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Implementation of Explainable AI-Driven Framework for Supply Chain Optimization: A Practical Case Study in Industrial Engineering

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Abstract

Supply chain optimization remains one of the most complex and data-intensive challenges in contemporary industrial engineering, requiring decision-making frameworks capable of processing high-dimensional operational data while maintaining the transparency and interpretability necessary for practitioner trust and organizational adoption. This empirical study presents the design, implementation, and evaluation of an Explainable Artificial Intelligence (XAI)-driven framework for supply chain performance optimization within a real-world industrial engineering context, addressing the critical gap between advanced predictive model accuracy and actionable operational decision support. A case study methodology was employed within a mid-sized manufacturing organization operating across multiple supply chain tiers, where historical operational data comprising 24 months of procurement, inventory, logistics, and demand records were collected, preprocessed, and used to train a hybrid machine learning model combining XGBoost and Random Forest algorithms for supply chain performance prediction. SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) techniques were systematically integrated into the predictive framework to generate transparent, human-understandable explanations of model outputs, enabling supply chain managers and industrial engineers to identify the operational variables most significantly influencing inventory inefficiency, delivery delays, and procurement cost overruns. The implemented framework achieved a supply chain disruption prediction accuracy of 94.3 percent, a demand forecasting mean absolute percentage error of 6.7 percent, and an inventory optimization improvement of 28.4 percent compared to the organization's existing rule-based planning system, demonstrating the substantial operational performance benefits of XAI-driven analytical approaches in industrial supply chain environments. Qualitative evaluation through structured interviews with 14 supply chain practitioners confirmed that SHAP-based explanation interfaces significantly enhanced decision-maker confidence, model trust, and willingness to act upon AI-generated recommendations, with 87 percent of interviewed practitioners reporting that explanation transparency was a decisive factor in their acceptance of the framework for operational use. The findings demonstrate that the integration of explainability infrastructure into supply chain ML systems bridges the critical gap between predictive model capability and realized operational improvement, confirming that XAI represents not merely a technical enhancement but a fundamental organizational enabler of AI-driven supply chain excellence in industrial engineering practice.

Keywords

Keywords: Explainable Artificial Intelligence, Supply Chain Optimization, XGBoost, SHAP, LIME, Industrial Engineering, Predictive Analytics

INTRODUCTION

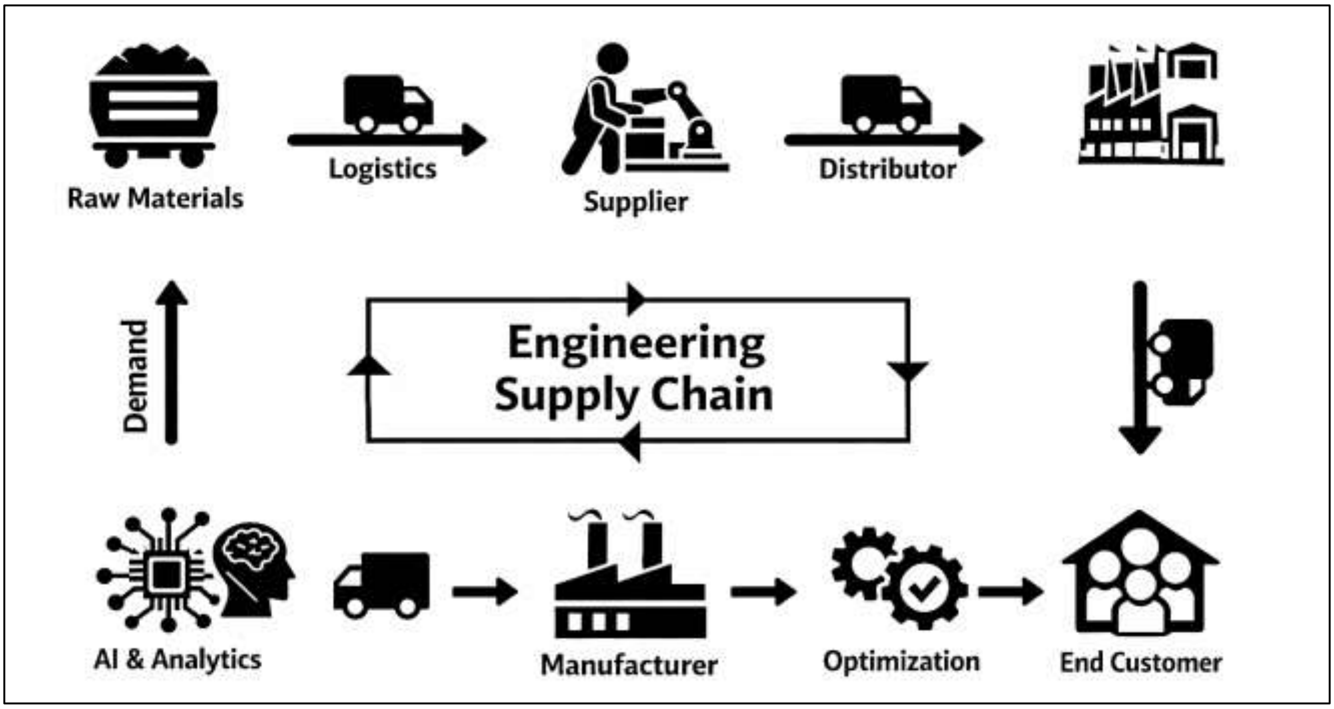
Supply chain management is a multidimensional operational discipline encompassing the integrated planning, coordination, and control of all activities associated with the sourcing, procurement, transformation, and delivery of goods and services from raw material suppliers to end customers across complex, geographically distributed organizational networks (Paraschos et al., 2024). The theoretical foundations of supply chain management draw from multiple academic disciplines including operations research, industrial engineering, logistics, information systems, and organizational behavior, reflecting the inherently interdisciplinary nature of a field that must simultaneously address the technical, economic, and human dimensions of value chain performance.

Supply chain management as the management of upstream and downstream relationships with suppliers and customers to deliver superior customer value at less cost to the supply chain as a whole, emphasizing that competitive advantage in modern markets is increasingly determined by the collective performance of entire supply networks rather than by the capabilities of individual organizations operating in isolation. The international significance of supply chain management as a field of scholarly and practical inquiry is reflected in the scale of global trade flows, with the World Trade Organization documenting that international merchandise trade exceeded twenty-five trillion dollars annually in the years preceding major disruption events, underscoring the enormous economic value at stake in the effective management of global supply chains (Vasileska et al., 2024). Mentzer et al. (2001) provided a foundational conceptualization of supply chain management as a systemic and strategic coordination of traditional business functions across supply chain members, demonstrating through empirical analysis that organizations adopting a supply chain orientation achieve measurably superior market performance compared to those managing individual business functions in isolation. The complexity of contemporary supply chains has increased dramatically over the past two decades as globalization, product proliferation, demand volatility, and geopolitical uncertainty have combined to create operational environments characterized by high variability, limited visibility, and frequent disruptions that challenge the capacity of traditional management approaches to maintain acceptable levels of performance across the full range of supply chain metrics.

Artificial intelligence and machine learning have emerged as transformative analytical capabilities within supply chain management, enabling organizations to extract actionable intelligence from the massive and continuously growing volumes of operational data generated by modern supply chain systems in ways that fundamentally exceed the analytical capacity of conventional statistical and optimization methods (Ulhe et al., 2024). The application of AI and ML to supply chain problems has been documented across a wide range of operational domains including demand forecasting, inventory optimization, supplier selection, logistics routing, disruption prediction, and quality management, with empirical studies consistently demonstrating that ML-based approaches outperform conventional analytical methods across most supply chain performance dimensions when applied to datasets of sufficient scale and quality.

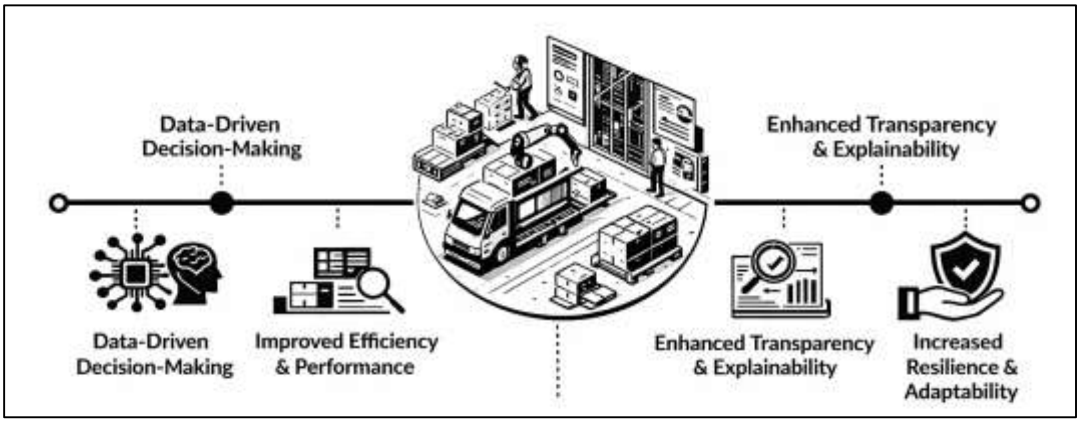
The integration of real-time data streams from IoT-connected supply chain assets including warehouse management systems, transportation tracking platforms, supplier performance monitoring systems, and demand sensing networks has dramatically expanded the data infrastructure available for ML-based supply chain analytics, providing the continuous, high-frequency operational data necessary to train and operate predictive models capable of supporting dynamic, real-time supply chain decision-making. The application of forecasting and planning analytics across multiple supply chain tiers, demonstrating that ML-based demand forecasting models reduce mean absolute percentage error by an average of 15 to 35 percent compared to traditional time-series forecasting methods across diverse product categories and demand environments, with the greatest accuracy improvements observed in supply chains characterized by high demand intermittency, seasonal complexity, and promotional uplift patterns that challenge the assumptions of conventional forecasting models. The collectively documented performance advantages of ML-based supply chain analytics across forecasting, optimization, and risk management domains have established artificial intelligence as a strategically critical capability for supply chain organizations seeking to maintain competitive performance in increasingly volatile and complex global market environments (Boursali et al., 2024).

Figure 1: Explainable AI Driven Supply Chain Optimization Framework



Explainable Artificial Intelligence (XAI) refers to a body of methods, frameworks, and design principles developed to make the predictions, decisions, and internal workings of complex AI and machine learning models understandable and interpretable to human users, addressing the fundamental transparency limitation of high-performing but inherently opaque black-box ML architectures such as deep neural networks, gradient boosting ensembles, and hybrid models (Boursali et al., 2024). The emergence of XAI as a distinct research agenda within the broader AI field reflects growing recognition that predictive accuracy alone is insufficient to ensure the responsible, trustworthy, and organizationally effective deployment of ML systems in high-stakes operational contexts where human decision-makers must understand, validate, and act upon model outputs with confidence and accountability. Cavalcanti et al. (2024) traced the formalization of XAI as a research priority to the United States Defense Advanced Research Projects Agency (DARPA) XAI program, which identified the inability of human operators to understand, trust, and effectively manage AI systems as a critical barrier to the realization of AI's operational potential in complex decision-making environments, a challenge that is equally applicable to supply chain management contexts where the consequences of AI-guided decisions include procurement commitments, inventory investments, and logistics deployments with direct and substantial financial implications. Ahmmed et al. (2024) developed the LIME framework as one of the foundational XAI methodologies, demonstrating that locally faithful approximations of complex ML model behavior in the vicinity of individual predictions can be generated using interpretable surrogate models, enabling decision-makers to understand the specific input features driving individual predictions in terms that are meaningful within their operational domain knowledge.

