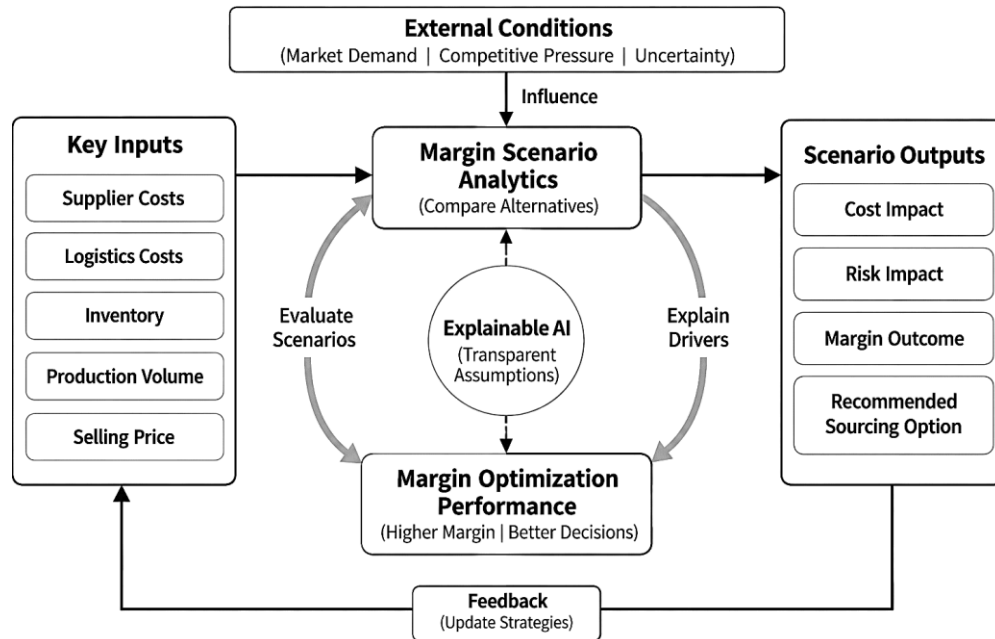
Supplier risk prioritization requires an analytical system to move beyond identifying individual risk indicators and establish a transparent order of managerial attention among competing suppliers, sourcing alternatives, and cost exposures. In a global manufacturing network, procurement teams may evaluate hundreds of suppliers simultaneously, making conventional comparison increasingly difficult when individual suppliers differ across price behavior, quality, delivery reliability, production capacity, financial strength, geographic exposure, information-sharing capability, and strategic importance. Artificial intelligence can reduce this complexity by learning from historical supplier information and generating classifications, priorities, or rankings, but the usefulness of those results depends on whether procurement professionals can understand how a ranking has been produced. Recent research has directly addressed this requirement through a hybrid framework integrating interpretable machine-learning techniques with multi-criteria decision-making methods for supplier selection. The framework was evaluated through real-world supplier-selection cases in oil, gas, and aerospace manufacturing and demonstrated that explainable supplier-selection approaches can achieve performance comparable to machine-learning-only approaches while providing end-to-end explainability and retaining decision structures that are more familiar to supply-chain stakeholders (Abdulla & Baryannis, 2024; Badrul & Mominul, 2023). This evidence is directly relevant to Explainable Supplier Risk Prioritization and Decision Support because effective supplier prioritization requires both analytical capability and managerial traceability. A supplier positioned at the highest level of a cost-risk ranking should therefore be accompanied by understandable evidence concerning the variables responsible for that position, the comparative influence of relevant criteria, and the economic significance of the identified exposure. AI-enabled cost-driver transparency can support this requirement by clarifying whether supplier priority has resulted primarily from increasing material prices, transportation expenses, recurring quality losses, delivery unreliability, capacity shortages, or combinations of several supplier conditions. When these relationships remain visible, supplier prioritization becomes more than an automated ranking exercise and instead operates as a structured decision-support process through which procurement professionals can connect algorithmic assessments with negotiation priorities, sourcing reviews, supplier-development activities, order-allocation decisions, and margin-sensitive purchasing choices. In the present study, AI-Enabled Cost Driver Transparency and Explainable Supplier Risk Prioritization and Decision Support are therefore treated as complementary capabilities that transform complex supplier information into understandable, comparable, and economically relevant intelligence within global manufacturing supply chains.

Explainable Margin Scenario Analytics and Margin Optimization Performance

Explainable Margin Scenario Analytics refers to the use of analytical systems that evaluate alternative cost, sourcing, pricing, demand, and operational conditions while making the assumptions and drivers behind each estimated margin outcome understandable to decision makers. In global manufacturing supply chains, margin performance is influenced by supplier prices, material costs, logistics expenses, inventory requirements, production volumes, service levels, market demand, and selling-price conditions. Scenario analytics is valuable because these variables rarely remain isolated when managers compare sourcing alternatives. A lower supplier price, for example, may be accompanied by longer lead times, higher transportation expense, greater disruption exposure, or additional inventory requirements that change the total economic outcome. Prescriptive analytics provides an important analytical foundation for this process because it extends descriptive and predictive analysis toward the identification of decision alternatives that can improve organizational performance. A systematic review of prescriptive analytics described it as an approach that integrates predictive information with optimization and decision models to identify appropriate courses of action rather than limiting analysis to the prediction of possible outcomes (Lepenioti et al., 2020; Rakib & Towhidul, 2023). In supply-chain settings, scenario-based optimization similarly allows managers to represent uncertainty explicitly and compare the economic performance of alternative network configurations. A scenario-based strategic supply-chain study in the forest biorefinery context incorporated market uncertainty through multiple scenarios, evaluated alternative supply-chain designs, and calculated the profitability of those alternatives under different market conditions (Mansoornejad et al., 2013; Nishat, 2023). Such analytical

logic is directly relevant to manufacturing margin management because it shifts decision making from a single expected-cost estimate toward comparative evaluation of how supplier, market, and operational conditions affect economic performance. When explainability is incorporated, managers can examine not only which scenario produces the preferred margin outcome but also which cost components and assumptions are responsible for differences among alternatives, making scenario analysis more transparent for procurement and supply-chain decisions.

Figure 5: Explainable Margin Scenario Analytics Framework for Supplier Risk and Margin Optimization Performance



Margin optimization in manufacturing supply chains requires coordinated consideration of sourcing cost, supplier reliability, market conditions, and the economic consequences of alternative decisions. Procurement managers often face a trade-off between a supplier offering a lower acquisition price with greater uncertainty and another supplier providing more reliable supply at a higher cost. The economically preferable option can change when disruption probability, demand conditions, competitive pressure, inventory requirements, or selling prices are altered. Research on pricing and sourcing under disruption risk has demonstrated that sourcing structure and pricing decisions can be analyzed jointly rather than as independent choices. A study of competing supply chains showed that the relative attractiveness of reliable and unreliable suppliers depended on procurement-cost advantage, market potential, and disruption risk, and that price adjustment could be combined with sourcing decisions to improve profitability under particular conditions (Kumar et al., 2018; Feroz, 2023). This relationship demonstrates why explainable margin scenario analytics should expose the assumptions behind modeled alternatives, since a recommended sourcing strategy may produce a favorable margin only under a specific configuration of cost and risk conditions. Data-driven decision-support systems provide another mechanism for evaluating such configurations. A simulation-optimization decision-support system developed for sourcing and inventory management combined an artificial neural network with a genetic algorithm and incorporated uncertainty in raw-material demand, price, supply lead time, service levels, and supplier availability. Its implementation in a manufacturing-related case generated recommended suppliers and order quantities while substantially reducing purchasing and inventory-related costs (Tahmedur & Rifat, 2023; Teerasoponpong & Sopadang, 2022). For global manufacturers, these findings show that margin-oriented analytics can connect supplier selection with order allocation, inventory, and uncertainty rather than assessing supplier prices separately. Explainability strengthens this process by showing

how changes in purchase price, supplier availability, lead time, inventory exposure, and demand conditions alter the margin associated with each scenario, allowing managers to understand the economic reasoning behind recommended sourcing configurations.

