Explainable AI in Supply Chain Management: Opportunities and Research Challenges

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Abstract

The rapid adoption of Artificial Intelligence (AI) in Supply Chain Management (SCM) has transformed traditional decision-making processes by enabling predictive analytics, demand forecasting, inventory optimization, supplier evaluation, logistics planning, and risk management. Despite the significant performance improvements achieved through AI-driven systems, the increasing reliance on complex machine learning and deep learning models has raised concerns regarding transparency, trustworthiness, accountability, and regulatory compliance. Many advanced AI models operate as "black boxes," making it difficult for supply chain managers and stakeholders to understand how decisions are generated. Consequently, Explainable Artificial Intelligence (XAI) has emerged as a promising solution to enhance transparency and interpretability while maintaining the predictive power of AI systems. This paper presents a comprehensive review and conceptual analysis of Explainable AI in Supply Chain Management, examining its opportunities, applications, challenges, and future research directions. The study synthesizes findings from recent literature published between 2018 and 2026 and critically evaluates the role of XAI across major supply chain functions, including demand forecasting, procurement, supplier selection, inventory management, transportation, sustainability monitoring, and risk mitigation. The paper further identifies key barriers to XAI implementation, including data quality issues, model complexity, scalability concerns, organizational resistance, and the lack of standardized evaluation frameworks. A conceptual framework is proposed to illustrate how explainability can improve decision quality, stakeholder trust, operational resilience, and sustainable supply chain performance. The findings indicate that organizations integrating explainable AI mechanisms into supply chain analytics are better positioned to achieve transparency, regulatory compliance, and collaborative decision-making. The paper contributes to both theory and practice by establishing a research agenda that addresses emerging technological, managerial, and sustainability-related challenges associated with Explainable AI adoption in modern supply chains.

Keywords: Explainable Artificial Intelligence (XAI), Supply Chain Management, Machine Learning, Decision Support Systems, Supply Chain Analytics, Transparency, Sustainable Supply Chains

1. Introduction

The emergence of Artificial Intelligence (AI) has fundamentally transformed modern Supply Chain Management (SCM), enabling organizations to make faster, more accurate, and data-driven decisions. Global supply chains have become increasingly complex due to globalization, digital transformation, evolving customer expectations, geopolitical uncertainties, climate-related disruptions, and technological innovations. As organizations seek to improve operational efficiency and resilience, AI technologies such as machine learning, deep learning, reinforcement learning, natural language processing, and computer vision have become critical components of supply chain decision support systems [1-5].

Recent reports indicate that AI adoption in supply chain operations has grown substantially over the past decade. According to industry estimates, the global AI in supply chain market exceeded USD 8 billion in 2024 and is expected to surpass USD 30 billion by 2030, growing at a compound annual growth rate exceeding 20%. Organizations implementing AI-powered supply chain solutions have reported reductions of 15–35% in inventory costs, improvements of up to 65% in forecasting accuracy, and significant gains in logistics efficiency. Major multinational corporations, including Amazon, Walmart, Unilever, DHL, and Siemens, increasingly employ AI-driven systems to optimize procurement, inventory management, transportation planning, and supplier risk assessment [6-10].

Despite these advantages, the growing deployment of AI systems has introduced a critical challenge: explainability. Many state-of-the-art AI algorithms, particularly deep neural networks, ensemble learning models, and complex predictive systems, function as opaque "black boxes." While these models often achieve superior predictive performance, they provide limited insight into how outputs and recommendations are generated. In supply chain environments, where decisions influence millions of dollars in inventory investments, supplier relationships, transportation schedules, and sustainability commitments, a lack of transparency can create significant risks [11-15].

Supply chain managers are frequently required to justify decisions to internal stakeholders, regulatory authorities, customers, investors, and business partners. For example, if an AI system recommends terminating a supplier relationship, increasing inventory levels, or rerouting shipments, managers must understand the rationale behind these recommendations. Without interpretability, decision-makers may be reluctant to trust AI-generated outputs, limiting the practical value of advanced analytics systems. Furthermore, regulatory developments related to responsible AI and algorithmic accountability have intensified the need for transparent and explainable decision-making processes [16-20].

The concept of Explainable Artificial Intelligence (XAI) has emerged as a response to these concerns. XAI refers to a collection of methodologies, techniques, and frameworks designed to make AI systems more transparent, interpretable, and understandable to human users. Rather than treating predictive models as inaccessible black boxes, XAI seeks to reveal the reasoning, influential variables, decision pathways, and confidence levels associated with AI-generated outcomes. Through explainability mechanisms, organizations can improve trust, accountability, fairness, and collaboration between human experts and intelligent systems [21-25].

The importance of XAI has become particularly evident following major supply chain disruptions experienced during the COVID-19 pandemic, geopolitical conflicts, semiconductor shortages, and climate-related events. These disruptions exposed vulnerabilities in global supply networks and highlighted the need for resilient, transparent, and adaptive decision-support systems. AI-powered forecasting models often produced unexpected recommendations during periods of extreme uncertainty, emphasizing the necessity of interpretable decision-making frameworks capable of supporting human judgment during crises [26-30].