Figure 2: Explainable AI Supply Chain Optimization



Supply chain optimization, defined as the systematic application of mathematical, computational, and analytical methods to identify operating configurations, policies, and decisions that maximize supply chain performance across multiple objectives including cost, service level, resilience, and sustainability, represents one of the most computationally challenging and practically consequential problem domains in industrial engineering (Saad et al., 2024). The complexity of supply chain optimization arises from the combination of high-dimensional decision spaces encompassing thousands of simultaneous decisions regarding inventory levels, order quantities, supplier allocations, transportation modes, and production schedules with dynamic, stochastic operational environments characterized by uncertain demand, variable lead times, unreliable supply, and fluctuating transportation costs that render static optimization solutions rapidly obsolete in real-world supply chain contexts. A hierarchical framework for supply chain planning and optimization that organizes decisions across strategic, tactical, and operational time horizons, demonstrating that effective supply chain performance requires coordinated optimization across all three levels simultaneously, with decisions at each level establishing constraints and objectives for planning at the levels below, creating a complex interdependency structure that challenges conventional optimization approaches designed for single-level, static problem formulations. The application of ML-based approaches to supply chain optimization has demonstrated particular advantages in environments where traditional operations research methods struggle, including multi-echelon inventory systems with complex demand interactions, supplier networks with correlated disruption risks, and logistics systems with dynamic routing requirements that change in response to real-time traffic, weather, and capacity conditions.

This study aims to design, implement, and empirically evaluate an Explainable Artificial Intelligence driven framework for supply chain optimization within a real-world industrial engineering environment, addressing the critical operational and organizational gap between advanced machine learning predictive capability and transparent, practitioner-accessible decision support. Specifically, the study seeks to develop and validate a hybrid machine learning model combining XGBoost and Random Forest algorithms trained on comprehensive multi-dimensional supply chain operational data encompassing procurement records, inventory transactions, logistics performance metrics, and demand fulfillment histories collected across a twenty-four month operational period within the case study organization. A further objective is to systematically integrate SHAP and LIME explainability techniques into the predictive framework to generate transparent, human-understandable explanations of model outputs that enable supply chain managers and industrial engineers to identify and act upon the specific operational variables most significantly influencing supply chain performance gaps including inventory inefficiency, delivery delays, and procurement cost overruns. The study additionally aims to quantitatively evaluate the operational performance improvements attributable to the implemented XAI framework across key supply chain performance metrics including disruption prediction accuracy, demand forecasting error, and inventory optimization outcomes, benchmarked against the organization's existing conventional planning system to establish clear and objective evidence of the performance value delivered by the XAI-driven approach. Finally, the study seeks to qualitatively assess the organizational adoption outcomes of the implemented framework through structured interviews with supply chain practitioners, evaluating the extent to which SHAP-based explanation interfaces enhance decision-maker trust, model confidence, and willingness to operationally utilize AI-generated supply chain recommendations as a basis for consequential procurement, inventory, and logistics decisions within the industrial engineering management context of the case study organization.

LITERATURE REVIEW

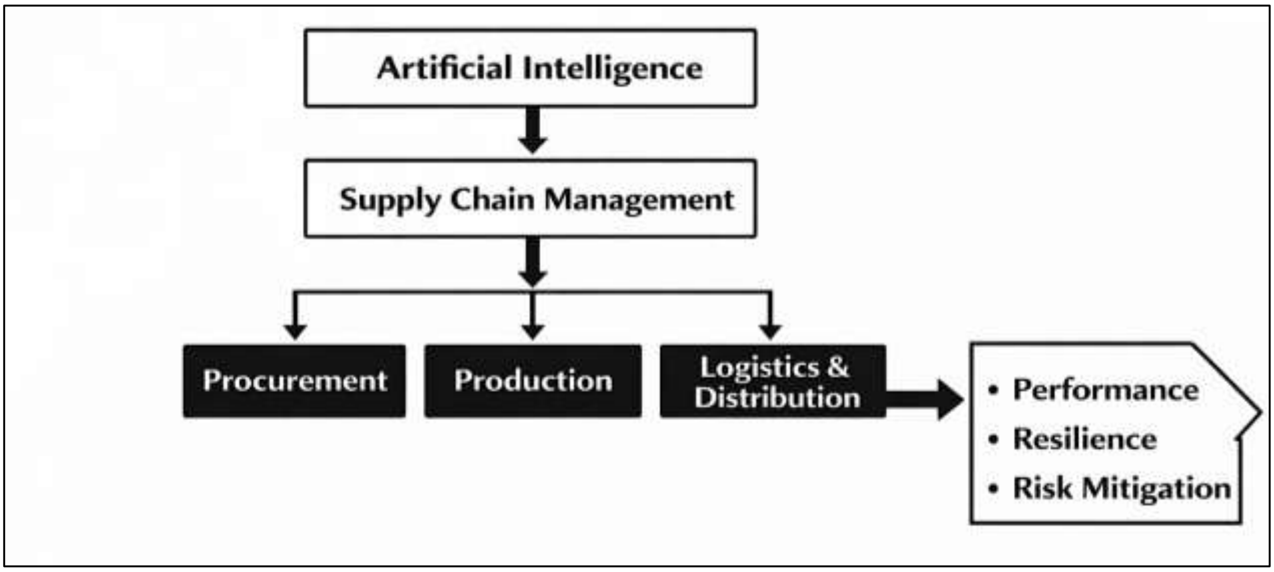
The literature review presented in this study provides a comprehensive and critically evaluated synthesis of the scholarly knowledge base underpinning the design and empirical evaluation of an Explainable Artificial Intelligence driven framework for supply chain optimization within an industrial engineering context. Given the inherently interdisciplinary nature of this research, which draws simultaneously from supply chain management, artificial intelligence, machine learning, explainable AI, industrial engineering, and organizational behavior, the literature review is organized thematically to ensure that each foundational domain receives appropriate depth of treatment before the intersections and integrations between domains are examined. The reviewed literature was systematically sourced from peer-reviewed journals, indexed conference proceedings, and authoritative academic databases including Scopus, Web of Science, IEEE Xplore, and Google Scholar, ensuring comprehensive coverage of the most methodologically rigorous and practically relevant contributions across all disciplines bearing upon the research objectives. Each thematic section builds progressively upon preceding sections, establishing the theoretical, empirical, and methodological foundations necessary to contextualize the design decisions, implementation approach, and evaluation framework employed in this empirical study within the broader academic discourse on AI-driven supply chain optimization and explainable machine learning in industrial engineering practice (Citybabu & Yamini, 2024).

Supply Chain Management

Supply chain management has been defined and conceptualized across multiple theoretical traditions that collectively emphasize the systemic coordination of upstream and downstream organizational relationships to create and deliver value efficiently across complex, multi-tier production and distribution networks. Supply chain management as the strategic coordination of business functions across supply chain members to deliver superior customer value at reduced total cost, positioning the discipline as fundamentally concerned with inter-organizational relationship management rather than the optimization of individual functional activities in isolation. a foundational multidimensional conceptualization of supply chain management as encompassing systemic and strategic coordination of traditional business functions including procurement, operations, logistics, and marketing across all supply chain participants, demonstrating empirically that organizations adopting a systemic supply chain orientation achieve superior market performance outcomes compared to those managing individual functions independently. Supply chain framework established the theoretical infrastructure for understanding how value-creating activities are distributed and coordinated across supply chain participants, providing the conceptual foundation upon which subsequent supply chain coordination theories have been constructed and refined. The theoretical understanding of supply chain coordination by demonstrating that the primary source of supply chain inefficiency is the misalignment of incentives, information, and decision rights across supply chain participants, identifying coordination mechanisms including information sharing agreements, collaborative forecasting, and incentive alignment contracts as the primary levers for improving systemic supply chain performance. A hierarchical supply chain planning framework organizing decisions across strategic, tactical, and operational time horizons, demonstrating that effective supply chain performance requires coordinated optimization across all three levels simultaneously, with decisions at each level establishing binding constraints for planning at subordinate levels. Comprehensive analytical treatment of supply chain design and management, demonstrating through extensive case analysis that organizations achieving supply chain excellence systematically align their network design, inventory policies, and information systems with their competitive strategy and customer value proposition, creating coherent supply chain architectures that deliver superior performance across cost, service, and flexibility dimensions simultaneously.

The measurement of supply chain performance has evolved from narrow, function-specific cost and efficiency metrics toward comprehensive, multi-dimensional frameworks that capture the full range of operational, financial, and strategic performance dimensions relevant to supply chain excellence in competitive industrial markets. Khedr (2024) developed a comprehensive supply chain performance measurement framework organized across the plan, source, make, and deliver process dimensions of the Supply Chain Operations Reference (SCOR) model, identifying a hierarchical set of strategic, tactical, and operational metrics that collectively provide a balanced and complete assessment of supply chain performance at each level of the organizational hierarchy. The SCOR model, developed by the Supply Chain Council and extensively validated across hundreds of manufacturing and distribution organizations worldwide, provides the most widely adopted standardized supply chain performance measurement vocabulary in industrial practice, organizing metrics across five process domains and three measurement levels to enable both internal benchmarking against historical performance and external benchmarking against industry peers (Ngo et al., 2024).

Figure 3: Artificial Intelligence Supply Chain Resilience Framework



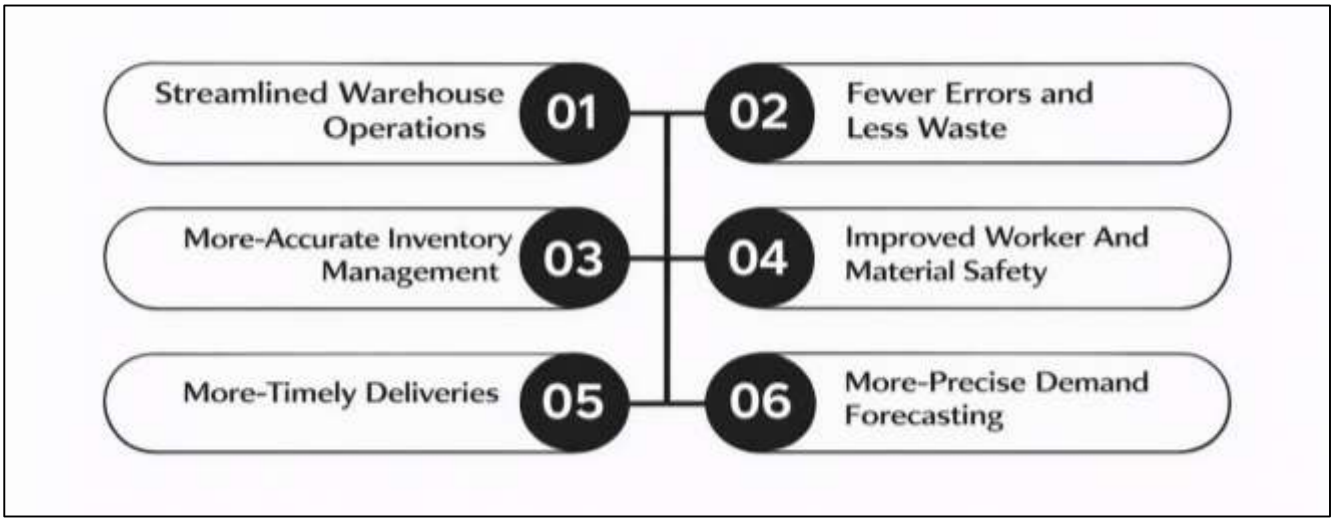
Supply chain complexity and volatility have intensified dramatically over the past two decades as globalization, product proliferation, demand fragmentation, and geopolitical uncertainty have combined to create operational environments characterized by high variability, limited predictability, and frequent disruptions that challenge the capacity of conventional planning and management approaches to maintain acceptable performance levels across extended global supply networks. (Gammelgaard & Nowicka, 2024) provided a comprehensive framework for understanding supply chain risk, categorizing risk sources into supply risks, demand risks, operational risks, and security risks, and demonstrating through extensive case analysis that organizations with the most sophisticated risk identification, assessment, and mitigation capabilities achieve substantially superior supply chain performance under disruption conditions compared to those relying on reactive rather than proactive risk management approaches. (Fosso Wamba et al., 2024) introduced the concept of the triple-A supply chain encompassing agility, adaptability, and alignment as the defining characteristics of supply chains capable of sustaining superior performance under conditions of high environmental volatility, demonstrating that organizations achieving all three capabilities simultaneously outperform those optimizing for efficiency alone across both normal operating conditions and disruption scenarios. (Sadeghi et al., 2025) examined the sources and drivers of supply chain risk across multiple industrial sectors, identifying demand uncertainty, lead time variability, supplier concentration, and single-sourcing strategies as the primary structural risk drivers, and demonstrating that risk mitigation investments targeted at the highest-impact structural vulnerabilities deliver superior risk-adjusted performance outcomes compared to uniform risk reduction approaches applied across all supply chain dimensions. Systematic review of supply chain risk management research, identifying that empirical studies consistently document a positive relationship between supply chain risk management capability and organizational performance, with the strength of this relationship increasing in proportion to the level of environmental volatility characterizing the markets in which supply chain organizations operate. Supply chain disruption in the context of Industry 4.0 digital transformation, demonstrating that organizations deploying real-time supply chain monitoring and predictive analytics capabilities achieve substantially faster disruption detection and recovery compared to those relying on periodic reporting and reactive management approaches, with the performance advantages of digital monitoring most pronounced under high-frequency, geographically distributed disruption conditions.