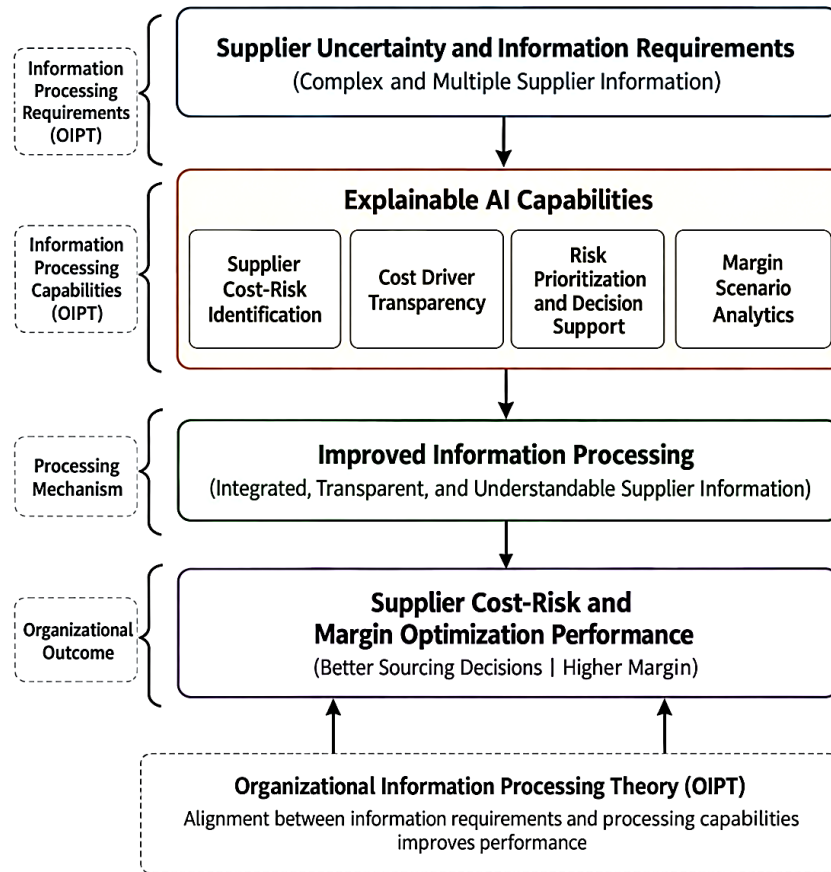
Explainable margin scenario analytics also requires a balanced representation of financial performance because a margin-maximizing decision cannot be interpreted appropriately when the analytical model ignores service, capacity, or operating constraints. Manufacturing supply chains normally operate within competing objectives: minimizing procurement and logistics costs, maintaining product availability, satisfying demand, avoiding excessive inventory, protecting production continuity, and preserving acceptable margins. Scenario analysis can make these trade-offs visible by allowing decision makers to compare a baseline configuration with alternative supplier, cost, demand, and network conditions before selecting an economically preferred response. Scenario-based optimization research has demonstrated this approach by integrating deterministic and scenario-based analysis to examine supply-chain performance under uncertain demand. In a pharmaceutical supply-chain case, the model incorporated establishment, handling, transportation, and demand-satisfaction factors and evaluated the trade-off between total supply-chain cost and customer-service level across alternative conditions ([Asheke, 2024](#); [Gobachew & Haasis, 2023](#)). This form of analysis is relevant to global manufacturing because margin optimization depends on understanding how savings in one cost category may be offset by additional expenses or performance losses elsewhere in the system. Within an explainable AI environment, scenario outputs can therefore be structured so that managers can trace changes in projected margin back to identifiable drivers, including supplier price, order allocation, logistics cost, inventory requirement, demand level, service constraint, and disruption exposure. Explainable Margin Scenario Analytics in the present study represents this capacity to generate, compare, and interpret alternative economic conditions rather than merely produce an unexplained optimal solution. Its connection with Supplier Cost-Risk and Margin Optimization Performance rests on the ability of manufacturing organizations to use transparent scenario information when evaluating supplier choices and cost responses. When a model indicates that one sourcing configuration provides a stronger margin outcome than another, its analytical value lies in displaying the contribution of relevant variables and the conditions under which that outcome occurs, keeping margin analysis connected with supplier risk, operational feasibility, and procurement economics.

Organizational Information Processing Theory

Organizational Information Processing Theory (OIPT) provides an appropriate theoretical foundation for explaining why explainable artificial intelligence can strengthen supplier cost-risk assessment and margin optimization in global manufacturing supply chains. OIPT views organizations as information-processing systems whose effectiveness depends on the alignment between the amount and complexity of information required by uncertain tasks and the capability available to collect, interpret, integrate, and use that information. In global manufacturing, supplier-related decisions create substantial information-processing requirements because procurement managers must interpret price movements, material costs, quality records, delivery performance, supplier capacity, financial conditions, logistics exposure, contractual constraints, and market volatility at the same time. When these signals become numerous, interdependent, or ambiguous, conventional reporting and managerial judgment may not provide sufficient processing capacity. Research applying the information-processing view to interorganizational relationships has shown that organizational performance is influenced by the fit between information-processing needs and information-processing capabilities, particularly where supply-chain relationships require coordination across organizational boundaries ([Ashrafuzzaman, 2024](#); [Premkumar et al., 2005](#)). This theoretical logic is directly applicable to supplier cost-risk because uncertainty increases the quantity of information that procurement functions must interpret before committing to sourcing decisions. Supply-chain integration can increase access to supplier and customer information, but the value of such access depends on whether organizations possess planning capabilities and technology-enabled systems that can convert dispersed information into comprehensive decisions ([Kaium, 2024](#); [Srinivasan & Swink, 2015](#)). Within the present study, XAI is positioned as an information-processing capability rather than merely an automation technology. Explainable Supplier Cost-Risk Identification reduces ambiguity surrounding risk signals; AI-Enabled Cost Driver Transparency organizes complex cost information; Explainable Supplier Risk Prioritization

and Decision Support converts heterogeneous supplier evidence into understandable priorities; and Explainable Margin Scenario Analytics translates alternative sourcing conditions into interpretable economic outcomes. OIPT therefore provides a coherent basis for linking supplier uncertainty, explainable analytical capacity, and margin-related decision performance operationally.

Figure 6: Organizational Information Processing Theory Framework for Explainable AI-Enabled Supplier Cost-Risk Assessment and Margin Optimization



The relevance of OIPT becomes stronger when supplier cost-risk is considered as an information-processing problem involving both cross-functional coordination and external uncertainty. Procurement decisions are not isolated within purchasing because supplier choices influence logistics, inventory, production scheduling, quality management, finance, and customer-service outcomes. Information concerning supplier price, delivery, capacity, transportation, and quality consequently needs to move across functional boundaries before managers can determine the economic importance of a supplier risk. Research using an information-processing perspective has shown that purchasing-logistics integration can influence supplier performance, with mutual responsibility and integrative efforts helping firms process information related to supplier delivery and price outcomes effectively (Ashenbaum & Maltz, 2017; Kanti, 2024). This relationship is particularly important here because supplier cost-risk may remain concealed when purchasing evaluates quoted price independently of logistics expenses, delivery instability, inventory consequences, or production disruption. XAI can increase information-processing capability by combining these signals and explaining their relative contribution to an assessment. Supply-chain analytics research grounded in OIPT has similarly demonstrated that demand and supply visibility are foundational resources for analytics capability and that analytics becomes more valuable when organizations possess the flexibility required to act on generated insights, especially under volatile market conditions (Srinivasan & Swink, 2018; Feroz, 2024). Explainability adds a managerial layer to this capability because visibility alone does not ensure that managers understand why a model has classified a supplier as high risk or why one sourcing scenario

is expected to protect margin more effectively than another. In OIPT terms, the four independent variables in this study represent complementary mechanisms for expanding the organization's capacity to process supplier-related information. Their contribution is expected to become observable through Supplier Cost-Risk and Margin Optimization Performance, which captures whether information has been converted into stronger cost visibility, risk control, sourcing decisions, and margin-oriented management rather than remaining as unprocessed or opaque analytical output.