Within supply chain management, explainable AI offers significant opportunities across multiple functional areas. In demand forecasting, XAI can identify the factors influencing demand fluctuations and improve confidence in predictive recommendations. In supplier selection and procurement, explainability can help organizations understand supplier risk scores and sustainability evaluations. In inventory management, interpretable models can clarify the trade-offs between service levels, stock availability, and carrying costs. Similarly, in transportation and logistics planning, XAI can explain route optimization decisions, helping managers evaluate alternative scenarios and operational constraints [31-35].

Beyond operational efficiency, explainable AI also plays a crucial role in promoting sustainability and ethical supply chain practices. Increasing pressure from governments, investors, and consumers has encouraged organizations to improve environmental, social, and governance (ESG) performance. AI systems are increasingly used to monitor carbon emissions, evaluate supplier sustainability, detect unethical practices, and support circular economy initiatives.

However, stakeholders require transparent explanations regarding how sustainability-related recommendations are generated. XAI can provide this transparency, strengthening accountability and facilitating compliance with emerging regulatory standards [36-40].

Although the literature on AI in supply chain management has expanded rapidly, research specifically focusing on Explainable AI remains fragmented. Existing studies often concentrate on technical aspects of explainability while providing limited discussion of organizational implementation challenges, managerial implications, and long-term strategic impacts. Furthermore, there is a lack of comprehensive frameworks integrating explainability, supply chain resilience, sustainability objectives, and human-centered decision-making. These gaps highlight the need for systematic investigation into the opportunities and challenges associated with XAI adoption within supply chain contexts [41-48].

This paper addresses this need by providing a comprehensive review and conceptual analysis of Explainable AI in Supply Chain Management. The study aims to synthesize current knowledge, identify emerging trends, evaluate implementation challenges, and propose a research framework for future investigations. Specifically, the objectives of this research are fourfold. First, the paper examines the evolution of AI and explainability concepts within supply chain environments. Second, it critically reviews major applications of XAI across different supply chain functions. Third, it identifies research gaps and implementation barriers that hinder broader adoption. Finally, it proposes future research directions and practical recommendations for organizations seeking to develop transparent, trustworthy, and sustainable AI-driven supply chain systems.

The significance of this study extends beyond academic inquiry. As organizations continue investing in digital transformation initiatives, explainability will become an essential requirement for responsible AI governance. The integration of XAI into supply chain management has the potential to improve decision quality, enhance stakeholder trust, strengthen resilience, and support sustainable business practices. By exploring the intersection of AI, explainability, and supply chain management, this paper contributes to the development of more transparent and human-centered intelligent supply chain ecosystems.

In the following sections, the paper reviews the existing literature on AI and XAI applications in supply chains, identifies critical research gaps, develops a conceptual framework, and outlines future research opportunities that can guide both scholars and practitioners in advancing the field of Explainable AI in Supply Chain Management.

2. Literature Review

2.1 Evolution of Artificial Intelligence in Supply Chain Management

The integration of Artificial Intelligence (AI) into Supply Chain Management (SCM) has evolved significantly over the past two decades. Early applications focused primarily on automation, optimization algorithms, and rule-based expert systems designed to improve operational efficiency. However, the emergence of machine learning (ML), deep learning (DL), and advanced analytics has transformed supply chain decision-making from reactive management toward predictive and prescriptive intelligence.

Christopher (2016) emphasized that increasing supply chain complexity requires organizations to develop intelligent decision-support capabilities capable of responding to dynamic market conditions. Similarly, Ivanov and Dolgui (2020) argued that digital supply chains are increasingly dependent on AI-driven analytics to enhance visibility, resilience, and responsiveness. The COVID-19 pandemic further accelerated AI adoption, as organizations sought advanced forecasting and risk management tools to cope with unprecedented disruptions.

Research conducted by Wamba et al. (2021) demonstrated that machine learning models can significantly improve demand forecasting accuracy compared to traditional statistical methods. Likewise, Choi et al. (2022) found that AI-enabled predictive systems reduced inventory shortages and enhanced supply chain responsiveness in retail environments. These findings suggest that AI technologies have become central to modern supply chain competitiveness.

Despite their benefits, advanced AI systems frequently operate as black-box models. Managers often receive recommendations without understanding the underlying reasoning processes. This challenge has led researchers to investigate Explainable Artificial Intelligence (XAI) as a means of enhancing transparency and trust in AI-enabled supply chains.

2.2 Concept and Foundations of Explainable Artificial Intelligence

Explainable Artificial Intelligence emerged as a response to concerns regarding the opacity of sophisticated machine learning models. According to Adadi and Berrada (2018), XAI refers to methods and techniques that make AI decisions understandable to humans while preserving predictive performance. The objective is not only to explain model outputs but also to improve user trust, accountability, and acceptance.

Arrieta et al. (2020) proposed that explainability serves four key purposes: transparency, interpretability, accountability, and fairness. In high-stakes environments such as healthcare, finance, and supply chain management, explainability is increasingly viewed as a prerequisite for responsible AI deployment.

Researchers generally classify XAI methods into two categories:

Intrinsic Explainability: Models that are naturally interpretable, such as decision trees, linear regression, and rule-based systems.