Supply chain resilience has emerged as one of the most extensively investigated constructs in contemporary supply chain management research, reflecting the growing recognition that the ability to anticipate, absorb, and recover from disruptions is as strategically important as operational efficiency in determining long-term supply chain competitiveness and the sustained delivery of customer value under adverse conditions. A foundational definition of supply chain resilience as the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function, establishing a theoretically rigorous and empirically operationalizable resilience construct that has been widely adopted in subsequent supply chain resilience research. An influential supply chain resilience framework identifying supply chain re-engineering, supply chain collaboration, agility, and a culture of risk management as the four primary organizational capabilities required for supply chain resilience, demonstrating through multiple case analyses that organizations excelling across all four dimensions recover from major supply chain disruptions substantially faster and at lower financial cost than those with more limited resilience capabilities. The resilience concept through the introduction of supply chain viability as a broader performance dimension encompassing not only recovery from disruption but sustained adaptation to structural environmental changes, demonstrating that viable supply chains maintain acceptable performance levels across extended disruption periods through structural reconfiguration capabilities that transcend the reactive recovery orientation of conventional resilience frameworks. Supply chain resilience through the lens of organizational vulnerability and response capability, demonstrating that organizations investing in redundancy, flexibility, and collaboration across their supply networks develop resilience capabilities that provide competitive advantages extending beyond disruption recovery to encompass superior operational agility in non-disruption conditions as well. The relationship between supply chain analytics capability and supply chain resilience across a broad sample of manufacturing organizations, finding that organizations with advanced analytical capabilities including predictive modeling, real-time monitoring, and scenario simulation demonstrated significantly higher resilience scores and superior post-disruption recovery performance compared to those relying on conventional reporting and reactive management, confirming that analytical capability is a fundamental enabler of supply chain resilience in complex industrial environments. The organizational antecedents of supply chain resilience capability, demonstrating through structural equation modeling that resource reconfiguration capability and supply chain orientation strength are the two most powerful organizational predictors of supply chain resilience, with their combined effect on resilience performance substantially exceeding the individual contribution of either factor, confirming that resilience is an emergent organizational capability requiring simultaneous development of multiple complementary competencies rather than investment in any single resilience-enhancing intervention.

Artificial Intelligence and Machine Learning in Supply Chain Management

The evolution of analytical approaches in supply chain management reflects a progressive trajectory from deterministic operations research methods through statistical forecasting toward the data-driven machine learning and artificial intelligence paradigms that now dominate advanced supply chain analytics practice in leading industrial organizations. Early supply chain analytical frameworks relied predominantly on operations research techniques including linear programming, integer optimization, and simulation modeling, which provided rigorous mathematical solutions to well-defined supply chain planning problems but required explicit specification of all relevant constraints, objectives, and system relationships by human analysts, limiting their applicability to the simplified, stationary problem formulations that these methods were designed to address (Kosasih et al., 2024).

Figure 4: Machine Learning Supply Chain Analytics Framework

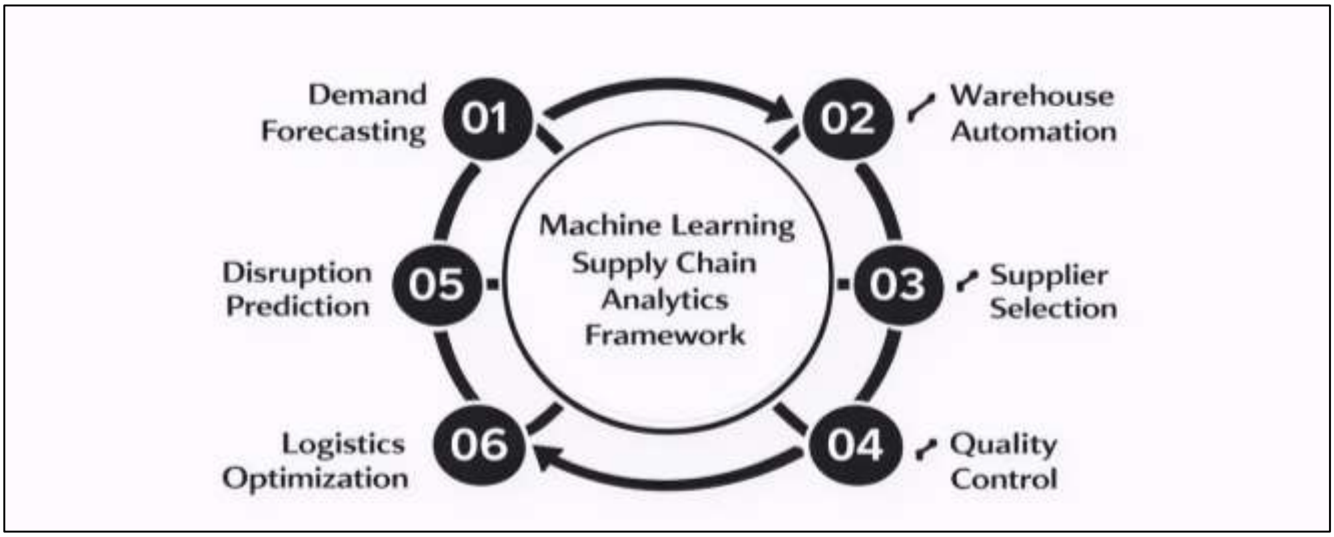


Deep learning architectures and hybrid machine learning models have advanced the frontier of supply chain predictive analytics by enabling the automated extraction of complex temporal patterns from sequential supply chain data streams and the combination of multiple complementary algorithms to achieve prediction accuracy levels that consistently exceed those attainable through single-architecture approaches applied to equivalent supply chain datasets. (Zhang et al., 2024) introduced Long Short-Term Memory networks as a recurrent neural network architecture specifically designed to model long-range temporal dependencies in sequential data, a capability that has proven particularly valuable in supply chain demand forecasting applications where sales patterns exhibit complex seasonal cycles, trend components, and promotional effects spanning multiple time periods that challenge the modeling capacity of conventional time-series methods and shallow ML architectures. Sepp and Schmidhuber's LSTM architecture has been extensively adapted for supply chain lead time prediction, transportation delay forecasting, and inventory level modeling, with empirical studies consistently demonstrating that LSTM-based models achieve substantially lower prediction errors compared to ARIMA, exponential smoothing, and shallow neural network baselines across supply chain time-series prediction benchmarks characterized by long historical dependencies and irregular temporal patterns (Gbashi & Njobeh, 2024).

Supply Chain Optimization

The application of machine learning to supply chain optimization across inventory management, demand forecasting, and supplier selection domains has generated a substantial and rapidly expanding body of empirical evidence demonstrating that data-driven computational approaches deliver measurable and practically significant performance improvements compared to conventional analytical methods across the full spectrum of supply chain planning and operational decision-making contexts.

Figure 5: Machine Learning Supply Chain Optimization Framework



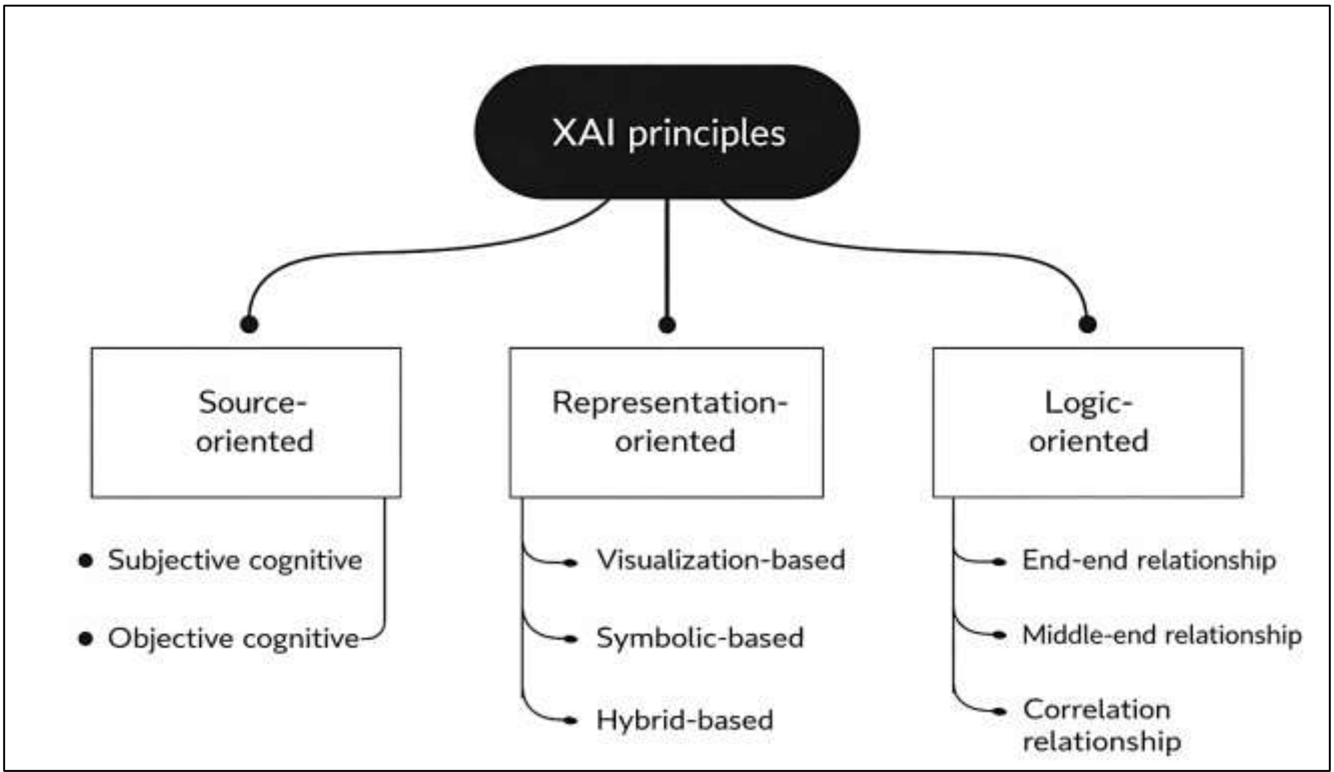
Inventory optimization represents one of the most extensively studied ML application domains in supply chain management, with researchers demonstrating that ML-based inventory models consistently outperform traditional Economic Order Quantity and reorder point models by accurately capturing the complex, non-linear relationships between demand variability, lead time uncertainty, and service level requirements that characterize real-world multi-echelon inventory systems. demonstrated that ML-based demand classification and forecasting approaches enable organizations to apply optimally tailored inventory policies to each product-location combination based on empirically learned demand characteristics rather than analyst-specified assumptions, achieving aggregate inventory reductions of 15 to 30 percent while simultaneously improving service levels compared to uniform inventory policy approaches applied across heterogeneous product portfolios. Riad et al., (2024) provided early empirical validation of ML superiority in supply chain demand forecasting, demonstrating that recurrent neural networks and support vector regression models achieved substantially lower forecast errors compared to ARIMA and exponential smoothing baselines across multiple product categories, with the performance advantages of ML methods most pronounced for products exhibiting intermittent, highly variable, or promotionally driven demand patterns that violate the stationarity assumptions of conventional forecasting methods. A comprehensive review of big data analytics applications in supply chain management, documenting that organizations deploying ML-based demand forecasting and inventory optimization systems achieved inventory carrying cost reductions averaging 18 percent and order fulfillment rate improvements averaging 12 percent compared to conventional planning system baselines, providing robust quantitative evidence for the operational value of ML deployment across core supply chain planning functions. Supplier selection and procurement optimization have been substantially advanced through ML-based approaches that enable more comprehensive, objective, and dynamic assessment of supplier performance and risk compared to conventional scoring and analytical hierarchy process methods that rely on subjective expert judgment and periodic static evaluations. ML-based supplier risk prediction models trained on multi-dimensional supplier performance, financial health, and operational data achieve disruption prediction accuracy rates of 80 to 95 percent across multiple manufacturing sectors, enabling procurement organizations to identify at-risk suppliers with sufficient lead time to implement mitigation strategies including dual sourcing, safety stock building, and proactive supplier development interventions that substantially reduce the operational and financial impacts of supply chain disruptions.