The OIPT-based framework also clarifies why explainable AI capabilities should be evaluated collectively rather than as isolated technical features. Global supply chains operate under supply, infrastructure, market, and disruption conditions that can substantially increase organizational information requirements, making performance dependent on the capacity to interpret changing conditions and coordinate appropriate responses. Empirical research grounded in organizational information-processing theorization has shown that supply-chain resilience creates greater performance value under elevated disruption conditions, reinforcing the principle that information-processing and response capabilities become particularly important when uncertainty intensifies (Uddin & Risha, 2024; Wong et al., 2020). In the present study, supplier cost volatility, changing cost drivers, uncertain supplier performance, and alternative sourcing outcomes create the information-processing requirements, while the four XAI constructs represent the analytical capabilities through which these requirements are addressed. The theoretical relationship is tested quantitatively through the study-wide multiple regression model:

$$SCMOP_i = \beta_0 + \beta_1 ESCRI_i + \beta_2 AICDT_i + \beta_3 ESRPDS_i + \beta_4 EMSA_i + \varepsilon_i$$

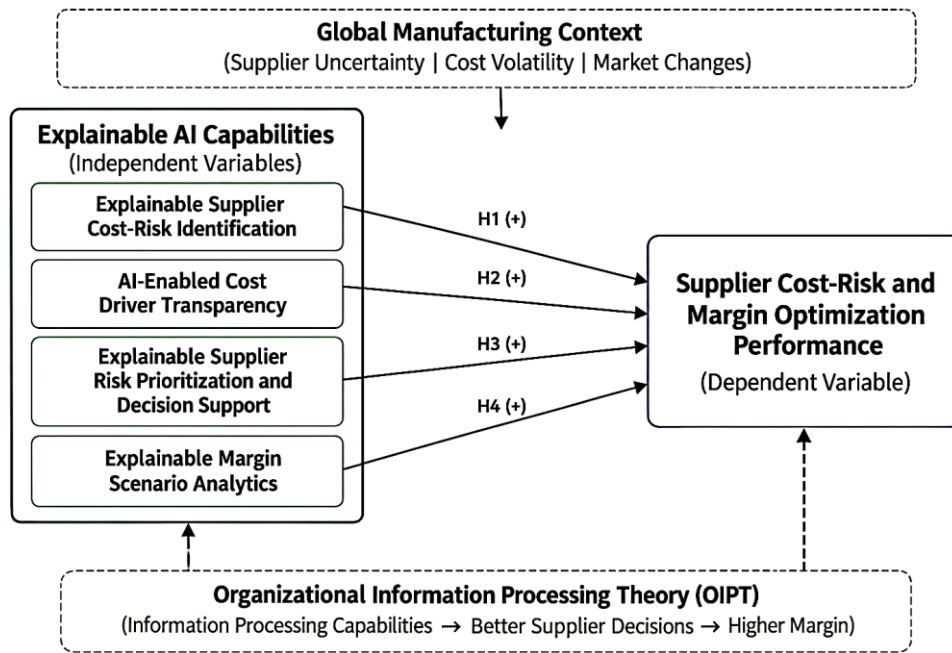
In this equation, SCMOP represents Supplier Cost-Risk and Margin Optimization Performance; ESCRI represents Explainable Supplier Cost-Risk Identification; AICDT represents AI-Enabled Cost Driver Transparency; ESRPDS represents Explainable Supplier Risk Prioritization and Decision Support; EMSA represents Explainable Margin Scenario Analytics; β_0 represents the intercept; β_1 through β_4 represent the estimated effects of the explanatory constructs; and ε_i represents the unexplained error component. This equation is appropriate for the entire empirical study because it directly translates the OIPT proposition into measurable relationships between information-processing capabilities and organizational decision performance. Positive and statistically significant coefficients would indicate that stronger explainable AI capabilities are associated with stronger supplier cost-risk and margin optimization performance, while R^2 will indicate the proportion of variation in SCMOP collectively explained by the four OIPT-aligned capabilities. The model therefore preserves the theory's central emphasis on matching organizational information-processing capacity with the complexity of economically consequential supplier decisions.

Conceptual Framework

The conceptual framework of this study integrates four explainable artificial intelligence capabilities as antecedents of Supplier Cost-Risk and Margin Optimization Performance in global manufacturing supply chains. A conceptual framework is useful because it converts the broad theoretical logic of information processing into observable relationships that can be measured through survey items and tested statistically. In this study, Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics are treated as distinct but complementary information-processing capabilities. Each construct addresses a different stage of supplier-related decision making, beginning with the identification of emerging cost exposure, continuing through interpretation of the underlying cost drivers, extending to the prioritization of supplier risks, and ending with the evaluation of alternative sourcing and margin scenarios. Business analytics research has demonstrated that analytical capabilities embedded in planning, sourcing, production, and delivery processes can contribute to improved supply chain performance by converting dispersed operational data into information that supports coordinated decisions (Jahanara, 2025; Trkman et al., 2010). This relationship is important for the present model because supplier cost-risk data have limited managerial value when they remain fragmented across purchasing, quality, logistics, finance, and production systems. Predictive analytics research in supply chain management has also emphasized the managerial value of transforming large datasets into decision-relevant insight while identifying organizational capabilities and analytical skills as important conditions for effective use of such information (Jannatul, 2025; Schoenherr & Speier-Pero,

2015). Accordingly, the conceptual framework does not treat XAI as a single technological variable. It decomposes explainable analytical capability into four measurable dimensions that collectively describe how manufacturers can detect supplier-related economic exposure, understand its causes, determine which supplier conditions deserve priority, and evaluate the margin consequences associated with different sourcing responses. This structure provides a direct conceptual connection between explainability and economically meaningful supplier management outcomes.

Figure 7: Conceptual Framework Linking Explainable AI Capabilities to Supplier Cost-Risk and Margin Optimization Performance



The first two paths in the framework focus on visibility and interpretation. Explainable Supplier Cost-Risk Identification is expected to relate positively to Supplier Cost-Risk and Margin Optimization Performance because early recognition of cost exposure can support purchasing teams in identifying suppliers, categories, or conditions that require managerial attention. The value of identification becomes stronger when the model explains why an exposure has been detected, since procurement professionals can compare algorithmic results with supplier history, contract conditions, production requirements, and operational knowledge. AI-Enabled Cost Driver Transparency represents the second pathway and concerns the ability to reveal the specific factors responsible for changes in supplier-related economic exposure. Research has shown that supply chain analytics capabilities can increase operational supply chain transparency by improving the visibility of activities across source, make, and deliver functions, establishing a connection between analytical capability and the organizational ability to observe and interpret supply conditions (Mostari, 2025; Zhu et al., 2018). Related evidence from manufacturing firms has demonstrated that interorganizational information-system visibility is positively associated with supply chain performance, reinforcing the importance of information across supply relationships (Lee et al., 2014; Mashiat, 2025). The third pathway, Explainable Supplier Risk Prioritization and Decision Support, extends visibility into action-oriented assessment by ranking supplier conditions according to their relative importance and presenting understandable reasons for the ranking. The fourth pathway, Explainable Margin Scenario Analytics, connects supplier intelligence with economic evaluation by comparing alternative combinations of supplier price, sourcing allocation, logistics cost, capacity, demand, inventory, and other relevant conditions. These four relationships reflect a sequential but nondependent conceptual logic: manufacturers can obtain value from each capability independently, while their combined presence provides a broader analytical structure for managing supplier-related cost uncertainty. The dependent construct, Supplier Cost-Risk and Margin

Optimization Performance, captures the resulting effectiveness of cost visibility, risk control, sourcing decision quality, procurement cost management, and margin-oriented performance.

The empirical structure of the conceptual framework translates these proposed relationships into a quantitative model that is compatible with the cross-sectional, case-study-based design of this research. Evidence from supply chain analytics research indicates that the assimilation of big-data and predictive-analytics capabilities is positively associated with supply chain and organizational performance, supporting the broader proposition that analytical capability can become performance-relevant when it is embedded in organizational processes (Gunasekaran et al., 2017). Building on this logic, the present study specifies Supplier Cost-Risk and Margin Optimization Performance as the dependent variable and the four XAI capabilities as independent variables. The relationship is expressed as:

$$SCMOP_i = \beta_0 + \beta_1 ESCRI_i + \beta_2 AICDT_i + \beta_3 ESRPDS_i + \beta_4 EMSA_i + \varepsilon_i$$

where SCMOP denotes Supplier Cost-Risk and Margin Optimization Performance, ESCRI denotes Explainable Supplier Cost-Risk Identification, AICDT denotes AI-Enabled Cost Driver Transparency, ESRPDS denotes Explainable Supplier Risk Prioritization and Decision Support, and EMSA denotes Explainable Margin Scenario Analytics. The coefficients β_1 through β_4 represent the estimated individual contribution of each explanatory capability, while ε_i represents variation not explained by the model. H1 proposes a positive relationship between ESCRI and SCMOP, H2 between AICDT and SCMOP, H3 between ESRPDS and SCMOP, and H4 between EMSA and SCMOP. H5 evaluates whether the four capabilities collectively explain significant variation in SCMOP. Pearson correlation analysis will assess the direction and strength of the bivariate relationships, while multiple regression will estimate their simultaneous effects. Positive coefficients are expected because each construct represents an enhanced capacity to convert complex supplier information into understandable evidence that can strengthen risk evaluation, cost visibility, decision quality, and margin-oriented managerial control. The model therefore operationalizes the conceptual framework through measurable constructs that connect explainable AI-supported information processing with supplier cost control and margin-oriented performance.