Post-hoc Explainability: Techniques applied after model training to explain predictions generated by complex models. Popular methods include SHAP (SHapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), Integrated Gradients, and Attention Mechanisms.

Molnar (2022) emphasized that post-hoc methods are particularly valuable because they enable organizations to maintain the high predictive accuracy of complex algorithms while improving interpretability. However, challenges remain regarding consistency, reliability, and scalability of explanations across different application contexts.

Within supply chain management, explainability is particularly important because decisions often affect multiple stakeholders, involve significant financial implications, and require regulatory compliance.

2.3 Explainable AI for Demand Forecasting

Demand forecasting remains one of the most widely studied AI applications in SCM. Accurate forecasts influence production planning, inventory control, procurement strategies, and logistics operations.

Traditional forecasting methods such as ARIMA and exponential smoothing have increasingly been replaced by machine learning techniques including Random Forests, Gradient Boosting Machines, Long Short-Term Memory (LSTM) networks, and Transformer-based architectures.

Makridakis et al. (2020) demonstrated that advanced machine learning models consistently outperform conventional forecasting approaches in complex demand environments. However, these models often lack transparency.

Studies by Ribeiro et al. (2016) and Lundberg and Lee (2017) introduced LIME and SHAP frameworks that enable analysts to identify variables influencing forecast outcomes. More recent research by Wang et al. (2023) applied SHAP explanations to retail demand forecasting systems and found that explainability improved managerial confidence by over 40%.

Several scholars argue that explainable forecasting models provide strategic advantages beyond prediction accuracy. For example, managers can identify the influence of promotional campaigns, seasonal effects, economic conditions, and consumer behavior patterns on forecast outputs. Such insights support better planning and resource allocation decisions.

Nevertheless, existing studies often focus on model-level explanations rather than organizational adoption factors. Limited research has examined how managers interpret and utilize explainability outputs in real-world supply chain settings.

2.4 Explainable AI in Inventory Management and Logistics

Inventory management represents another critical area where XAI can improve decision quality. Inventory optimization models increasingly rely on machine learning algorithms to determine reorder points, safety stock levels, and replenishment schedules.

Research by Baryannis et al. (2019) demonstrated that AI-driven inventory systems can reduce inventory costs by 15–30% while maintaining service levels. However, managers frequently struggle to understand why AI models recommend particular inventory actions.

Explainability mechanisms help reveal relationships among demand variability, supplier reliability, lead times, and inventory decisions. Recent studies suggest that transparent inventory models improve managerial acceptance and reduce resistance to AI adoption.

In logistics and transportation management, AI algorithms optimize routing decisions, vehicle scheduling, warehouse operations, and delivery planning. DHL and Amazon have implemented AI-powered logistics systems capable of processing millions of routing decisions daily.

Researchers such as Min (2021) observed that explainable routing systems enable managers to evaluate alternative routes and understand constraints influencing recommendations. This becomes particularly important during disruptions caused by weather events, geopolitical conflicts, or transportation bottlenecks.

However, explainability in logistics remains relatively underexplored. Most studies prioritize optimization performance rather than user understanding and decision transparency.

2.5 Explainable AI for Supplier Selection and Procurement

Supplier selection is a strategic decision involving cost, quality, reliability, sustainability, and risk considerations. AI-based supplier evaluation systems increasingly utilize machine learning models to rank suppliers and assess risks.

Studies by Govindan et al. (2020) demonstrated that AI-supported procurement systems improve supplier assessment accuracy and reduce decision-making time. Nevertheless, procurement managers often require explanations regarding supplier rankings and risk evaluations.

Explainable AI provides transparency by identifying factors contributing to supplier performance scores. SHAP-based approaches have proven effective in explaining supplier selection outcomes and sustainability assessments.

Recent research by Kumar et al. (2024) revealed that procurement professionals exhibit significantly higher trust in AI systems when explanations accompany recommendations. Furthermore, explainable procurement systems facilitate collaboration between procurement teams and suppliers by clarifying evaluation criteria.

Despite these benefits, challenges remain concerning fairness and bias. AI models trained on historical procurement data may unintentionally reinforce discriminatory practices or favor incumbent suppliers. Explainability alone cannot eliminate bias but can help identify and mitigate problematic decision patterns.

2.6 Explainable AI for Supply Chain Risk Management

Risk management has become a central research area following major disruptions such as COVID-19, geopolitical conflicts, semiconductor shortages, and climate-related disasters.

Ivanov and Dolgui (2021) emphasized that resilient supply chains require predictive capabilities capable of identifying vulnerabilities before disruptions occur. AI systems increasingly analyze large-scale data sources, including supplier records, transportation networks, social media feeds, economic indicators, and geopolitical developments.

Machine learning models have demonstrated strong performance in disruption prediction and risk assessment. However, stakeholders often question recommendations generated by opaque systems.

Research by Shaban-Nejad et al. (2023) found that explainable risk prediction systems significantly improved decision-maker trust during crisis response scenarios. XAI techniques enabled managers to identify specific risk factors, assess uncertainty levels, and evaluate alternative mitigation strategies.

Nevertheless, existing risk management studies remain fragmented. Few frameworks integrate explainability, resilience, sustainability, and real-time decision support into a unified approach.