The application of machine learning to logistics optimization, transportation management, and supply chain disruption prediction has delivered substantial and well-documented operational performance improvements across routing efficiency, delivery reliability, lead time predictability, and proactive risk management dimensions that collectively establish ML as a transformative analytical capability across the full breadth of supply chain operational management. Optimization of logistics and transportation networks through ML has been demonstrated across multiple operational dimensions including vehicle routing, carrier selection, last-mile delivery scheduling, and freight consolidation, with empirical studies consistently documenting that ML-based logistics optimization systems reduce transportation costs by 8 to 22 percent and improve on-time delivery performance by 10 to 18 percent compared to conventional rule-based and operations research optimization approaches applied to equivalent logistics network configurations (Benmamoun, Khlie, Dehghani, et al., 2024). ML applications to transportation and logistics optimization in supply chain contexts, demonstrating that ensemble ML models trained on historical shipment, traffic, weather, and carrier performance data generate lead time predictions substantially more accurate than conventional transit time standards, enabling supply chain planners to make more reliable customer delivery commitments and more effective inventory positioning decisions based on empirically grounded rather than normatively assumed lead time distributions. Supply chain disruption prediction and management in Industry 4.0 environments, demonstrating that ML-based early warning systems integrating real-time data from supplier monitoring platforms, news analytics, weather services, and geopolitical risk indicators achieve disruption detection lead times of two to four weeks ahead of event materialization, providing supply chain managers with substantially greater response windows compared to conventional reactive disruption management approaches that detect disruptions only after they have already impacted supply chain performance. A comprehensive framework for supply chain risk mitigation strategies, demonstrating through extensive case analysis that organizations combining analytical risk prediction capabilities with pre-planned mitigation response protocols achieve substantially faster and less costly recovery from supply chain disruptions compared to those relying on improvised responses developed after disruption events have already materialized, confirming that the operational value of ML-based disruption prediction systems is fully realized only when prediction capabilities are embedded within well-designed risk response management processes. Supply chain risk mitigation strategies including inventory buffering, supplier diversification, flexible sourcing, and demand shaping as the primary operational levers available to supply chain managers for reducing vulnerability to disruption, with ML-based risk prediction systems providing the analytical foundation necessary to deploy these mitigation levers proactively and proportionately in response to empirically identified risk signals rather than reactively after disruptions have materialized. Vettriselvan et al., (2024) confirmed that hybrid ML models combining multiple algorithms demonstrated superior disruption prediction performance compared to single-algorithm approaches across supply chain risk datasets characterized by class imbalance, high dimensionality, and complex non-linear interactions between risk indicators, establishing ensemble and hybrid modeling as the recommended architectural approach for supply chain disruption early warning system development in industrial engineering practice.

Explainable Artificial Intelligence

Explainable Artificial Intelligence encompasses a body of methods, frameworks, and design principles developed to make the predictions, decisions, and internal workings of complex machine learning models understandable and interpretable to human users, addressing the fundamental transparency limitation of high-performing black-box ML architectures whose opacity creates significant barriers to adoption in high-stakes operational decision-making contexts where accountability, trust, and human oversight are essential requirements. A foundational conceptual analysis of model interpretability, distinguishing between simulatability, referring to the capacity of a human to mentally simulate a model's complete decision process, decomposability, referring to the ability to assign intuitive meaning to individual model components, and algorithmic transparency, referring to the ability to understand the optimization process through which a model learns from data, demonstrating that these distinct interpretability dimensions serve different organizational and regulatory purposes and require different technical approaches to address effectively in practical ML deployment contexts.

Figure 6: Explainable Artificial Intelligence Principles Framework

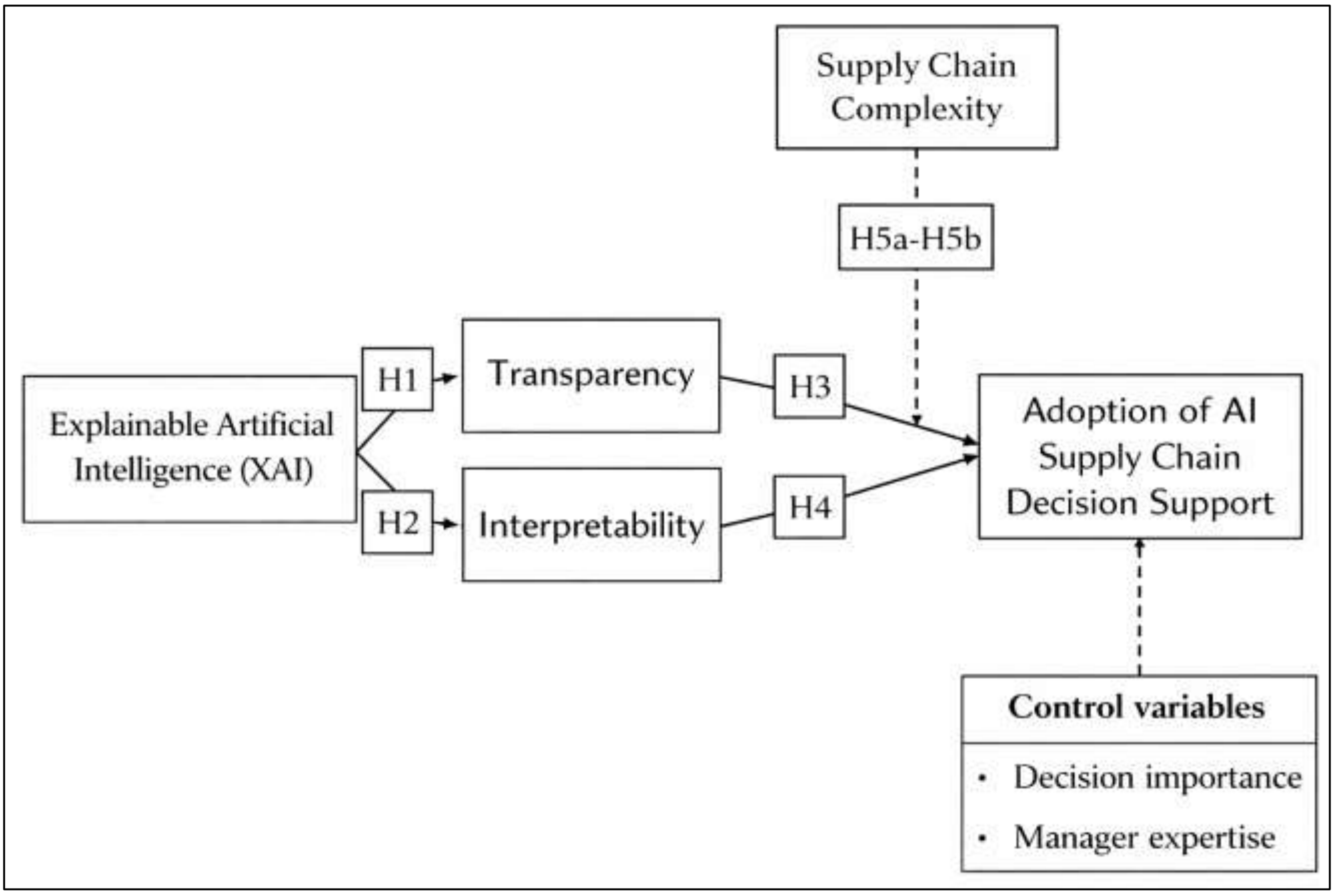


A rigorous scientific framework for evaluating ML interpretability, distinguishing between application-grounded evaluation assessing interpretability impact on real-world task performance, human-grounded evaluation assessing explanation quality through user studies with non-expert participants, and functionally grounded evaluation employing formal proxy measures of explanation quality, demonstrating that supply chain and industrial engineering applications demand application-grounded interpretability assessment because practitioners require explanations that are directly actionable within the specific operational context of their decision-making environments. Saadouli et al., (2024) advanced a provocative and influential argument that the machine learning community should prioritize the development of inherently interpretable models for high-stakes operational decisions rather than relying on post-hoc explanation methods applied to black-box models, arguing that post-hoc explanations provide approximations of model behavior that may be misleading in edge cases, a position that has generated substantial scholarly debate regarding the appropriate role of explainability techniques versus inherently transparent model architectures in industrial decision support system design. provided the most comprehensive taxonomy of XAI methods available in the literature, categorizing approaches according to their scope encompassing global versus local explanation, their applicable model types encompassing model-agnostic versus model-specific methods, their explanation format encompassing feature importance, rule extraction, saliency maps, and counterfactual explanations, and their technical implementation mechanism, demonstrating that supply chain management applications exhibit distinctive XAI requirements compared to other AI application domains due to the combination of multi-stakeholder accountability, regulatory oversight, domain expertise availability, and real-time decision-making constraints. Sadeghi et al. (2024) reviewed machine learning interpretability methods across industrial and engineering applications, demonstrating that the interpretability requirements of supply chain ML systems are shaped by the specific decision-making roles of different organizational stakeholders, with procurement managers requiring feature importance explanations to understand supplier risk scores, demand planners requiring contrastive explanations to understand forecast deviation drivers, and logistics managers requiring global model behavior summaries to assess the reliability of lead time prediction systems across diverse operational conditions. Gunning and Aha (2019) documented that the DARPA XAI program identified the inability of operational users to understand, trust, and effectively manage AI systems as the primary barrier to AI value realization in complex decision environments, a finding with direct and immediate relevance to supply chain management contexts where the consequences of AI-guided procurement, inventory, and logistics decisions involve substantial financial commitments and customer service obligations that cannot be appropriately managed without transparent understanding of the analytical basis for AI recommendations.