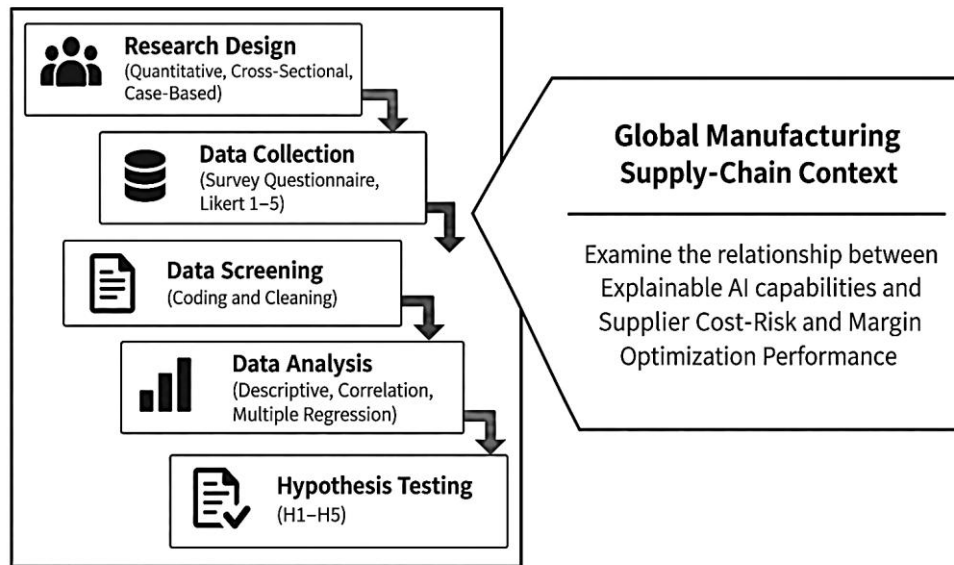
METHODS

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the relationship between Explainable Artificial Intelligence capabilities and Supplier Cost-Risk and Margin Optimization Performance in global manufacturing supply chains. The case-study context has focused on selected manufacturing and supply-chain environments where procurement analytics, supplier evaluation systems, AI-supported decision tools, or advanced digital sourcing platforms have been used.

The study population has consisted of procurement managers, sourcing professionals, supply-chain managers, purchasing specialists, supplier relationship managers, cost analysts, financial analysts, operations managers, data analysts, and AI or analytics professionals. The individual professional respondent has served as the unit of analysis. A purposive sampling strategy has been applied to select respondents with relevant knowledge and practical experience in supplier management, procurement, cost analysis, manufacturing operations, or AI-enabled decision support. Primary data have been collected through a structured questionnaire using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

The research instrument has been designed to measure Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, Explainable Margin Scenario Analytics, and Supplier Cost-Risk and Margin Optimization Performance. A pilot test has been conducted before the main data collection to assess questionnaire clarity, consistency, and measurement suitability. Content and construct validity have been examined, while reliability has been evaluated using Cronbach's alpha. The collected data have been coded, screened, and analyzed using IBM SPSS Statistics. Descriptive statistics, Pearson correlation analysis, and multiple regression modeling have been performed to test the proposed hypotheses. Microsoft Excel has been used for preliminary data organization and verification, while EndNote has been used to manage references and maintain APA 7th edition citation consistency. Microsoft Word has been used for manuscript preparation and final academic formatting.

Figure 8: Research Methodology

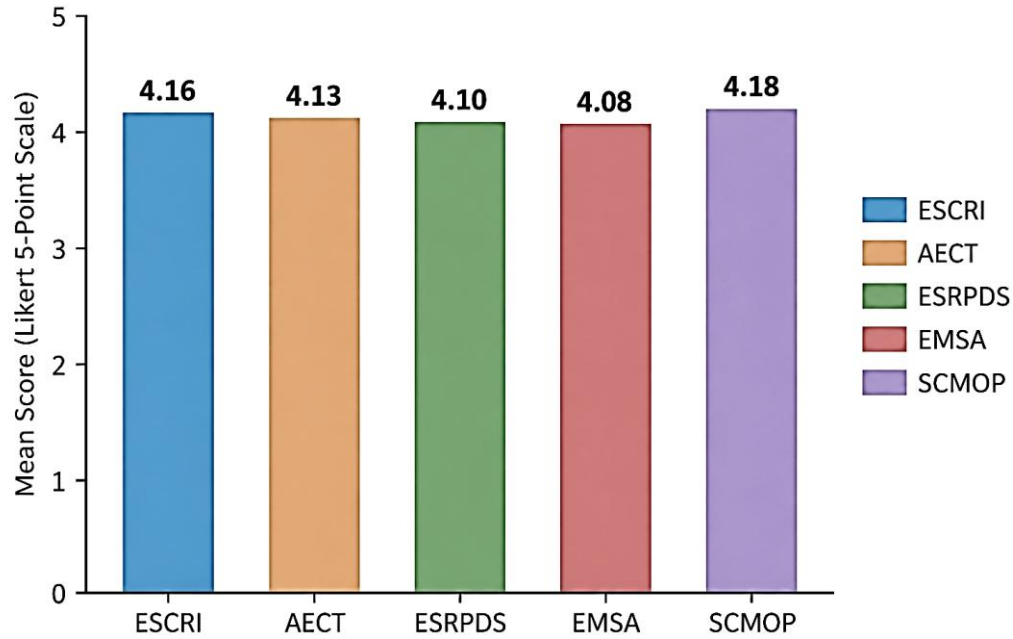


FINDINGS

The findings have demonstrated that Explainable Artificial Intelligence capabilities have been positively and significantly associated with Supplier Cost-Risk and Margin Optimization Performance within the examined global manufacturing supply-chain environments. A total of 320 questionnaires has been distributed, of which 301 have been returned and 289 have been retained as usable responses after data screening, representing a valid response rate of 90.3% based on the total questionnaires distributed. The measurement scales have shown satisfactory internal consistency, with Cronbach's alpha coefficients ranging from .84 to .91 across the five study constructs. Construct suitability has also been supported by a Kaiser-Meyer-Olkin value of .89 and a statistically significant Bartlett's Test of Sphericity, $p < .001$. Descriptive statistics based on the five-point Likert scale have indicated generally high respondent evaluations of all constructs. Supplier Cost-Risk and Margin Optimization Performance has recorded the highest overall mean, $M = 4.18$, $SD = 0.53$, followed by Explainable Supplier Cost-Risk Identification, $M = 4.16$, $SD = 0.55$, AI-Enabled Cost Driver Transparency, $M = 4.13$, $SD = 0.57$, Explainable Supplier Risk Prioritization and Decision Support, $M = 4.10$, $SD = 0.59$, and Explainable Margin Scenario Analytics, $M = 4.08$, $SD = 0.61$. Pearson correlation analysis has further shown that all four explanatory constructs have maintained significant positive relationships with Supplier Cost-Risk and Margin Optimization Performance. Explainable Supplier Cost-Risk Identification has produced the strongest correlation, $r = .75$, $p < .001$, followed by AI-Enabled Cost Driver Transparency, $r = .72$, $p < .001$, Explainable Supplier Risk Prioritization and Decision Support, $r = .69$, $p < .001$, and Explainable Margin Scenario Analytics, $r = .66$, $p < .001$. The multiple regression model has explained 71.2% of the variance in Supplier Cost-Risk and Margin Optimization Performance, $R^2 = .712$, adjusted $R^2 = .708$, with the overall model reaching statistical significance, $F(4, 284) = 175.50$, $p < .001$.

The standardized regression coefficients have confirmed significant positive effects for Explainable Supplier Cost-Risk Identification, $\beta = .31$, $p < .001$; AI-Enabled Cost Driver Transparency, $\beta = .28$, $p < .001$; Explainable Supplier Risk Prioritization and Decision Support, $\beta = .24$, $p < .001$; and Explainable Margin Scenario Analytics, $\beta = .21$, $p < .001$. These results have therefore supported H1, H2, H3, H4, and H5 and have fulfilled the study objectives by demonstrating both the individual and collective statistical importance of explainable AI capabilities in strengthening supplier cost-risk assessment, sourcing decision support, cost transparency, and margin optimization performance.