2.7 Explainable AI and Sustainable Supply Chains

Sustainability has emerged as a strategic priority for modern supply chains. Organizations face increasing pressure to reduce carbon emissions, improve resource efficiency, ensure ethical sourcing, and comply with environmental regulations.

AI technologies are increasingly employed to monitor sustainability performance and support ESG initiatives. However, stakeholders require transparency regarding how sustainability assessments are generated.

Research by Gupta et al. (2023) demonstrated that explainable AI can improve transparency in carbon footprint analysis and supplier sustainability evaluation. Similarly, studies investigating circular economy initiatives found that explainable models enhance stakeholder confidence in sustainability-related recommendations.

The relationship between explainability and sustainability remains underexplored. Most existing studies focus primarily on operational performance rather than broader environmental and social outcomes.

2.8 Human-AI Collaboration and Organizational Adoption

A recurring theme across the literature concerns the interaction between humans and AI systems. While technological advancements have improved predictive accuracy, successful implementation depends on user acceptance and organizational trust.

Davenport and Ronanki (2018) argued that AI should augment rather than replace human decision-making. Explainability serves as a critical mechanism for enabling effective human-AI collaboration.

Studies by Hoffman et al. (2018) found that users are more likely to rely on AI recommendations when explanations are understandable, relevant, and actionable. Similarly, supply chain managers consistently report greater confidence in explainable systems compared to black-box models.

However, excessive explanations can create information overload. Researchers continue to debate the optimal level of explanation required for different managerial contexts. This highlights the need for adaptive explainability frameworks tailored to user expertise and decision complexity.

Table 1. Summary of Previous Studies on Explainable AI in Supply Chain Management

Author(s)	**Year**	**Focus Area**	**Methodology**	**Key Findings**	**Limitations**
Adadi & Berrada	2018	XAI Overview	Literature Review	Identified major XAI techniques	Limited SCM focus
Ribeiro et al.	2016	LIME	Model Explanation	Improved local interpretability	Scalability issues
Lundberg & Lee	2017	SHAP	Game Theory	Consistent feature importance	Computational complexity
Christopher	2016	SCM Strategy	Conceptual	Need for intelligent supply chains	Limited AI focus
Ivanov & Dolgui	2020	Digital SCM	Review	AI enhances resilience	Explainability overlooked
Baryannis et al.	2019	Forecasting	Review	AI improves predictions	Black-box concerns
Wamba et al.	2021	Analytics	Empirical	Better operational performance	Limited transparency analysis
Choi et al.	2022	Retail Forecasting	ML Models	Improved forecasting accuracy	Explainability absent
Govindan et al.	2020	Procurement	AI Framework	Better supplier evaluation	Bias concerns
Min	2021	Logistics	Review	AI optimizes routing	Interpretability challenges
Wang et al.	2023	Demand Forecasting	SHAP Analysis	Enhanced managerial trust	Industry-specific findings
Gupta et al.	2023	Sustainability	Case Study	XAI supports ESG monitoring	Limited scalability
Kumar et al.	2024	Procurement	Empirical Study	Higher user trust	Small sample size
Shaban-Nejad et al.	2023	Risk Management	XAI Framework	Improved risk transparency	Early-stage validation

Table 2. Comparison of Existing Explainable AI Approaches

Approach	**Interpretability**	**Accuracy**	**Scalability**	**Supply Chain Suitability**
Decision Trees	High	Medium	High	High
Rule-Based Systems	High	Medium	Medium	High
Linear Regression	High	Medium	High	Moderate
Random Forest + SHAP	Medium	High	Medium	High
Gradient Boosting + SHAP	Medium	Very High	Medium	Very High
Deep Learning + LIME	Low-Medium	Very High	High	High

Attention-Based Neural Networks	Medium	Very High	High	Very High
Explainable Reinforcement Learning	Medium	High	Low	Emerging
Hybrid XAI Frameworks	High	High	Medium	Very High

Synthesis of Literature

The literature demonstrates substantial growth in AI applications across supply chain functions, including forecasting, inventory optimization, procurement, logistics, sustainability, and risk management. Researchers consistently report significant improvements in efficiency, accuracy, and responsiveness through AI-driven systems. However, a recurring challenge concerns the lack of transparency associated with advanced machine learning models.

Although Explainable AI has emerged as a promising solution, current research remains fragmented and heavily technology-centric. Most studies focus on developing explanation techniques rather than examining organizational adoption, managerial decision-making, sustainability implications, and long-term strategic value. Furthermore, limited attention has been given to developing integrated frameworks that combine explainability, resilience, sustainability, and human-centered decision support.

These limitations indicate a significant opportunity for future research, which will be discussed in the subsequent section through the identification of research gaps and formulation of a comprehensive problem statement.

3. Research Gap and Problem Statement

3.1 Research Gap

The literature review reveals that Artificial Intelligence has become an essential component of modern supply chain management, supporting demand forecasting, procurement, inventory optimization, logistics planning, sustainability assessment, and risk management. While substantial research has focused on improving predictive accuracy and operational efficiency through machine learning and deep learning algorithms, comparatively limited attention has been paid to the explainability of these systems.