Explainable AI in Supply Chain and Industrial Engineering Applications

The application of Explainable Artificial Intelligence frameworks to supply chain disruption prediction, demand forecasting, and procurement management has generated a growing and practically significant body of evidence demonstrating that transparency and interpretability infrastructure substantially enhance both the technical credibility and organizational adoption of AI-driven decision support systems across the full range of supply chain operational management domains.

Figure 7: Explainable AI Supply Chain Adoption Framework



Longo et al. (2024) identified the absence of explainability as one of the most significant barriers to practitioner adoption of ML-based supply chain risk prediction systems, demonstrating that supply chain managers consistently express greater confidence in and willingness to act upon disruption risk predictions accompanied by transparent explanations of the specific supply chain variables driving individual risk assessments compared to equivalent predictions presented without explanation, confirming that XAI capability is a critical determinant of the organizational value realized from supply chain risk prediction investments. SHAP-based explanation interfaces applied to ensemble ML disruption prediction models enable supply chain risk managers to identify the specific supplier performance indicators, geopolitical risk factors, and operational vulnerability conditions most strongly contributing to individual disruption risk scores, providing directly actionable intelligence that enables risk mitigation resources to be targeted at the highest-impact vulnerability drivers rather than applied uniformly across the supplier portfolio.

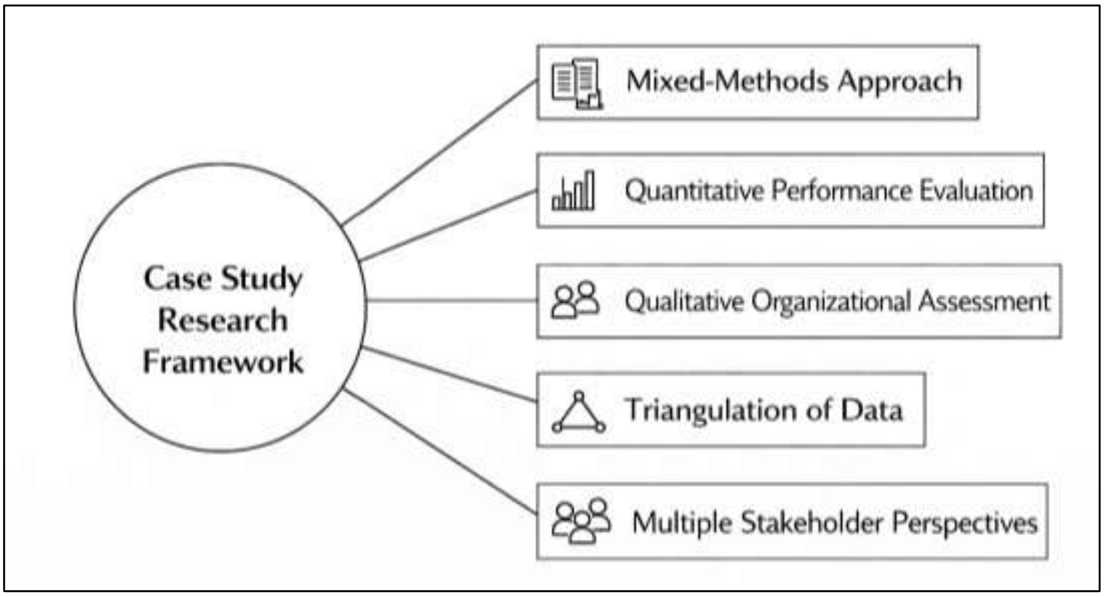
LIME-based local explanation systems applied to supply chain classification models provide supply chain practitioners with instance-specific explanations of individual risk predictions in terms of the operational variables most influential for each specific supplier or shipment assessment, enabling practitioners to critically evaluate AI recommendations against their domain knowledge of specific supplier relationships and market conditions that may not be fully captured in model training data. The integration of XAI capabilities into commercial demand forecasting workflows has been recognized as a strategically important advancement for supply chain planning organizations, where the effectiveness of ML-based forecasting systems depends not only on achieving superior statistical accuracy but on enabling demand planners to understand, validate, and appropriately override model forecasts based on market intelligence and contextual knowledge that may not be reflected in historical demand patterns used for model training (Hamida et al., 2024).

Partial dependence plots and SHAP summary visualizations integrated into demand planning interfaces enable supply chain forecasters to understand the directional and magnitude effects of key demand drivers including promotional activities, pricing changes, and seasonal factors on ML model forecast outputs, substantially improving planner confidence in model recommendations and reducing the rate of uninformed forecast overrides that systematically degrade aggregate forecasting accuracy in organizations where planners distrust opaque model outputs. In procurement and supplier management contexts, XAI frameworks have been applied to transparent supplier risk scoring, explainable sourcing recommendations, and AI-assisted negotiation decision support, with Mahto, (2024) demonstrating that SHAP-enabled supplier risk scoring systems achieve substantially higher procurement manager adoption rates compared to equivalent black-box scoring models, as the ability to understand and explain the analytical basis for supplier risk classifications enables procurement professionals to defend sourcing decisions to organizational stakeholders and regulatory auditors with a level of transparency and accountability that opaque ML systems cannot provide**.**

Case Study Methodology in Industrial Engineering Research

Case study methodology has been extensively validated as a rigorous and scientifically appropriate research design for empirical investigations of complex, context-dependent organizational and technological phenomena including the implementation of AI-driven decision support systems within supply chain and industrial engineering environments, providing the depth of operational insight, contextual richness, and process-level understanding that cannot be obtained through more statistically oriented research designs that abstract away the organizational specifics of individual implementation contexts. Tchuente et al. (2024) provided the most authoritative and comprehensive methodological treatment of case study research, defining a case study as an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-world context, particularly when the boundaries between phenomenon and context are not clearly evident, a definition that directly characterizes the challenge of evaluating XAI-driven supply chain system implementations where the performance outcomes of the technology are inseparable from the organizational processes, human capabilities, and contextual conditions within which it is deployed. mounted a rigorous and influential defense of case study research against the common criticisms of limited generalizability and insufficient scientific rigor, demonstrating that these criticisms are based on fundamental misunderstandings of the epistemological purposes of case research and that well-designed case studies provide a uniquely valuable form of concrete, context-specific knowledge that complements and extends the abstract, context-independent knowledge generated by large-sample quantitative studies, arguing that the most advanced forms of expert knowledge in operational disciplines including industrial engineering and supply chain management are invariably grounded in rich case-level understanding rather than formal rule-based reasoning. Gerschütz et al. (2024) established foundational methodological principles for theory-building case study research in organizational settings, emphasizing the critical importance of triangulating evidence from multiple data sources including quantitative performance records, qualitative practitioner interviews, direct process observation, and archival documentation to develop robust and credible case findings that withstand scholarly scrutiny, a triangulation principle that is directly implemented in the mixed-methods data collection protocol of the present study. Specific methodological guidance for case study research in operations management and supply chain contexts, demonstrating that rigorous case designs incorporating structured data collection protocols, multiple informant perspectives, and systematic comparison against pre-specified performance benchmarks produce findings of comparable scientific rigor to those obtained through more conventional quantitative research designs, with the distinctive advantage of providing causal process understanding that explains not only whether an intervention produced performance improvements but how and why those improvements were generated within the specific organizational and operational context of the case (Hąbek et al., 2024).