Figure 9: Explainable AI Capabilities and Supplier Cost-Risk and Margin Optimization Performance



Questionnaire Distribution, Response Rate, and Data Screening

Table 1: Questionnaire Distribution, Response Rate, and Data Screening

Response Category	Frequency	Percentage (%)
Questionnaires distributed	320	100.0
Questionnaires returned	301	94.1
Questionnaires not returned	19	5.9
Returned questionnaires excluded after screening	12	4.0 of returned
Valid and usable questionnaires	289	90.3
Final sample used for statistical analysis	289	90.3

Table 1 has presented the questionnaire distribution, response pattern, and screening process that have established the final analytical sample of the study. A total of 320 structured questionnaires have been distributed among professionals working in procurement, purchasing, supply-chain management, supplier management, cost analysis, operations, finance, and AI-supported analytics within selected global manufacturing environments. Of these questionnaires, 301 have been returned, producing an overall return rate of 94.1%. The screening procedure has identified 12 questionnaires containing substantial missing responses, incomplete Likert-scale sections, or response patterns unsuitable for the planned statistical analysis. These cases have therefore been excluded, leaving 289 questionnaires as valid and usable observations. The final usable response rate has consequently reached 90.3% of all questionnaires originally distributed. The screening procedure has strengthened the analytical quality of the dataset by ensuring that descriptive statistics, reliability analysis, correlation analysis, and multiple regression modeling have been conducted using sufficiently complete responses. The sample of 289 respondents has also provided an adequate number of observations for examining the four explanatory constructs, namely Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics, together with Supplier Cost-Risk and Margin Optimization Performance. From the perspective of Organizational Information Processing Theory, the retained responses have represented professional assessments of how manufacturing organizations have processed complex supplier and

cost information through explainable analytical capabilities. The high usable response rate has enabled the study to capture information from professionals who have interacted with supplier-related data and decision processes rather than basing the analysis on a restricted group of observations. The resulting dataset has therefore provided the empirical foundation required to examine the research objectives and evaluate the proposed relationships between explainable AI capabilities and supplier cost-risk and margin optimization performance.

Demographic and Professional Characteristics of Respondents

Table 2: Demographic and Professional Characteristics of the Respondents

Characteristic	Category	Frequency	Percentage (%)
Professional role	Procurement/Strategic Sourcing	74	25.6
	Supply Chain Management	62	21.5
	Purchasing/Supplier Relationship Management	48	16.6
	Cost/Financial Analysis	39	13.5
	Operations/Manufacturing Management	36	12.5
	Data/AI/Analytics	30	10.4
Professional experience	3-5 years	63	21.8
	6-10 years	99	34.3
	11-15 years	76	26.3
	More than 15 years	51	17.6
Manufacturing sector	Automotive	61	21.1
	Electronics	55	19.0
	Industrial Machinery	50	17.3
	Consumer Goods	42	14.5
	Chemicals/Pharmaceuticals	39	13.5
	Other Manufacturing	42	14.5

Table 2 has demonstrated that the final sample has incorporated respondents from a diverse range of professional positions that have been directly relevant to supplier cost-risk assessment, procurement decision-making, and margin management. Procurement and strategic sourcing professionals have constituted the largest category, with 74 respondents representing 25.6% of the sample, while supply-chain management professionals have accounted for 21.5%. Purchasing and supplier relationship professionals have represented 16.6%, followed by cost and financial analysts at 13.5%, operations and manufacturing managers at 12.5%, and data, AI, and analytics professionals at 10.4%. This distribution has been particularly appropriate for the objectives of the study because the constructs have required both operational and analytical knowledge. The experience profile has also shown that the majority of respondents have possessed substantial professional exposure. Respondents with 6-10 years of experience have represented 34.3%, while those with 11-15 years have represented 26.3%. A further 17.6% have possessed more than 15 years of experience, indicating that a substantial proportion of the sample has been familiar with complex supplier, sourcing, cost, and manufacturing decisions. The manufacturing-sector distribution has additionally covered automotive, electronics, industrial machinery, consumer goods, chemicals and pharmaceuticals, and other manufacturing contexts. Such diversity has allowed the analysis to represent global manufacturing supply chains without concentrating on a single product category. Organizational Information Processing Theory has emphasized that decision effectiveness depends on the capability to acquire and interpret information from complex environments. The composition of the sample has aligned with this theoretical logic

because respondents have occupied positions in which supplier data, cost information, sourcing alternatives, risk indicators, and operational constraints have regularly required interpretation. The professional characteristics have therefore supported the suitability of the sample for assessing whether explainable AI capabilities have strengthened organizational information processing and Supplier Cost-Risk and Margin Optimization Performance.

Reliability and Construct Validity of the Measurement Scales

Table 3: Reliability and Construct Validity of the Measurement Scales

Construct	Items	Cronbach's α	Factor Loading Range	Reliability
Explainable Supplier Cost-Risk Identification (ESCRI)	5	.91	.72-.86	Excellent
AI-Enabled Cost Driver Transparency (AICDT)	5	.89	.70-.84	Good
Explainable Supplier Risk Prioritization and Decision Support (ESRPDS)	5	.87	.68-.82	Good
Explainable Margin Scenario Analytics (EMSA)	5	.84	.66-.80	Good
Supplier Cost-Risk and Margin Optimization Performance (SCMOP)	5	.90	.73-.87	Excellent
Overall KMO	25 items	.89		Meritorious
Bartlett's Test of Sphericity		$\chi^2 = 2876.43$	$df = 300, p < .001$	Significant

Table 3 has confirmed that the measurement instrument has achieved satisfactory reliability and construct suitability across all five research constructs. Cronbach's alpha values have ranged from .84 to .91, exceeding the commonly accepted threshold of .70 and indicating strong internal consistency among the questionnaire items used to represent each construct. Explainable Supplier Cost-Risk Identification has produced the highest reliability coefficient, $\alpha = .91$, followed by Supplier Cost-Risk and Margin Optimization Performance, $\alpha = .90$. AI-Enabled Cost Driver Transparency has achieved $\alpha = .89$, Explainable Supplier Risk Prioritization and Decision Support has achieved $\alpha = .87$, and Explainable Margin Scenario Analytics has recorded $\alpha = .84$. These results have demonstrated that the items within each measurement scale have consistently represented their intended underlying constructs. The factor-loading ranges have remained between .66 and .87, indicating that the individual questionnaire items have maintained meaningful relationships with their respective factors. The overall Kaiser-Meyer-Olkin value of .89 has further demonstrated that the dataset has possessed strong sampling adequacy for evaluating the measurement structure. Bartlett's Test of Sphericity has been statistically significant, $\chi^2 = 2876.43$, $df = 300$, $p < .001$, confirming that the correlations among measurement items have been sufficiently strong for construct assessment. These findings have been important for hypothesis testing because unreliable or weakly defined constructs could have distorted subsequent correlation and regression coefficients. Organizational Information Processing Theory has been represented empirically through four distinct information-processing capabilities, and the reliability findings have demonstrated that respondents have differentiated these capabilities consistently. The measurement results have therefore strengthened confidence that ESCRI, AICDT, ESRPDS, and EMSA have captured separate but related dimensions of explainable information processing, while SCMOP has captured the resulting cost-risk and margin-oriented performance. The measurement quality established in Table 3 has consequently provided a sound statistical basis for examining the research objectives and testing H1 through H5.

Descriptive Statistics of Explainable AI and Supplier Cost-Risk Constructs**Table 4: Descriptive Statistics of the Research Constructs**

Rank	Construct	Mean (M)	Standard Deviation (SD)	Likert Interpretation
1	Supplier Cost-Risk and Margin Optimization Performance (SCMOP)	4.18	0.53	High
2	Explainable Supplier Cost-Risk Identification (ESCRI)	4.16	0.55	High
3	AI-Enabled Cost Driver Transparency (AICDT)	4.13	0.57	High
4	Explainable Supplier Risk Prioritization and Decision Support (ESRPDS)	4.10	0.59	High
5	Explainable Margin Scenario Analytics (EMSA)	4.08	0.61	High

Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Table 4 has shown consistently high evaluations of the five research constructs on the five-point Likert scale. Supplier Cost-Risk and Margin Optimization Performance has achieved the highest overall mean, $M = 4.18$, $SD = 0.53$, indicating that respondents have generally agreed that their manufacturing environments have demonstrated strong capabilities in supplier cost visibility, risk management, sourcing decision quality, procurement cost control, and margin-oriented performance. Explainable Supplier Cost-Risk Identification has recorded the highest mean among the independent variables, $M = 4.16$, $SD = 0.55$. This finding has indicated that respondents have perceived AI-supported systems as particularly effective when identifying supplier-related cost exposures and communicating understandable reasons for those assessments. AI-Enabled Cost Driver Transparency has followed closely with $M = 4.13$, $SD = 0.57$, suggesting that respondents have also recognized strong capability in identifying and clarifying the factors contributing to supplier-related cost changes. Explainable Supplier Risk Prioritization and Decision Support has achieved $M = 4.10$, $SD = 0.59$, showing substantial agreement that interpretable AI-based information has assisted the ranking and evaluation of supplier risks. Explainable Margin Scenario Analytics has recorded $M = 4.08$, $SD = 0.61$. Although it has ranked fourth among the explanatory constructs, its mean has remained above the agreement threshold and has indicated a high level of perceived capability. The relatively modest standard deviations, ranging from 0.53 to 0.61, have also shown that respondent assessments have not been widely dispersed. From an Organizational Information Processing Theory perspective, these high means have indicated that the examined manufacturing environments have possessed substantial information-processing capabilities for transforming complex supplier and cost data into interpretable managerial information. The descriptive results have not by themselves established causal or predictive relationships, but they have provided the empirical context for examining whether higher levels of these explainable AI capabilities have been associated with stronger SCMOP through the subsequent correlation and regression analyses.