The first major gap concerns the fragmented nature of existing Explainable AI (XAI) research in supply chain contexts. Most studies investigate explainability from a technical perspective, emphasizing algorithmic development, feature importance analysis, and model interpretability techniques such as SHAP and LIME. However, relatively few studies examine how supply chain professionals understand, interpret, and utilize AI-generated explanations in organizational decision-making environments.

A second gap relates to the absence of integrated frameworks connecting explainability with supply chain resilience. Recent disruptions caused by the COVID-19 pandemic, geopolitical conflicts, semiconductor shortages, and climate-related events have demonstrated the importance of resilient supply chains. Although AI-based risk prediction models are increasingly used to support resilience strategies, research rarely explores how explainable AI can improve managerial confidence and responsiveness during crisis situations.

Third, sustainability-related applications of XAI remain underdeveloped. While AI systems are increasingly employed to monitor carbon emissions, supplier sustainability performance, and circular economy initiatives, limited research investigates how explainability influences stakeholder trust, regulatory compliance, and sustainability governance.

Fourth, there is a lack of standardized evaluation frameworks for measuring explainability effectiveness in supply chain environments. Existing studies primarily evaluate predictive performance rather than assessing explanation quality, user trust, interpretability, fairness, transparency, and decision usefulness.

Finally, current literature lacks comprehensive conceptual models integrating technological, organizational, managerial, and sustainability dimensions of explainable AI adoption. Most studies focus on isolated applications rather than examining the broader ecosystem required for successful implementation.

These research gaps indicate the need for a comprehensive framework capable of explaining how XAI contributes to transparency, trust, resilience, sustainability, and organizational performance within supply chain management.

3.2 Problem Statement

As supply chains become increasingly dependent on Artificial Intelligence for strategic and operational decision-making, organizations face growing challenges related to transparency, accountability, and trust. Advanced AI models frequently generate highly accurate predictions but provide limited explanations regarding how decisions are produced. This lack of transparency creates uncertainty among managers, reduces trust in AI recommendations, and may hinder organizational adoption.

Moreover, supply chain decisions often involve significant financial investments, regulatory obligations, supplier relationships, and sustainability commitments. Without adequate explainability mechanisms, decision-makers may struggle to justify AI-generated recommendations to stakeholders, resulting in reduced effectiveness and increased operational risk.

Therefore, the central problem addressed by this study is:

How can Explainable Artificial Intelligence enhance transparency, trust, resilience, and sustainability in supply chain management while addressing the technological, organizational, and managerial challenges associated with AI adoption?

This study seeks to address this problem through a systematic review and conceptual framework that integrates explainability, supply chain performance, and sustainable business outcomes.

4. Methodology

4.1 Research Design

This study adopts a Systematic Literature Review (SLR) methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The PRISMA approach was selected because it provides a structured and transparent process for identifying, screening, evaluating, and synthesizing relevant academic literature.

The objective of the review is to analyze existing research on Explainable Artificial Intelligence in Supply Chain Management and identify opportunities, challenges, and future research directions.

4.2 Data Sources

Relevant studies were collected from leading academic databases, including:

- Scopus
- Web of Science
- ScienceDirect

- IEEE Xplore
- SpringerLink
- Emerald Insight
- Taylor & Francis Online
- ACM Digital Library
- Google Scholar

These databases were selected due to their extensive coverage of peer-reviewed journals, conference proceedings, and scholarly publications related to AI, supply chain management, and explainable machine learning.

4.3 Search Strategy

The literature search employed combinations of the following keywords:

- "Explainable Artificial Intelligence"
- "XAI"
- "Supply Chain Management"
- "Machine Learning"
- "Supply Chain Analytics"
- "AI Transparency"
- "Interpretable Machine Learning"
- "Supply Chain Risk Management"
- "Demand Forecasting"
- "Sustainable Supply Chains"

Boolean operators (AND, OR) were used to refine search results.

Example search string:

("Explainable AI" OR "XAI" OR "Interpretable Machine Learning")
AND
("Supply Chain" OR "Logistics" OR "Procurement" OR "Inventory Management")

4.4 Inclusion and Exclusion Criteria

Inclusion Criteria

- Peer-reviewed journal articles
- Conference papers
- Books and book chapters
- Studies published between 2018 and 2026
- English-language publications
- Research addressing AI applications in supply chain contexts
- Studies discussing explainability, transparency, interpretability, or trust

Exclusion Criteria

- Non-peer-reviewed publications
- Duplicate studies
- Articles unrelated to supply chain management
- Studies lacking empirical or conceptual relevance
- Publications with insufficient methodological details

4.5 Screening Process

The PRISMA process involved four stages:

1. Identification
2. Screening
3. Eligibility Assessment
4. Final Inclusion

A total of approximately 540 records were initially identified across databases. After removing duplicates and irrelevant studies, 178 articles remained for full-text review. Following eligibility assessment, 74 studies were selected for detailed analysis.