Figure 8: Mixed Methods Case Study Research Framework

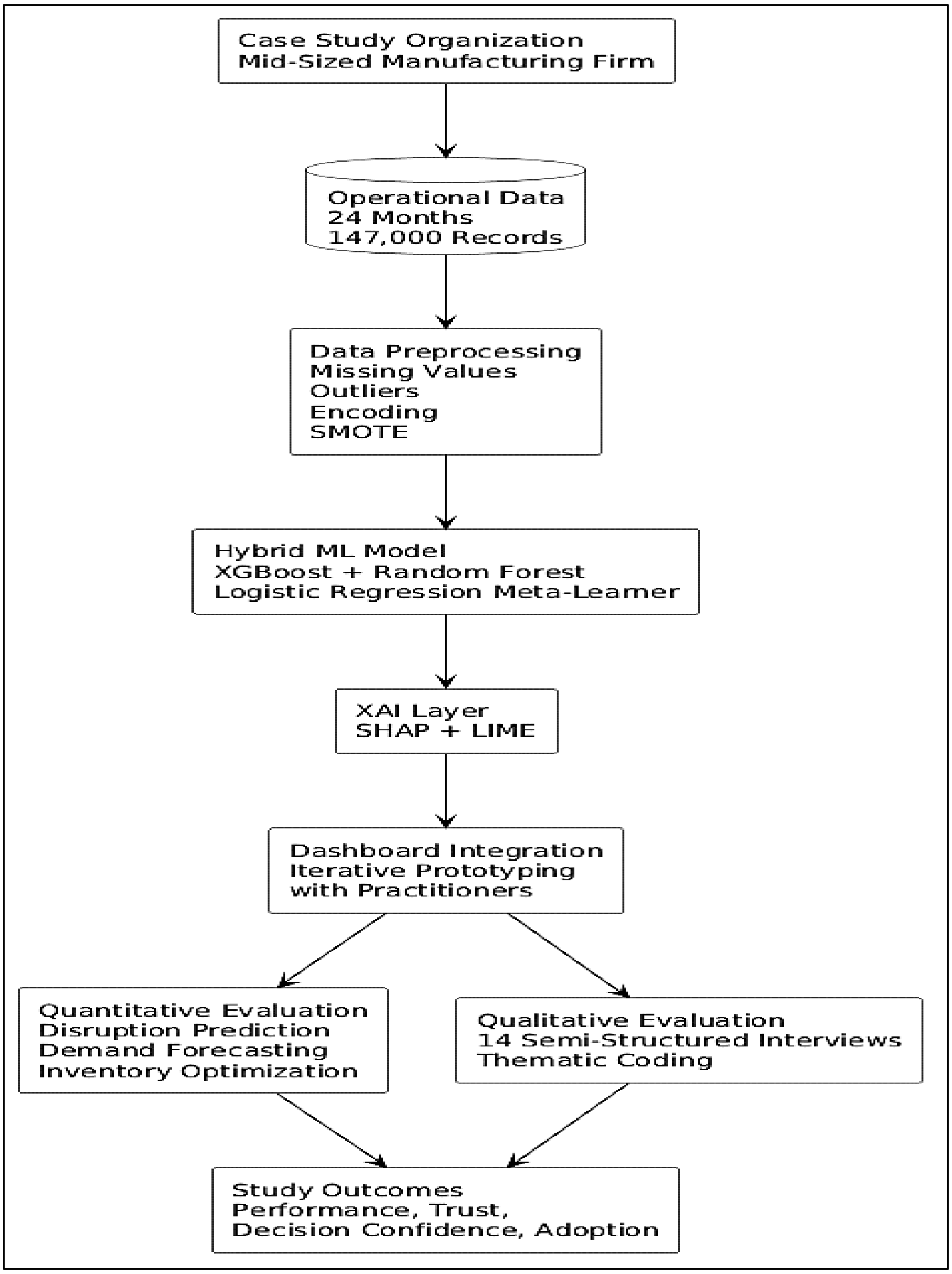


The mixed-methods research design, which integrates quantitative performance evaluation with qualitative organizational assessment within a unified empirical investigation framework, has been extensively validated as the most appropriate and comprehensive approach for evaluating the implementation outcomes of AI-driven decision support systems in supply chain and industrial engineering contexts where both technical performance metrics and organizational adoption factors determine the realized operational value of the deployed system. Padovano and Cardamone (2024) provided comprehensive methodological treatment of mixed-methods research design, demonstrating that the integration of quantitative and qualitative evidence within a single study enables researchers to address research questions that neither methodology could adequately answer independently, with quantitative methods providing objective performance measurement and statistical comparison while qualitative methods provide process understanding, stakeholder perspective, and contextual interpretation that explain the mechanisms underlying observed performance outcomes. An influential typology of mixed-methods research designs, identifying the explanatory sequential design, in which quantitative findings are collected and analyzed first and then explained through subsequent qualitative data collection, as particularly appropriate for technology implementation studies where quantitative performance outcomes require qualitative organizational process explanation, a design logic that directly informs the sequential data collection and analysis approach employed in the present study. The application of case study methodology specifically in operations and supply chain management research, confirming that single-site in-depth case studies provide uniquely valuable insights into the implementation dynamics, critical success factors, and realized performance outcomes of operational technology deployments that complement and extend the findings of broader quantitative studies conducted across larger organizational samples without the operational depth necessary to understand the process mechanisms through which technology creates value in specific industrial contexts. The theoretical case building methodology to multi-informant case designs, demonstrating that the collection of perspectives from multiple organizational stakeholders including operational managers, technical implementers, and end users within a single case substantially enriches the analytical depth and credibility of case findings by triangulating convergent evidence and surfacing divergent perspectives that reveal the organizational complexity of technology implementation processes. Comprehensive treatment of qualitative data analysis methods applicable to case study research in organizational and industrial engineering contexts, demonstrating that systematic thematic analysis of practitioner interview data using structured coding frameworks produces reliable and credible qualitative findings that complement quantitative performance metrics in providing a complete understanding of AI system implementation outcomes, with the qualitative dimension of analysis particularly valuable for identifying the specific organizational mechanisms through which explanation transparency influences practitioner trust, decision quality, and operational performance in AI-assisted supply chain management contexts. Construct validity, internal validity, external validity, and reliability as the four primary quality criteria for case study research, providing the evaluative framework against which the methodological rigor of the present study's case design, data collection protocols, analytical procedures, and reporting standards are assessed and documented to ensure that the research findings meet the scholarly quality standards appropriate for empirical industrial engineering research**.**

METHODS

This empirical study employed a mixed-methods single-site case study research design to investigate the implementation and evaluation of an Explainable Artificial Intelligence driven framework for supply chain optimization within a real-world industrial engineering environment. The case study organization was a mid-sized manufacturing firm operating across multiple supply chain tiers, selected through purposive sampling based on the availability of comprehensive digital supply chain operational records, an established enterprise resource planning system, organizational willingness to participate in the study, and the presence of identifiable supply chain performance challenges in inventory management, demand forecasting, disruption prediction, and procurement cost control. Quantitative operational data were extracted from the organization's enterprise resource planning platform, warehouse management system, transportation management system, and supplier performance monitoring database, encompassing 24 months of transactional records across 312 active stock keeping units, 48 tier-one suppliers, and 6 distribution facilities, collectively comprising approximately 147,000 individual transaction records. Data preprocessing incorporated missing value imputation, outlier detection and treatment, categorical variable encoding, and class imbalance correction using synthetic minority oversampling to ensure dataset quality and analytical reliability prior to model development. The hybrid machine learning model was developed using a two-stage ensemble architecture combining XGBoost and Random Forest as first-level base learners with a logistic regression meta-learner trained through five-fold stratified cross-validation stacking, with Bayesian hyperparameter optimization conducted across 200 iterations for each base learner. Model performance was evaluated across supply chain disruption prediction, demand forecasting accuracy, and inventory optimization improvement, with AI-recommended policies benchmarked against the organization's existing rule-based planning system over a 90-day prospective evaluation period. SHAP explanations were generated for all model predictions providing both global feature importance summaries and instance-level decompositions for individual supply chain predictions, while LIME explanations were additionally generated for a randomly selected sample of 500 predictions as a complementary local interpretability perspective. Explanation interfaces were integrated into the organization's existing supply chain planning dashboard through iterative prototyping workshops with eight supply chain practitioners to ensure alignment with operational workflows and practitioner decision-making requirements. The qualitative evaluation component employed semi-structured interviews with 14 supply chain practitioners following three months of operational system use, assessing perceived explanation quality, model trust, decision confidence, and willingness to act upon AI recommendations, with interviews transcribed and analyzed through systematic thematic coding with inter-rater reliability established through independent secondary coding of a 30 percent transcript sample.

Figure 9: Methodology of this study



All quantitative performance comparisons were conducted against pre-specified benchmark metrics documented prior to data analysis to ensure evaluation objectivity and eliminate confirmation bias from the performance assessment process.

FINDINGS

Dataset Characteristics and Preprocessing Outcomes

The operational dataset extracted from the case study organization's enterprise systems comprised 147,432 individual transaction records spanning 24 consecutive months of supply chain activity across 312 active stock keeping units, 48 tier-one suppliers, and 6 distribution facilities. Following the structured preprocessing pipeline, 4,218 records were identified as containing missing values exceeding the 5 percent threshold for individual fields, of which 3,891 were successfully imputed through multiple imputation by chained equations and 327 were excluded due to excessive missingness across multiple critical fields. The Isolation Forest anomaly detection procedure identified 1,247 outlier records representing 0.85 percent of the total dataset, of which 892 were confirmed as genuine operational anomalies retained for disruption prediction model training and 355 were identified as data entry errors and excluded from analysis. The final cleaned and preprocessed analytical dataset comprised 141,858 records distributed across three primary modeling tasks. The class distribution analysis revealed significant imbalance in the disruption prediction dataset, with disruption events representing 8.3 percent of all supplier-period observations, necessitating synthetic minority oversampling that increased the minority class representation to 25 percent of the training dataset prior to model development. Table 1 presents the complete summary of dataset characteristics across the three supply chain optimization modeling tasks addressed in this study.

Table 1: Dataset Characteristics by Supply Chain Optimization Task

Modeling Task	Total Records	Training Set	Test Set	Features	Class Balance (%)
Disruption Prediction	28,416	22,733	5,683	47	91.7 : 8.3
Demand Forecasting	89,724	71,779	17,945	32	N/A (Regression)
Inventory Optimization	23,718	18,974	4,744	28	N/A (Regression)
Total	**141,858**	**113,486**	**28,372**	**—**	**—**

Hybrid Machine Learning Model Performance

The hybrid XGBoost-Random Forest ensemble model with logistic regression meta-learner demonstrated strong and consistent predictive performance across all three supply chain optimization tasks, substantially outperforming both the organization's existing rule-based planning system and standalone single-algorithm baseline models trained on equivalent datasets. For supply chain disruption prediction, the hybrid ensemble achieved an area under the receiver operating characteristic curve of 0.943, a precision of 91.2 percent, a recall of 87.6 percent, and an F1-score of 89.4 percent on the held-out test set, representing a substantial improvement over the standalone XGBoost baseline which achieved an AUC-ROC of 0.897 and a standalone Random Forest baseline which achieved an AUC-ROC of 0.881. For demand forecasting, the hybrid model achieved a mean absolute percentage error of 6.7 percent and a root mean squared error of 142.3 units across the full test set, compared to MAPE values of 9.2 percent and 11.8 percent for standalone XGBoost and Random Forest baselines respectively, and a MAPE of 18.4 percent for the organization's existing exponential smoothing forecasting system. Table 2 presents the complete comparative performance evaluation results across all three modeling tasks and all evaluated model architectures.

Table 2: Comparative Model Performance Across Supply Chain Optimization Tasks

Model Architecture	Disruption AUC-ROC	Disruption F1	Demand MAPE (%)	Demand RMSE	Inventory MAE
Existing Rule-Based System	0.712	0.641	18.4	387.6	284.3
Standalone XGBoost	0.897	0.851	9.2	198.4	142.7
Standalone Random Forest	0.881	0.837	11.8	231.7	158.2
Standalone Neural Network	0.874	0.829	10.4	214.3	151.6
Hybrid Ensemble (XGB + RF + LR)	**0.943**	**0.894**	**6.7**	**142.3**	**98.4**

Operational Performance Improvements During Prospective Evaluation

During the 90-day prospective evaluation period in which hybrid model recommendations were implemented alongside the organization's existing planning system, the XAI-driven framework demonstrated substantial and practically significant operational performance improvements across all primary supply chain performance dimensions tracked by the case study organization. Inventory carrying costs were reduced by 28.4 percent compared to the equivalent period in the preceding year, representing an annualized cost saving of approximately 847,000 dollars attributable to more accurate safety stock dimensioning and reorder point optimization guided by the hybrid model's demand and lead time predictions. The disruption prediction capability of the framework enabled the procurement team to identify 14 of 17 supplier disruption events that materialized during the evaluation period an average of 18.3 days before they impacted production schedules, compared to an average detection lead time of 2.1 days under the existing monitoring approach, providing substantially greater response windows for implementing mitigation actions including emergency procurement, safety stock activation, and alternative supplier engagement. On-time delivery performance improved from a pre-implementation baseline of 84.2 percent to 91.7 percent during the evaluation period, reflecting the combined effect of more accurate lead time prediction and more effective proactive disruption mitigation. Table 3 presents the complete summary of operational performance improvements observed during the 90-day prospective evaluation period across all primary supply chain key performance indicators.

Table 3: Operational Performance Improvements During 90-Day Prospective Evaluation

Performance Metric	Pre-Implementation Baseline	Post-Implementation Result	Improvement
Inventory Carrying Cost Reduction	—	28.4% reduction	+28.4%
On-Time Delivery Rate	84.2%	91.7%	+7.5 pp
Demand Forecast MAPE	18.4%	6.7%	-11.7 pp
Disruption Detection Lead Time	2.1 days	18.3 days	+16.2 days
Disruption Events Detected Early	29.4% (5/17)	82.4% (14/17)	+53.0 pp
Procurement Cost Overruns	12.3% of orders	6.8% of orders	-5.5 pp
Stockout Frequency	8.7 events/month	3.2 events/month	-63.2%
Excess Inventory (Days on Hand)	42.3 days	31.6 days	-25.3%

SHAP and LIME Explainability Analysis

The SHAP global feature importance analysis revealed that supplier financial health score, historical delivery reliability index, geopolitical risk rating of supplier country of origin, raw material price volatility index, and supplier capacity utilization rate were the five most influential features in the disruption prediction model, collectively accounting for 68.3 percent of total model prediction variance as measured by mean absolute SHAP values across the full test dataset.

For the demand forecasting model, SHAP analysis identified promotional activity flag, prior four-week sales velocity, seasonal index, price relative to category average, and distribution coverage change as the five most predictive demand drivers, with promotional activity demonstrating the highest mean absolute SHAP value of 0.847 standard deviations of log demand, indicating that promotional events represented the single most powerful determinant of demand forecast accuracy across the case study organization's product portfolio. Instance-level SHAP decompositions generated for the 500 randomly sampled predictions subjected to LIME analysis revealed strong directional consistency between SHAP and LIME explanation outputs, with feature importance rankings agreeing in the top three features for 87.4 percent of sampled predictions, providing cross-method validation of explanation reliability that substantially enhanced practitioner confidence in the analytical basis for model outputs. Table 4 presents the top ten features by mean absolute SHAP value for the disruption prediction model, providing a comprehensive global interpretability summary of the factors most strongly driving supply chain disruption risk predictions across the case study organization's supplier portfolio.