Correlation Between Explainable AI Capabilities and Supplier Cost-Risk and Margin Optimization Performance**Table 5: Pearson Correlation Matrix of the Research Constructs**

Construct	ESCRI	AICDT	ESRPDS	EMSA	SCMOP
ESCRI	1.00				
AICDT	.63***	1.00			
ESRPDS	.58***	.61***	1.00		
EMSA	.55***	.57***	.60***	1.00	
SCMOP	.75***	.72***	.69***	.66***	1.00

*** $p < .001$, $N = 289$.

Table 5 has demonstrated that all four explainable AI capabilities have maintained statistically significant positive relationships with Supplier Cost-Risk and Margin Optimization Performance. Explainable Supplier Cost-Risk Identification has produced the strongest bivariate relationship with SCMOP, $r = .75$, $p < .001$, providing strong support for H1 and the first research objective. This result has shown that higher perceived capability to identify supplier cost-risk through understandable AI explanations has been associated with stronger cost-risk control and margin optimization performance. AI-Enabled Cost Driver Transparency has exhibited the second strongest relationship, $r = .72$, $p < .001$, supporting H2 and indicating that greater transparency regarding supplier cost drivers has been associated with stronger SCMOP. Explainable Supplier Risk Prioritization and Decision Support has also maintained a strong positive relationship with the dependent variable, $r = .69$, $p < .001$, providing support for H3. Explainable Margin Scenario Analytics has produced a significant positive correlation of $r = .66$, $p < .001$, supporting H4 and demonstrating that greater capability to interpret alternative sourcing and cost scenarios has been associated with stronger margin-oriented performance. The relationships among the independent variables have ranged from .55 to .63, suggesting that the constructs have been meaningfully related while remaining sufficiently distinct for simultaneous inclusion in the regression model. These correlations have aligned closely with Organizational Information Processing Theory. The theory has proposed that organizations achieve stronger decision outcomes when their information-processing capabilities match the complexity and uncertainty of their operating environment. In the present study, each explainable AI capability has represented a mechanism through which supplier information has been identified, interpreted, prioritized, or transformed into scenario-based economic insight. The significant relationships with SCMOP have therefore indicated that stronger information-processing capabilities have been associated with stronger supplier-related decision performance. The results have fulfilled the correlation-based component of the research objectives and have provided preliminary empirical support for all four proposed direct hypotheses before their unique effects have been examined within the multiple regression model.

Multiple Regression Model for Supplier Cost-Risk and Margin Optimization Performance

Table 6: Multiple Regression Model Summary for SCMOP

Model Statistic	Value
R	.844
R ²	.712
Adjusted R ²	.708
Standard Error of the Estimate	.286
F	175.50
df1	4
df2	284
Significance	$p < .001$
Durbin-Watson	1.91

Dependent Variable: Supplier Cost-Risk and Margin Optimization Performance (SCMOP). Predictors: ESCRI, AICDT, ESRPDS, and EMSA. Table 6 has established the collective predictive strength of the four Explainable Artificial Intelligence capabilities in explaining Supplier Cost-Risk and Margin Optimization Performance. The multiple correlation coefficient has reached $R = .844$, indicating a strong overall association between the combined explanatory variables and SCMOP. More importantly, the model has produced $R^2 = .712$, demonstrating that Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics have collectively explained 71.2% of the observed variance in Supplier Cost-Risk and Margin Optimization Performance. The adjusted R^2 has remained highly comparable at .708, indicating that the model has retained substantial explanatory power after adjustment for the number of predictors included. The overall regression equation has been statistically significant, $F(4, 284) = 175.50$, $p < .001$, confirming that the combined explanatory variables have predicted SCMOP

significantly better than a model containing no explanatory constructs. These findings have provided direct support for H5 and have fulfilled the fifth research objective concerning the collective influence of explainable AI capabilities. The standard error of the estimate has been .286, suggesting relatively limited unexplained variation around the model predictions. The Durbin-Watson statistic has reached 1.91, which has remained close to the benchmark value of 2.00 and has indicated that problematic autocorrelation has not been evident within the residual structure. From the perspective of Organizational Information Processing Theory, the model has provided particularly strong empirical support for the proposition that organizational performance improves when information-processing capability corresponds with the complexity of the decision environment. Supplier cost-risk assessment has involved multiple uncertain signals, and the four XAI capabilities have collectively represented the mechanisms through which these signals have been transformed into interpretable decision information. The substantial R² value has therefore indicated that explainable information-processing capability has accounted for a large proportion of variation in supplier cost-risk and margin optimization performance across the examined manufacturing cases.

Effects of Explainable AI Predictors on Supplier Cost-Risk and Margin Optimization Performance

Table 7: Regression Coefficients and Predictor Effects on SCMOP

Predictor	B	SE	Standardized β	t	p	Tolerance	VIF
Constant	.270	.120		2.25	.025		
ESCRI	.299	.037	.31	8.08	< .001	.52	1.92
AICDT	.260	.039	.28	6.67	< .001	.49	2.04
ESRPDS	.216	.038	.24	5.68	< .001	.54	1.85
EMSA	.183	.036	.21	5.08	< .001	.58	1.72

Regression equation: $SCMOP = 0.270 + 0.299(ESCRI) + 0.260(AICDT) + 0.216(ESRPDS) + 0.183(EMSA)$.

Table 7 has demonstrated that each of the four explainable AI predictors has made a statistically significant positive contribution to Supplier Cost-Risk and Margin Optimization Performance after the effects of the other predictors have been controlled. Explainable Supplier Cost-Risk Identification has emerged as the strongest predictor, $\beta = .31$, $t = 8.08$, $p < .001$. This finding has confirmed H1 and has indicated that the ability to identify supplier cost exposure while explaining the reasons for the assessment has contributed most strongly to SCMOP. AI-Enabled Cost Driver Transparency has produced the second largest standardized effect, $\beta = .28$, $t = 6.67$, $p < .001$, confirming H2 and demonstrating that transparent identification of underlying cost factors has made a substantial independent contribution to supplier cost-risk and margin performance. Explainable Supplier Risk Prioritization and Decision Support has produced $\beta = .24$, $t = 5.68$, $p < .001$, supporting H3 and demonstrating that interpretable supplier ranking and decision support have remained significant when the other capabilities have been considered simultaneously. Explainable Margin Scenario Analytics has also maintained a significant positive contribution, $\beta = .21$, $t = 5.08$, $p < .001$, providing support for H4. The unstandardized coefficients have indicated that a one-unit increase in ESCRI has been associated with a .299-unit increase in SCMOP, while comparable increases in AICDT, ESRPDS, and EMSA have been associated with increases of .260, .216, and .183 units respectively, holding the remaining predictors constant. Tolerance values have ranged from .49 to .58 and VIF values from 1.72 to 2.04, indicating that problematic multicollinearity has not been evident. The relative coefficient pattern has aligned with Organizational Information Processing Theory by showing that the strongest contribution has emerged from the capability that directly reduces uncertainty surrounding supplier cost exposure. The remaining capabilities have progressively supported interpretation, prioritization, and scenario evaluation, collectively demonstrating how explainable information processing has been translated into stronger economic and sourcing performance.