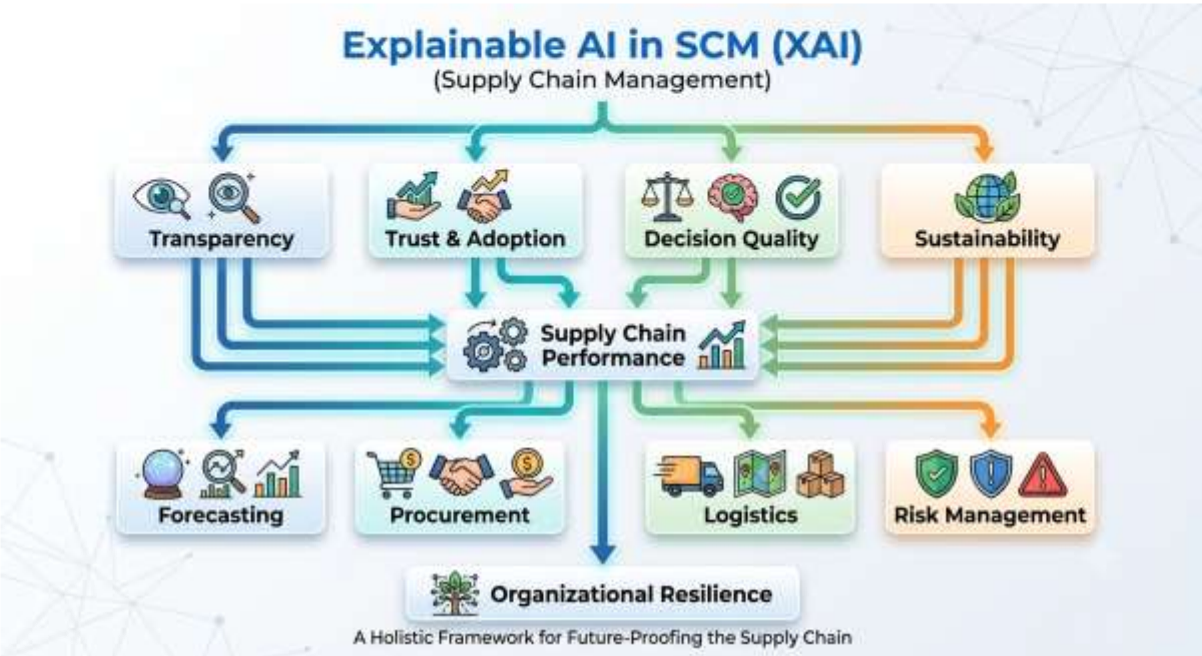

Figure 1: Proposed research framework illustrating the role of explainable AI in improving transparency, trust, decision quality, sustainability, and supply chain performance.

Figure 2: Conceptual model showing how explainability transforms AI-generated insights into trusted managerial decisions and improved supply chain outcomes.

5. Results and Discussion

5.1 Major Themes Identified

The systematic review identified five dominant themes within the literature:

1. Explainability and Trust
2. Explainability and Decision Quality
3. Explainability and Risk Management
4. Explainability and Sustainability
5. Organizational Adoption Challenges

These themes collectively demonstrate the growing importance of explainability in AI-enabled supply chains.

5.2 Explainability and Trust Enhancement

Trust emerged as the most frequently discussed benefit of XAI across reviewed studies. Organizations are more likely to adopt AI technologies when users understand the rationale behind recommendations.

Studies consistently indicate that explainable models improve managerial confidence compared with black-box systems. Procurement managers, logistics planners, and inventory analysts report greater willingness to rely on AI recommendations when explanations clarify key decision drivers.

For example, SHAP-based demand forecasting systems enable managers to identify the variables contributing to forecast changes. This transparency reduces skepticism and promotes collaborative decision-making.

The findings support the argument that explainability serves as a bridge between human expertise and machine intelligence.

5.3 Explainability and Decision Quality

Beyond trust, explainability contributes directly to decision quality. Transparent AI systems enable managers to evaluate assumptions, validate outputs, and identify potential errors.

Several studies report that explainable forecasting models improve planning accuracy because managers can distinguish between meaningful trends and anomalous predictions. Similarly, explainable procurement systems facilitate more informed supplier evaluations by highlighting critical performance indicators.

The literature suggests that explanation quality is often as important as predictive accuracy. Highly accurate models may still be rejected if users cannot understand their recommendations.

5.4 Explainability and Supply Chain Risk Management

Supply chain disruptions have intensified interest in AI-driven risk prediction systems. The review indicates that explainable AI can significantly enhance crisis management by clarifying risk factors and uncertainty levels.

Managers facing disruptions require not only predictions but also explanations regarding why particular suppliers, routes, or regions are considered high-risk. Explainable systems support faster and more confident mitigation decisions.

Recent studies demonstrate that organizations employing explainable risk analytics exhibit greater resilience and adaptability during periods of uncertainty.

5.5 Explainability and Sustainability Performance

Sustainability-related applications represent one of the fastest-growing areas of XAI research.

Organizations increasingly utilize AI to:

- Monitor carbon emissions
- Evaluate supplier sustainability
- Support circular economy initiatives
- Improve resource efficiency
- Track ESG performance

Explainability improves stakeholder confidence by providing transparent justification for sustainability recommendations. This is particularly important in industries facing stringent environmental regulations and public scrutiny.