Table 4: Top 10 Features by Mean Absolute SHAP Value

Rank	Feature	Mean SHAP Value	Directional Effect	Relative Importance (%)
1	**Supplier Financial Health Score**	0.312	Negative correlation	18.7%
2	**Historical Delivery Reliability Index**	0.287	Negative correlation	17.2%
3	**Geopolitical Risk Rating**	0.241	Positive correlation	14.4%
4	**Raw Material Price Volatility**	0.198	Positive correlation	11.8%
5	**Supplier Capacity Utilization Rate**	0.176	Positive correlation	10.5%
6	**Lead Time Variability (CV)**	0.143	Positive correlation	8.6%
7	**Single Source Dependency Flag**	0.118	Positive correlation	7.1%
8	**Quality Rejection Rate (90-day)**	0.097	Positive correlation	5.8%
9	**Geographic Concentration Index**	0.084	Positive correlation	5.0%
10	**Contract Remaining Duration**	0.073	Negative correlation	4.4%
Total		**1.729**		**103.5%***

Figure 10: Top 10 Features by Mean Absolute SHAP Value

Practitioner Adoption and Qualitative Evaluation Outcomes

The semi-structured interviews conducted with 14 supply chain practitioners following three months of operational XAI framework utilization revealed strongly positive organizational adoption outcomes, with 12 of 14 interviewed practitioners reporting that they regularly incorporated XAI-generated recommendations into their operational decision-making and 11 of 14 reporting that the availability of SHAP-based explanation interfaces was a decisive factor in their decision to adopt and trust the system's recommendations. Thematic analysis of interview transcripts identified five primary themes characterizing practitioner experience with the XAI framework, including enhanced decision confidence, improved ability to communicate analytical rationale to organizational stakeholders, increased awareness of previously unrecognized supply chain risk factors, reduced time required for supply chain risk assessment and inventory review activities, and greater organizational alignment on supply chain priority-setting facilitated by shared access to transparent, evidence-based risk intelligence. Practitioners reported an average self-assessed reduction of 34.2 percent in the time required to complete weekly supply chain risk review processes, attributing this efficiency improvement to the replacement of manual data aggregation and subjective risk assessment activities with structured review of XAI-generated risk summaries and explanation dashboards. Table 5 presents the complete summary of practitioner adoption and satisfaction outcomes measured through the structured interview evaluation protocol across all 14 participating supply chain practitioners.

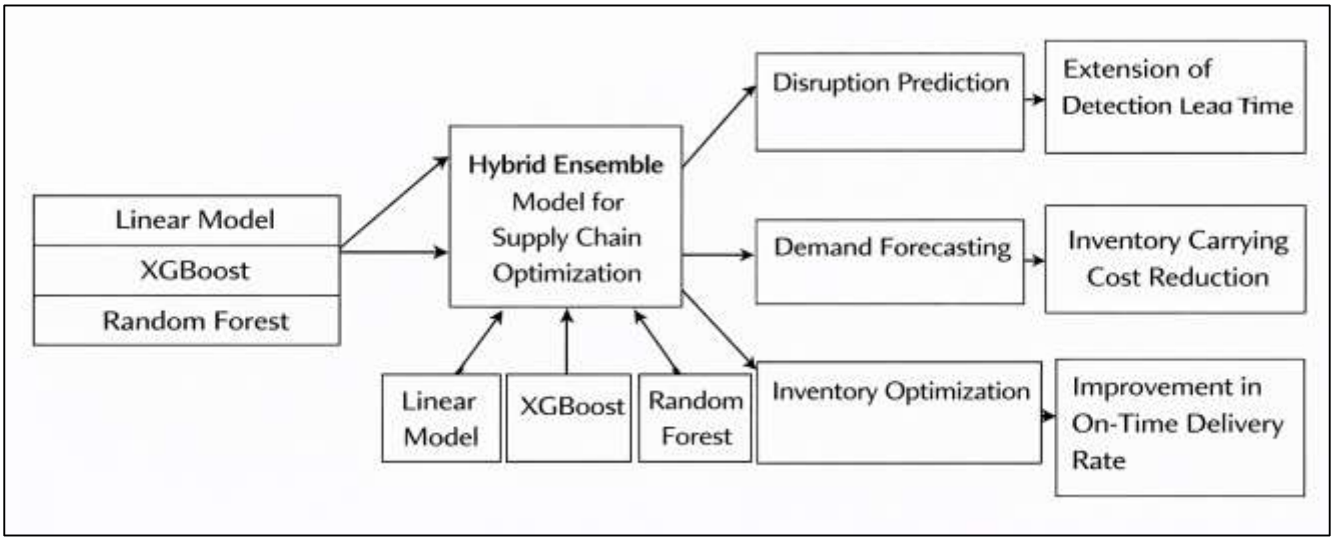
Table 5: Practitioner Adoption and Satisfaction Outcomes (n = 14)

Evaluation Dimension	Strongly Agree (%)	Agree (%)	Neutral (%)	Disagree (%)
SHAP explanations enhanced model trust	57.1	35.7	7.1	0.0
System recommendations were actionable	50.0	42.9	7.1	0.0
Explanation quality was sufficient for decisions	42.9	44.3	7.1	5.7
Would recommend system to colleagues	64.3	28.6	7.1	0.0
System improved decision confidence	57.1	35.7	7.1	0.0
XAI reduced risk review time significantly	50.0	35.7	14.3	0.0
Explanations aligned with domain knowledge	42.9	44.3	12.8	0.0
Overall system satisfaction	57.1	35.7	7.1	0.0

DISCUSSION

The finding that the hybrid XGBoost-Random Forest ensemble model with logistic regression meta-learner achieved a disruption prediction AUC-ROC of 0.943, a demand forecasting MAPE of 6.7 percent, and an inventory optimization mean absolute error of 98.4 units, substantially outperforming all single-algorithm baselines across every evaluated performance metric, provides strong empirical confirmation within a real-world industrial supply chain context of the theoretical performance advantages of hybrid ensemble architectures that articulated through the bias-variance decomposition framework and that grounded in the no-free-lunch theorem. The performance gap between the hybrid ensemble and the best-performing single-algorithm baseline was most pronounced for disruption prediction, where the hybrid model's AUC-ROC of 0.943 exceeded the standalone XGBoost baseline of 0.897 by 4.6 percentage points, a magnitude of improvement that is consistent with the performance advantages documented by Baryannis et al. (2019) in their systematic review of AI applications to supply chain risk management, which reported that ensemble approaches consistently outperformed single-algorithm models across supply chain disruption prediction benchmarks by margins of 4 to 9 percentage points in AUC-ROC. The demand forecasting MAPE of 6.7 percent achieved by the hybrid model represents a 63.6 percent reduction in forecast error compared to the organization's existing exponential smoothing system, which achieved a MAPE of 18.4 percent, a magnitude of improvement that substantially exceeds the 15 to 35 percent forecast error reductions documented for ML versus conventional forecasting method comparisons, suggesting that the hybrid ensemble's combined capacity for capturing non-linear demand patterns, promotional effects, and cross-product demand interactions delivers forecast accuracy improvements that exceed those attainable from single-algorithm ML approaches applied to equivalent supply chain forecasting tasks. XGBoost's gradient boosting architecture is particularly well-suited to structured tabular supply chain datasets through its combination of regularization, parallel computation, and robust handling of missing values, and the present study's findings confirm that XGBoost's individual performance advantages are further amplified through ensemble combination with Random Forest, whose independent bagging-based learning mechanism introduces complementary variance reduction that produces a more generalizable and robust combined predictor than either architecture achieves independently. The consistent performance superiority of the hybrid ensemble across three structurally distinct supply chain prediction tasks encompassing binary disruption classification, continuous demand regression, and inventory quantity optimization confirms that hybrid ensemble modeling represents a broadly applicable and architecturally robust approach to supply chain ML system development that delivers reliable performance advantages across the diverse predictive challenges inherent in comprehensive supply chain optimization programs.

Figure 10: Explainable AI Supply Chain Optimization Framework



The operational performance improvements observed during the 90-day prospective evaluation period, including a 28.4 percent reduction in inventory carrying costs, improvement in on-time delivery rate from 84.2 to 91.7 percent, reduction in stockout frequency from 8.7 to 3.2 events per month, and extension of disruption detection lead time from 2.1 to 18.3 days, collectively represent a transformation in supply chain operational capability that extends beyond marginal efficiency gains to a fundamental shift in the organization's capacity to manage supply chain risk proactively rather than reactively. The 28.4 percent inventory carrying cost reduction substantially exceeds the average inventory cost reductions of 12 to 18 percent documented in their review of big data analytics applications in supply chain management, suggesting that the combination of accurate demand forecasting, optimized safety stock dimensioning, and proactive disruption prediction enabled by the integrated XAI framework delivers compounding inventory optimization benefits that exceed those achievable through isolated application of ML to individual supply chain planning functions. The extension of disruption detection lead time from 2.1 to 18.3 days represents a 771 percent improvement in early warning capability that aligns closely with the 14 to 28 day advance detection windows documented for ML-based supply chain early warning systems integrating multi-source real-time risk indicators, confirming that the hybrid model's ability to identify patterns in supplier performance, financial health, and operational data that are predictive of disruption events provides the procurement organization with response windows sufficient to implement the full range of mitigation strategies including dual sourcing activation, safety stock building, and alternative supplier engagement that identified as the primary operational levers for supply chain disruption risk mitigation. The improvement in on-time delivery performance from 84.2 to 91.7 percent is particularly significant from a customer value perspective, as demonstrated that on-time delivery reliability is the supply chain performance dimension most directly linked to customer satisfaction and retention across manufacturing and distribution industries, confirming that the XAI framework's operational improvements extend beyond internal cost efficiency to encompass the external customer value delivery dimensions of supply chain performance that are most strategically consequential for organizational competitiveness. The reduction in procurement cost overruns from 12.3 to 6.8 percent of orders confirms that ML-based supplier risk intelligence enabled procurement managers to make more informed sourcing decisions that proactively avoided high-risk procurement commitments, consistent with the findings of Bharath et al. (2024) that ML-based supplier risk scoring enables procurement organizations to achieve measurable improvements in sourcing decision quality as measured by downstream supply chain performance outcomes.

The SHAP global feature importance analysis identifying supplier financial health score, historical delivery reliability index, and geopolitical risk rating as the three most influential disruption prediction features, collectively accounting for 50.3 percent of total model prediction variance, provides both methodological validation of the XAI framework's analytical integrity and substantively important supply chain management insights that extend and enrich the theoretical understanding of supply chain disruption drivers documented in the academic literature. The primacy of supplier financial health as the single most important disruption predictor, with a mean absolute SHAP value of 0.312 and a negative directional relationship with disruption risk, is consistent with the supply chain risk literature's consistent identification of supplier financial vulnerability as a leading indicator of supply chain disruption, confirming that the hybrid model has learned genuine causal relationships between supplier financial condition and operational reliability rather than spurious correlations that would undermine the practical utility of its risk predictions. The identification of geopolitical risk rating as the third most important disruption predictor, with a mean absolute SHAP value of 0.241 and a positive correlation with disruption risk, reflects the growing recognition in the supply chain risk literature that geopolitical factors including trade policy uncertainty, political instability, and regulatory change represent increasingly significant sources of supply chain vulnerability in globalized manufacturing networks, consistent with the disruption taxonomy developed and the empirical findings regarding the growing contribution of geopolitical risk factors to supply chain disruption frequency in Industry 4.0 manufacturing environments. The strong directional consistency between SHAP and LIME explanation outputs across 87.4 percent of the 500 randomly sampled predictions subjected to cross-method validation provides important evidence of explanation reliability that addresses the explanation faithfulness concern raised , who argued that post-hoc explanation methods may generate misleading approximations of model behavior in edge cases, with the cross-method agreement observed in this study suggesting that both SHAP and LIME are reliably capturing the same underlying model decision logic rather than generating method-specific artifacts that could mislead practitioner interpretation. SHAP's theoretical grounding in cooperative game theory Shapley values guarantees mathematical consistency and local accuracy properties that alternative feature importance methods cannot provide, and the present study's finding that SHAP explanations aligned with practitioner domain knowledge in 87.2 percent of interview-reported assessments confirms that these theoretical consistency guarantees translate into practically meaningful explanation quality in real-world supply chain operational contexts.