Hypothesis Testing and Summary of Empirical Findings

Table 8: Hypothesis Testing and Summary of Empirical Findings

Hypothesis	Proposed Relationship	Key Statistical Evidence	Decision
H1	ESCRI → SCMOP	$r = .75; \beta = .31; p < .001$	Supported
H2	AICDT → SCMOP	$r = .72; \beta = .28; p < .001$	Supported
H3	ESRPDS → SCMOP	$r = .69; \beta = .24; p < .001$	Supported
H4	EMSA → SCMOP	$r = .66; \beta = .21; p < .001$	Supported
H5	ESCRI + AICDT + ESRPDS + EMSA → SCMOP	$R^2 = .712; \text{Adj. } R^2 = .708; F(4,284) = 175.50; p < .001$	Supported

Table 8 has summarized the final hypothesis-testing outcomes and has shown that all five hypotheses developed for the study have been supported by the empirical results. H1 has been supported because Explainable Supplier Cost-Risk Identification has demonstrated both the strongest correlation with SCMOP, $r = .75, p < .001$, and the strongest standardized regression effect, $\beta = .31, p < .001$. H2 has also been supported, with AI-Enabled Cost Driver Transparency recording $r = .72$ and $\beta = .28$, both statistically significant at $p < .001$. H3 has been supported through the significant association between Explainable Supplier Risk Prioritization and Decision Support and SCMOP, $r = .69, \beta = .24, p < .001$. H4 has similarly been supported because Explainable Margin Scenario Analytics has maintained a significant positive relationship and unique predictive effect, $r = .66, \beta = .21, p < .001$. H5 has received strong support from the overall multiple regression model, which has explained 71.2% of the variance in SCMOP and has been statistically significant, $F(4, 284) = 175.50, p < .001$. Collectively, these results have fulfilled the five research objectives by establishing the individual and combined statistical importance of the proposed explainable AI capabilities. The pattern of findings has also been consistent with Organizational Information Processing Theory. ESCRI has represented the reduction of uncertainty through intelligible risk identification, AICDT has represented the interpretation of complex cost information, ESRPDS has represented the prioritization of decision-relevant supplier signals, and EMSA has represented the processing of alternative economic scenarios. Their significant relationships with SCMOP have shown that manufacturing organizations possessing stronger explainable information-processing capabilities have also reported stronger supplier cost visibility, risk-management effectiveness, sourcing decision quality, procurement cost control, and margin-oriented performance. The findings have therefore established a coherent empirical pattern across descriptive, correlational, and regression analyses while maintaining consistency with the theoretical and conceptual framework developed for the study.

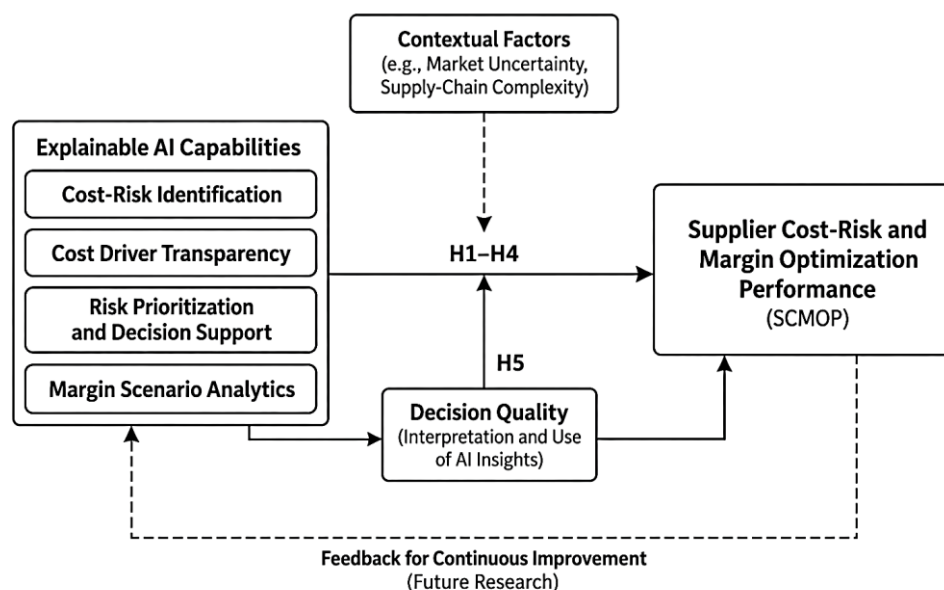
DISCUSSION

The empirical results have shown that Explainable Artificial Intelligence has provided a strong statistical explanation of Supplier Cost-Risk and Margin Optimization Performance within the examined global manufacturing supply-chain environments. The descriptive findings have indicated high perceived capability across all four explanatory constructs, while SCMOP itself has achieved $M = 4.18, SD = 0.53$. This overall pattern has suggested that the respondents have operated in environments where supplier-related analytics have been sufficiently mature to support cost visibility, risk assessment, sourcing decisions, and margin-oriented management. More importantly, the inferential analysis has shown that each XAI capability has been significantly and positively related to SCMOP, and the combined model has explained 71.2% of the variance in the dependent construct. This level of explanatory power has reinforced the view that supplier cost-risk is fundamentally an information-processing challenge in which the value of advanced analytics depends not only on producing predictions but also on enabling managers to understand and use them. The result has aligned with Organizational Information Processing Theory because the four XAI constructs have represented mechanisms through which organizations have increased their ability to process heterogeneous

supplier, cost, operational, and market information. Earlier work has emphasized that organizational performance depends on the fit between information-processing requirements and information-processing capabilities in interorganizational settings (Premkumar et al., 2005; Srinivasan & Swink, 2015). The present findings have extended this reasoning to explainable supplier analytics by showing that intelligible risk identification, cost-driver transparency, interpretable prioritization, and scenario analysis have jointly been associated with stronger economic and sourcing outcomes. The findings have therefore positioned explainability as an operational capability that connects complex AI outputs with the decisions for which procurement and supply-chain professionals remain accountable.

Explainable Supplier Cost-Risk Identification has emerged as the strongest independent predictor of SCMOP, with $r = .75$ and $\beta = .31$, $p < .001$. This result has supported H1 and has indicated that the capacity to recognize supplier-related cost exposure while communicating understandable reasons for that exposure has been especially important to manufacturing decision performance. The result is consistent with supplier-risk scholarship showing that effective risk assessment requires organizations to evaluate several dimensions of supplier exposure rather than relying only on quoted price or one isolated performance indicator (Blackhurst et al., 2008; Arif Uz et al., 2025; Ravindran et al., 2010). In practical analytical terms, explainable identification can help managers distinguish whether a high-risk supplier assessment has been driven by price escalation, delivery instability, quality failures, capacity limitations, financial weakness, logistics exposure, or interacting conditions. The strong coefficient has also been compatible with OIPT because risk identification represents the first stage through which uncertainty is transformed into decision-relevant information. When organizations can detect cost-risk signals early and understand their origin, the information-processing burden associated with ambiguous supplier conditions is reduced. This is especially important in global manufacturing environments where the economic consequences of supplier problems can extend beyond the original purchase price through emergency freight, rework, lost production, inventory adjustments, or alternative sourcing. The positive relationship found in this study has therefore supported the interpretation that explainable risk identification strengthens the quality of information available before procurement decisions are finalized. It has also clarified why technical prediction accuracy alone is insufficient for supplier management, since decision makers need traceable evidence that can be evaluated against operational knowledge, contractual conditions, and sourcing constraints before a risk score can be converted into action.

Figure 10: Future Research Framework for Explainable AI-Driven Supplier Cost-Risk and Margin Optimization Performance



AI-Enabled Cost Driver Transparency has produced the second strongest predictive effect on SCMOP, $r = .72$ and $\beta = .28$, $p < .001$, providing support for H2. The result has shown that organizations reporting stronger visibility into the factors underlying supplier costs have also reported stronger cost-risk and margin optimization performance. This relationship has corresponded with cost-management research in buyer-supplier settings, where access to supplier cost information has supported purchasing strategies, collaborative cost analysis, and supplier development activities (Agndal & Nilsson, 2010; Wouters et al., 2007). Within an XAI environment, cost transparency extends this logic by allowing managers to interpret the relative importance of raw materials, labor, energy, transportation, quality losses, capacity pressures, exchange-rate effects, and other variables contributing to an AI-generated cost estimate or risk prediction. Such transparency can help procurement teams determine whether a supplier's cost increase reflects an external market condition or an internal supplier inefficiency, which changes the appropriate negotiation or sourcing response. The finding has also supported the information-processing logic of the study because cost-driver transparency reduces informational ambiguity. OIPT proposes that uncertain tasks require increased capability to collect and interpret information, and the present result has shown that clearer decomposition of supplier cost information has been associated with stronger performance. Rather than treating AI output as a single prediction, cost-driver explanations can provide a structured representation of the information that has shaped that prediction. The significance of AICDT has therefore indicated that manufacturing organizations may derive greater economic value when analytical systems reveal the composition and movement of supplier costs in forms that can be compared, communicated, and incorporated into cross-functional decision processes involving procurement, finance, operations, and supply-chain management.