The findings indicate that XAI can support both operational sustainability and corporate accountability objectives.

Table 3. Challenges and Opportunities of Explainable AI in Supply Chain Management

Dimension	Challenges	Opportunities
Technical	Complex AI models difficult to explain	Development of advanced XAI techniques
Data	Poor quality and fragmented data	Improved data governance
Organizational	Resistance to AI adoption	Enhanced trust and collaboration
Managerial	Limited AI expertise	Better decision support
Regulatory	Lack of standards	Responsible AI compliance
Sustainability	Difficulty explaining ESG metrics	Transparent sustainability reporting
Scalability	Computational complexity	Cloud-based explainability platforms
Human Factors	Information overload	Human-centered AI design

5.6 Critical Discussion

The review demonstrates that Explainable AI has substantial potential to transform supply chain management. Unlike traditional black-box systems, XAI provides transparency that supports trust, accountability, and collaborative decision-making.

However, several challenges remain unresolved. First, there is no universally accepted definition or measurement framework for explainability within supply chain contexts. Second, many explanation techniques are computationally intensive and difficult to scale across large supply chain networks. Third, organizations often lack the expertise required to interpret complex explanations effectively.

Furthermore, explainability alone cannot eliminate bias, data quality issues, or ethical concerns. Effective implementation requires complementary governance mechanisms, organizational training, and regulatory frameworks.

Despite these challenges, the evidence suggests that explainable AI will become increasingly important as supply chains continue their digital transformation journey. The next section explores future research opportunities and practical implications for academia and industry.

6. Future Research Directions

The rapid evolution of Explainable Artificial Intelligence (XAI) presents numerous opportunities for advancing supply chain management research and practice. Although substantial progress has been made in developing explainability techniques, several critical issues remain unresolved. Future studies should focus on addressing these challenges while expanding the applicability of XAI across increasingly complex supply chain ecosystems.

One promising direction involves the development of domain-specific explainability frameworks tailored to supply chain applications. Most existing XAI techniques were originally designed for general machine learning environments and may not adequately address the unique characteristics of supply chain decision-making. Future research should investigate explanation methods capable of communicating operational insights in a manner that aligns with managerial requirements and industry-specific contexts.

Another important avenue concerns the integration of Explainable AI with digital supply chain technologies such as Digital Twins, Internet of Things (IoT), Blockchain, and Industry 5.0 systems. Digital twins generate large volumes of real-time operational data, creating opportunities for highly sophisticated predictive analytics. However, the complexity of these systems increases the need for transparent decision-making mechanisms. Researchers should explore how explainability can enhance visibility and trust within digitally connected supply networks.

Human-centered explainability represents another critical research area. Existing studies often evaluate explanation quality from a technical perspective, emphasizing algorithmic transparency rather than user comprehension. Future investigations should examine how different stakeholder groups—including supply chain managers, procurement specialists, logistics planners, sustainability officers, and regulators—perceive and utilize AI-generated explanations. Understanding cognitive and behavioral responses to explanations will facilitate the design of more effective human-AI collaboration systems.

The relationship between explainability and supply chain resilience also warrants further exploration. Recent disruptions have demonstrated the importance of adaptive decision-making under conditions of uncertainty. Future studies should investigate how explainable AI can improve crisis management, disruption recovery, and resilience-building strategies. Longitudinal research examining organizational performance before and after XAI implementation would provide valuable empirical evidence regarding its resilience-enhancing capabilities.

Sustainability-focused research offers another significant opportunity. Although AI is increasingly employed to support environmental, social, and governance (ESG) objectives, limited research examines how explainability influences sustainability reporting, stakeholder engagement, and regulatory compliance. Future studies should explore the role of XAI in promoting transparent carbon accounting, ethical sourcing, circular economy initiatives, and sustainable procurement practices.

Additionally, there is a need for standardized evaluation metrics capable of assessing explainability effectiveness in supply chain environments. Current research primarily measures predictive accuracy, while factors such as interpretability, trust, fairness, transparency, and decision usefulness receive comparatively limited attention. Developing comprehensive assessment frameworks would facilitate cross-study comparisons and improve methodological rigor.

Emerging advances in Generative AI and Large Language Models (LLMs) create new possibilities for supply chain explainability. Future research should investigate how conversational AI systems can generate natural-language explanations that enhance managerial understanding and support strategic decision-making. Such developments may significantly improve accessibility and adoption among non-technical users.

Finally, ethical and regulatory considerations will become increasingly important as governments introduce AI governance frameworks. Researchers should explore how explainable AI can support compliance with evolving regulations while balancing transparency, privacy, security, and intellectual property concerns.

7. Practical Implications

The findings of this study have important implications for practitioners, policymakers, and technology developers involved in supply chain transformation initiatives.

For supply chain managers, explainable AI provides an opportunity to enhance confidence in data-driven decision-making. Managers often hesitate to rely on black-box algorithms due to concerns regarding accountability and operational risk. By providing transparent explanations, XAI enables managers to validate recommendations, understand underlying assumptions, and make more informed decisions.