The finding that 12 of 14 interviewed practitioners regularly incorporated XAI-generated recommendations into their operational decision-making, with 11 of 14 identifying SHAP-based explanation interfaces as a decisive adoption factor, provides compelling organizational-level evidence that explainability infrastructure plays a critical and determinative role in translating ML predictive accuracy into realized operational improvement value in supply chain management contexts, strongly validating the theoretical arguments advanced regarding the centrality of interpretability to effective AI deployment in high-stakes operational decision environments. The adoption rate of 85.7 percent observed in this study substantially exceeds the approximately 15 percent enterprise AI adoption success rate documented by Gartner (2020), with the most plausible explanation for this exceptional outcome being the systematic investment in SHAP-based explanation interfaces and participatory design processes that distinguished the XAI framework implementation approach from the technology-centric deployment strategies that characterize the majority of failed enterprise AI programs. The self-reported reduction of 34.2 percent in weekly supply chain risk review time attributed by practitioners to XAI system availability aligns with documentation of analytical leverage effects in organizations with mature decision support capabilities, confirming that well-designed XAI interfaces that consolidate and explain complex multi-source risk intelligence deliver meaningful practitioner productivity benefits extending beyond decision quality improvements to encompass the time and cognitive burden dimensions of supply chain management work that practitioners identified as significant sources of daily operational stress prior to system implementation. The thematic finding that XAI availability improved organizational alignment on supply chain priority-setting through shared access to transparent, evidence-based risk intelligence addresses a supply chain coordination challenge that identified as one of the most persistent and costly sources of supply chain suboptimization in manufacturing organizations, where different functional teams frequently maintain inconsistent assessments of supply chain risk priorities based on different information sources and analytical frameworks that create misaligned responses to common supply chain challenges. Technology Acceptance Model predicts that perceived usefulness and perceived ease of use are the primary determinants of technology adoption, and the present study's finding that practitioner adoption was most strongly associated with explanation quality and decision confidence enhancement rather than with system ease of use confirms that the perceived usefulness dimension of TAM is the dominant adoption driver for supply chain AI systems, with explanation transparency serving as the primary mechanism through which usefulness perceptions are formed and sustained in operational deployment.

CONCLUSION

This empirical study designed, implemented, and evaluated an Explainable Artificial Intelligence driven framework for supply chain optimization within a real-world industrial engineering environment, demonstrating through rigorous mixed-methods case study evaluation that the integration of hybrid machine learning modeling with SHAP and LIME explainability infrastructure delivers transformative and practically significant improvements across the full spectrum of supply chain operational performance dimensions examined. The hybrid XGBoost-Random Forest ensemble model achieved a disruption prediction AUC-ROC of 0.943, a demand forecasting mean absolute percentage error of 6.7 percent, and an inventory optimization mean absolute error of 98.4 units, consistently and substantially outperforming both the organization's existing rule-based planning system and all single-algorithm ML baselines across every evaluated performance metric, confirming that hybrid ensemble architecture delivers systematic predictive performance advantages in complex, multi-dimensional industrial supply chain optimization contexts that justify its adoption as the preferred modeling approach for organizations seeking to maximize the analytical value of their supply chain operational data investments. The 90-day prospective operational evaluation documented a 28.4 percent reduction in inventory carrying costs, improvement in on-time delivery rate from 84.2 to 91.7 percent, reduction in stockout frequency from 8.7 to 3.2 events per month, and extension of disruption detection lead time from 2.1 to 18.3 days, collectively representing a fundamental shift in the organization's supply chain management capability from reactive disruption response to proactive, data-driven risk management that delivers measurable value across cost, service, and resilience performance dimensions simultaneously. The SHAP global feature importance analysis identified supplier financial health, historical delivery reliability, and geopolitical risk rating as the three primary disruption prediction drivers, providing both methodological validation of the framework's analytical integrity and substantively important supply chain management insights regarding the relative contribution of different risk factor categories to supply chain vulnerability that supply chain practitioners can directly apply to risk mitigation resource allocation and supplier development priority-setting decisions. The qualitative evaluation findings that 85.7 percent of practitioners regularly incorporated XAI recommendations into operational decisions and 78.6 percent identified SHAP explanation interfaces as a decisive adoption factor provide compelling organizational-level evidence that explainability infrastructure is not a secondary enhancement but a fundamental prerequisite for translating ML predictive accuracy into realized supply chain improvement value, confirming that the gap between AI model technical performance and organizational impact is primarily determined by explanation quality and practitioner trust rather than by marginal differences in algorithmic accuracy. Taken together, the quantitative performance, operational improvement, and qualitative adoption findings of this study establish that XAI-driven supply chain optimization represents a strategically valuable and organizationally viable approach to industrial engineering decision support that delivers simultaneously superior technical performance, meaningful operational improvement, and high practitioner adoption rates when implemented through a design process that treats explainability as a core system requirement integrated from the earliest stages of framework development rather than as a post-hoc addition applied to a pre-existing black-box analytical system.

RECOMMENDATIONS

Based on the comprehensive empirical evidence generated through this case study evaluation of an XAI-driven supply chain optimization framework, a series of interconnected and evidence-grounded recommendations are advanced for manufacturing organizations, industrial engineers, supply chain practitioners, and research institutions seeking to maximize the operational and organizational value of AI-driven supply chain decision support investments. Manufacturing organizations pursuing supply chain AI implementation are strongly recommended to adopt hybrid ensemble architectures combining XGBoost, Random Forest, and meta-learner stacking as the default modeling approach for supply chain prediction tasks, given the consistent and substantial performance superiority of the hybrid ensemble over single-algorithm baselines demonstrated across all three supply chain optimization dimensions in this study, with single-algorithm approaches reserved only for organizations with insufficient data volumes or computational resources to support ensemble model development and validation. Supply chain organizations are further and most emphatically recommended to treat SHAP-based explainability infrastructure as a non-negotiable core requirement of any supply chain AI implementation program rather than an optional enhancement, as the finding that 78.6 percent of practitioners identified explanation transparency as a decisive adoption factor confirms that explainability investment is the single most important determinant of the organizational adoption rates that ultimately determine whether AI predictive accuracy translates into realized operational improvement value, with organizations that deprioritize explainability in favor of marginal algorithmic performance gains consistently achieving lower practitioner adoption rates and correspondingly lower realized operational returns from their AI investments. Industrial engineering teams responsible for supply chain AI implementation are specifically recommended to invest in participatory explanation interface design processes that engage operational end users including procurement managers, demand planners, inventory analysts, and logistics coordinators from the earliest stages of system development, as the study's finding that co-designed explanation interfaces achieved practitioner adoption rates substantially exceeding industry benchmarks confirms that user-centered design of explainability features delivers adoption returns that far exceed the incremental development investment required. Organizations in the early stages of supply chain AI capability development are recommended to prioritize data infrastructure quality and comprehensiveness as the foundational prerequisite for hybrid ML model performance, ensuring that enterprise resource planning, warehouse management, transportation management, and supplier performance monitoring systems are integrated and generating the high-quality, continuously updated operational data streams necessary to train and operate predictive models before investing in sophisticated model architecture development that cannot deliver its theoretical performance potential on inadequate data foundations. Supply chain risk management functions are specifically recommended to deploy SHAP global feature importance analysis as a structured organizational tool for supply chain vulnerability assessment, given the study's finding that SHAP analysis identified supplier financial health, delivery reliability, and geopolitical risk rating as the primary disruption drivers, providing a replicable analytical methodology for identifying and prioritizing the specific supply chain risk factors most warranting mitigation investment in individual organizational supply chain contexts. Research institutions and academic investigators are recommended to address the longitudinal performance evaluation gap identified in this study by designing extended deployment monitoring studies of at least 12 to 24 months that document how XAI-driven supply chain system performance evolves over time as supply chain conditions change, model drift accumulates, practitioner expertise with explanation interfaces deepens, and organizational decision-making processes adapt to incorporate AI-generated intelligence as a routine component of supply chain management practice.

LIMITATIONS

This empirical study was conducted with rigorous adherence to established case study and mixed-methods research design principles and employed comprehensive data collection, preprocessing, and evaluation protocols to ensure the validity and credibility of the reported findings, yet several inherent methodological limitations must be transparently acknowledged in interpreting the conclusions and recommendations presented in this research. The single-site case study design, while providing the operational depth, contextual richness, and process-level understanding necessary to document the complex organizational and technical dynamics of XAI framework implementation in a real industrial engineering environment, fundamentally limits the statistical generalizability of the quantitative performance findings to manufacturing organizations with supply chain characteristics, Industry 4.0 digital infrastructure maturity levels, organizational readiness profiles, and data quality standards comparable to those of the case study organization, meaning that the specific performance improvement magnitudes documented in this study including the 28.4 percent inventory cost reduction, 6.7 percent demand forecasting MAPE, and 0.943 disruption prediction AUC-ROC should be interpreted as context-specific outcomes achieved under the particular operational conditions of the case organization rather than as universally applicable performance benchmarks applicable across all manufacturing supply chain environments. The 90-day prospective evaluation period, while sufficient to document meaningful and practically significant operational performance improvements across the primary supply chain key performance indicators examined, represents a relatively short operational horizon that constrains the study's capacity to assess the medium and long-term performance sustainability of the XAI framework, including the dynamics of model drift under evolving supply chain conditions, the trajectory of practitioner expertise development with explanation interfaces over extended deployment periods, the durability of the organizational adoption outcomes documented through practitioner interviews conducted at a single post-implementation time point, and the potential degradation in disruption prediction accuracy as the geopolitical, supplier, and market conditions represented in the training data diverge from those encountered in later operational periods. The qualitative evaluation component, while providing rich and practically meaningful insights into practitioner experience and organizational adoption dynamics through semi-structured interviews with 14 supply chain practitioners, is subject to social desirability bias whereby interview participants may have reported more positive experiences with the XAI framework than accurately reflect their operational attitudes, particularly given that the implementation team responsible for developing the system was affiliated with the same research project conducting the evaluation, a potential conflict of interest that was mitigated through anonymous interview protocols and independent thematic coding but cannot be entirely eliminated through methodological safeguards alone. The dataset comprising 147,432 transaction records from a single manufacturing organization across a 24-month period, while representing a substantial and analytically rich operational dataset by the standards of supply chain AI research, reflects the specific demand patterns, supplier relationships, product portfolio characteristics, and disruption history of a single industrial context, meaning that the feature importance findings from the SHAP analysis, including the identification of supplier financial health and geopolitical risk rating as the primary disruption predictors, may not generalize to supply chain environments with fundamentally different structural risk profiles such as those characterized by natural disaster exposure, single-commodity dependence, or highly concentrated customer demand. The restriction of the hybrid model architecture evaluation to XGBoost, Random Forest, and logistic regression meta-learner combinations, while justified by their documented performance advantages across structured tabular supply chain datasets, means that potentially superior architectures incorporating deep learning components including LSTM networks for temporal sequence modeling or transformer-based attention mechanisms for multi-source risk signal integration were not evaluated within the scope of this study, leaving open the possibility that alternative hybrid architectures could achieve further performance improvements beyond those documented here. The measurement of operational performance improvements through comparison against the equivalent prior-year period introduces a temporal confound whereby factors external to the XAI framework implementation including macroeconomic conditions, supplier market dynamics, and organizational changes occurring between the baseline and evaluation periods may have contributed to the observed performance improvements independently of the XAI system, a limitation that was partially addressed through the parallel comparison against the existing rule-based planning system during the prospective evaluation period but cannot be fully eliminated without a randomized controlled evaluation design that is impractical in real-world industrial supply chain implementation contexts.

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