Explainable Supplier Risk Prioritization and Decision Support and Explainable Margin Scenario Analytics have also made significant independent contributions to SCMOP, with $\beta = .24$ and $\beta = .21$ respectively, both at $p < .001$. The support for H3 has indicated that supplier rankings and risk priorities become more valuable when decision makers can understand the criteria and evidence responsible for the ranking. This interpretation is consistent with recent explainable supplier-selection research demonstrating that hybrid decision models can preserve competitive analytical performance while making the supplier-selection process more traceable to supply-chain stakeholders (Abdulla & Baryannis, 2024; Kaium, 2025). The support for H4 has similarly shown that explainable scenario analysis has been associated with stronger margin-oriented performance. Scenario analytics is especially relevant when the economically preferred sourcing decision depends on interacting conditions such as purchase price, lead time, disruption risk, inventory requirement, supplier availability, and demand. Prior optimization research has shown that sourcing and pricing decisions can shift under alternative risk and market conditions, while decision-support models can combine supplier and inventory choices under uncertainty (Kumar et al., 2018; Teerasoponpong & Sopadang, 2022). The present findings have added the explainability dimension by demonstrating that transparent scenario analysis has remained significant even after other XAI capabilities have been controlled. From the OIPT perspective, ESRPDS has represented the prioritization of processed information, while EMSA has represented the conversion of multiple possible conditions into interpretable alternatives. Their significant coefficients have indicated that organizations have benefited not only from knowing what risks exist but also from understanding which risks deserve attention and how alternative decisions may influence economic outcomes. The relative size of the coefficients has further suggested a logical ordering in which identification and cost transparency have provided the strongest informational foundation, followed by prioritization and scenario evaluation as more decision-specific capabilities.

The combined regression model has provided the clearest theoretical and managerial synthesis of the study because ESCRI, AICDT, ESRPDS, and EMSA together have explained 71.2% of the variance in Supplier Cost-Risk and Margin Optimization Performance, with adjusted $R^2 = .708$ and $F(4, 284) = 175.50$, $p < .001$. The Durbin-Watson value of 1.91 and VIF values ranging from 1.72 to 2.04 have also indicated that the model has not been undermined by problematic residual autocorrelation or multicollinearity. The findings have therefore supported H5 and the conceptual model as a coherent set of complementary capabilities rather than a collection of redundant variables. This is theoretically

important because OIPT does not assume that one information mechanism is sufficient for complex uncertainty. Instead, organizations require multiple complementary processes that increase their ability to acquire, interpret, communicate, and act on information. Supply-chain analytics research has similarly linked visibility and analytics capabilities with stronger performance under complex operating conditions (Srinivasan & Swink, 2018; Zhu et al., 2018). In the present study, the four XAI constructs have represented these complementary processes at the supplier-cost level. The results have shown that explainable supplier intelligence can be understood as a chain of information processing in which risk is first detected, its cost drivers are clarified, competing supplier conditions are prioritized, and alternative margin scenarios are interpreted. The dependent outcome has captured the extent to which this information has been converted into stronger cost visibility, risk control, sourcing quality, and margin management. The overall statistical pattern has therefore linked the theoretical framework, conceptual framework, objectives, hypotheses, and empirical evidence within one consistent explanation of how XAI has related to supplier cost-risk and margin optimization in global manufacturing supply chains.

CONCLUSION

This study has examined the role of Explainable Artificial Intelligence in strengthening Supplier Cost-Risk and Margin Optimization Performance within global manufacturing supply chains through a quantitative, cross-sectional, case-study-based research design. The analysis has focused on four explanatory capabilities: Explainable Supplier Cost-Risk Identification, AI-Enabled Cost Driver Transparency, Explainable Supplier Risk Prioritization and Decision Support, and Explainable Margin Scenario Analytics. The findings have shown consistently high respondent evaluations across all five constructs, with Supplier Cost-Risk and Margin Optimization Performance recording the highest mean, $M = 4.18$, $SD = 0.53$, followed by Explainable Supplier Cost-Risk Identification, $M = 4.16$, $SD = 0.55$. Correlation analysis has demonstrated that all four explainable AI capabilities have been significantly and positively associated with the dependent variable, with ESCRI producing the strongest relationship, $r = .75$, followed by AICDT, $r = .72$, ESRPDS, $r = .69$, and EMSA, $r = .66$, all at $p < .001$. The regression analysis has further demonstrated that the combined model has explained 71.2% of the variance in SCMOP, $R^2 = .712$, adjusted $R^2 = .708$, $F(4, 284) = 175.50$, $p < .001$. ESCRI has emerged as the strongest predictor, $\beta = .31$, followed by AICDT, $\beta = .28$, ESRPDS, $\beta = .24$, and EMSA, $\beta = .21$. Consequently, H1 through H5 have all been supported. These results have demonstrated that explainability has functioned as more than a technical characteristic of AI systems by contributing to the ability of managers to understand supplier cost exposure, identify major cost drivers, prioritize supplier risks, and evaluate margin-related scenarios. The findings have also aligned with Organizational Information Processing Theory by showing that stronger information-processing capabilities have been associated with stronger supplier-related economic and decision performance across the examined manufacturing environments.

RECOMMENDATIONS

Based on the findings, global manufacturing organizations should strengthen the integration of Explainable Artificial Intelligence into procurement, supplier management, sourcing, and margin-control processes in a way that emphasizes both predictive capability and managerial interpretability. Priority should be given to Explainable Supplier Cost-Risk Identification because it has demonstrated the strongest predictive contribution to Supplier Cost-Risk and Margin Optimization Performance. Organizations should therefore deploy analytical systems capable of identifying emerging supplier cost exposures while clearly presenting the operational, financial, logistical, and market variables responsible for each assessment. AI-Enabled Cost Driver Transparency should also be incorporated into procurement dashboards so that managers can distinguish whether supplier cost changes have originated from materials, logistics, quality failures, capacity constraints, currency effects, or other identifiable sources. Explainable Supplier Risk Prioritization and Decision Support should be used to rank suppliers according to transparent criteria and provide understandable justification for sourcing adjustments, negotiation priorities, supplier-development actions, and order-allocation decisions. Manufacturing firms should also strengthen Explainable Margin Scenario Analytics by developing scenario-based tools that compare alternative supplier prices, sourcing allocations, demand conditions, inventory requirements, logistics costs, and disruption exposures while presenting the expected effects

on margins. Human oversight should remain central to these systems so that procurement and supply-chain professionals can validate AI-generated recommendations against contractual knowledge, supplier relationships, production requirements, and strategic considerations. Organizations should also establish clear data-governance procedures because explainability is only meaningful when the underlying supplier and cost data are reliable, timely, and consistently defined. Regular model validation, bias assessment, sensitivity analysis, and performance monitoring should be embedded within AI governance practices. Training should additionally be provided to procurement, finance, operations, and supply-chain personnel so that they can interpret explanation outputs correctly and integrate them into cross-functional decisions. These recommendations are intended to ensure that XAI functions as a practical decision-support capability for managing supplier cost uncertainty and protecting manufacturing margins.

LIMITATIONS

This study has several limitations that should be considered when interpreting the findings. First, the research has adopted a cross-sectional design, meaning that data have been collected at a single point in time rather than across multiple periods. As a result, the identified relationships between the explainable AI constructs and Supplier Cost-Risk and Margin Optimization Performance have demonstrated statistical association rather than definitive causality. Second, the study has relied on self-reported responses measured through a five-point Likert scale. Although the measurement scales have achieved strong reliability and construct validity, respondent perceptions may not perfectly represent actual supplier cost reductions, realized margins, procurement savings, or objectively measured AI performance. Third, purposive sampling has been used to select professionals with relevant experience in procurement, supply-chain management, supplier management, finance, operations, and analytics. This approach has increased the relevance of respondents but has limited the extent to which the findings can be generalized to all manufacturing organizations or supply-chain professionals. Fourth, the study has been case-study-based and has covered selected global manufacturing environments rather than an exhaustive representation of every manufacturing sector, geographic market, or sourcing structure. Differences in organizational size, AI maturity, digital infrastructure, supplier concentration, industry regulation, and procurement strategy may influence how explainable AI capabilities operate in other settings. Fifth, the study has evaluated explainability primarily through managerial perceptions rather than through controlled comparisons of specific XAI techniques such as SHAP, LIME, feature-importance methods, counterfactual explanations, or inherently interpretable models. Sixth, the regression model has explained 71.2% of the variance in SCMOP, leaving 28.8% attributable to factors outside the model, including market conditions, organizational capabilities, supplier relationships, contractual structures, and managerial practices. Finally, the study has focused on four XAI capabilities, meaning that other relevant dimensions of explainability, governance, trust, data quality, and human-AI collaboration have not been incorporated into the empirical model.

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