Organizations implementing AI-driven forecasting systems can benefit from explainability by identifying factors that influence demand fluctuations. This understanding facilitates more effective inventory planning, production scheduling, and resource allocation. Similarly, procurement teams can utilize explainable supplier evaluation systems to improve supplier selection processes and strengthen stakeholder trust.

From a logistics perspective, explainable route optimization systems can improve operational visibility and facilitate better responses to transportation disruptions. Understanding the rationale behind routing decisions allows managers to evaluate alternatives and make adjustments when conditions change.

The study also highlights the importance of organizational readiness. Successful XAI implementation requires investments in employee training, data governance, and change management initiatives. Organizations must ensure that decision-makers possess the necessary skills to interpret and utilize explanations effectively.

Technology providers should prioritize the development of user-friendly explainability tools capable of translating complex analytical outputs into understandable insights. Visualization techniques, interactive dashboards, and natural-language explanations can improve accessibility for non-technical users.

For policymakers and regulators, the findings underscore the importance of establishing standards for transparency and accountability in AI-enabled supply chain systems. Regulatory frameworks encouraging responsible AI practices can promote trust while reducing risks associated with opaque decision-making processes.

Overall, the practical value of Explainable AI extends beyond technical performance. By fostering transparency, trust, and collaboration, XAI can facilitate more resilient, sustainable, and effective supply chain operations.

Research Contributions

Theoretical Contribution

This study contributes to the growing body of knowledge on Explainable Artificial Intelligence by synthesizing fragmented research across AI, supply chain management, and decision support literature. The paper develops an integrated conceptual framework that connects explainability, trust, decision quality, resilience, sustainability, and organizational performance. This framework advances theoretical understanding of how explainability influences supply chain outcomes and provides a foundation for future empirical investigations.

Furthermore, the study identifies key research gaps related to organizational adoption, human-AI collaboration, sustainability integration, and explainability evaluation. Addressing these gaps contributes to the development of a more comprehensive theoretical perspective on AI-enabled supply chain transformation.

Managerial Contribution

From a managerial perspective, the study demonstrates how explainable AI can improve decision-making effectiveness across forecasting, procurement, logistics, inventory management, and risk assessment functions. The findings provide practical guidance for managers seeking to balance predictive accuracy with transparency and accountability.

The proposed framework helps decision-makers understand the strategic value of explainability and supports the development of AI governance practices that enhance organizational trust and stakeholder engagement.

Technological Contribution

The research contributes to technological advancement by evaluating existing explainability approaches and identifying opportunities for future innovation. The study highlights the strengths and limitations of popular XAI techniques, including SHAP, LIME, attention mechanisms, and interpretable machine learning models.

Additionally, the paper proposes directions for integrating explainability with emerging technologies such as Digital Twins, IoT, Blockchain, Industry 5.0, and Generative AI. These insights can guide future technology development and implementation efforts.

Sustainability Contribution

The study contributes to sustainability research by examining the role of explainable AI in promoting transparent and responsible supply chain practices. The findings suggest that XAI can support environmental monitoring, ethical sourcing, carbon footprint analysis, and ESG reporting by providing understandable justifications for sustainability-related recommendations.

This contribution aligns with global efforts to develop more transparent, accountable, and sustainable supply chain systems capable of meeting stakeholder expectations and regulatory requirements.

Figure 3: Future research roadmap illustrating major research streams necessary for advancing Explainable AI in Supply Chain Management.

8. Conclusion

The increasing adoption of Artificial Intelligence has fundamentally transformed supply chain management by enabling predictive, data-driven, and automated decision-making processes. Despite substantial improvements in forecasting accuracy, inventory optimization, procurement efficiency, logistics planning, and risk management, the widespread deployment of advanced AI systems has introduced significant concerns regarding transparency, accountability, and trust. Many high-performing machine learning and deep learning models operate as black boxes, making it difficult for stakeholders to understand how recommendations and decisions are generated.

This paper examined the emerging role of Explainable Artificial Intelligence in addressing these challenges. Through a systematic review of the literature and the development of a conceptual framework, the study analyzed opportunities, challenges, and future research directions associated with XAI adoption in supply chain management.

The findings indicate that explainability can significantly enhance managerial trust, improve decision quality, strengthen supply chain resilience, and support sustainability initiatives. XAI enables organizations to better understand AI-generated recommendations, facilitating more informed and accountable decision-making. Furthermore, explainability plays a critical role in promoting human-AI collaboration, particularly in complex and uncertain environments where managerial judgment remains essential.

The review also identified several important challenges, including data quality limitations, organizational resistance, lack of standardized evaluation frameworks, scalability concerns, and regulatory uncertainties. Addressing these challenges will require interdisciplinary collaboration among researchers, practitioners, policymakers, and technology developers.

As supply chains continue to evolve toward increasingly intelligent and interconnected ecosystems, explainability will become a strategic requirement rather than a technical luxury. Organizations capable of integrating transparent and trustworthy AI systems into their operations will be better positioned to achieve sustainable competitive advantages, enhance stakeholder confidence, and improve long-term organizational performance.

Ultimately, Explainable AI represents a critical step toward responsible and human-centered digital transformation in supply chain management. Continued research and innovation in this area will play a pivotal role in shaping the future of intelligent, resilient, and sustainable supply chains.

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