UKR Journal of Economics, Business and Management (UKRJEBM)
Homepage: https://ukrpublisher.com/ukrjebm/
Email: submit.ukrpublisher@gmail.com
Volume 2, Issue 1, 2026 ISSN: 3049-429X (Online)

Responsible AI Deployment in United States Manufacturing Supply Chains

Ankit Sharma[1], Adarsh Srivastava[2], Priyanshi Joshi[3], Vinisha Parswani[4]

Independent Researcher, United States of America [1,2,3,4]
ORCID: 0000-0003-2288-6992[1], 0009-0008-3762-805X[2], 0000-0002-5777-2816[3], 0009-0008-8315-5126[4]

***Corresponding Author**: Ankit Sharma
DOI: *https://doi.org/10.5281/zenodo.18383713*

Article History
Original Research Article
Received: 03-11-2025
Accepted: 02-12-2025
Published: 27-01-2026

Citation: Ankit Sharma, Adarsh Srivastava, Priyanshi Joshi3, Vinisha Parswani. (2026). Responsible AI Deployment in United States Manufacturing Supply Chains. UKR Journal of Economics, Business and Management (UKRJEBM), Volume 2(1), 153-166.

Abstract

The use of Artificial Intelligence (AI) in the manufacturing supply chains of the United States is revolutionizing industries through process optimization and better decision-making and resilience. However, there are significant challenges in this deployment, having to do with governance, accountability, and ethical considerations. As AI systems are applied to manufacturing, the need for responsible AI deployment has become a growing problem. This paper discusses the idea of accountable AI in the context of supply chains in manufacturing, focusing on ensuring accountability, transparency and ethics is maintained throughout the lifecycle of the deployment of an AI. Through the perspective of the AI governance concept and supply chain management (SCM), we examine how the AI systems need to be carefully designed in order to preserve trust and supply chain resilience. A conceptual framework for the deployment of AI is proposed, which emphasizes the AI governance mechanisms, risk management, and accountability structures that are required to assure ethical decision making. Furthermore, the paper discusses issues challenging the manufacturers implementing AI-driven technologies and managerial and policy implications for AI governance. This work adds to the knowledge on how AI-driven innovation can be responsibly integrated with manufacturing supply chains, especially in the US context.

Keywords: *Responsible AI, AI governance, manufacturing supply chains, United States manufacturing, decision accountability, human-in-the-loop, explainable AI, AI risk management, digital transformation, supply chain resilience, AI deployment lifecycle, auditability and compliance.*

1. Introduction: Adoption of AI in US Manufacturing Supply Chains

1.1 Background

Integration of Artificial Intelligence (AI) in manufacturing and supply chains has brought about remarkable improvements to operational efficiency, production quality and supply chain resiliency. As industries in the United States compete with each other globally and demand more flexibility, the role of AI is becoming invaluable. AI technologies, specifically in predictive maintenance, forecasting, and inventory management allow manufacturers to optimize their resources, waste, and decision-making capabilities (Brintrup et al., 2023).

In Industry 5.0, however, the focus has moved far beyond the simple automation of processes and instead looks at installing human intelligence in partnership with AI systems to develop a more collaborative and resilient manufacturing environment (Ejjami and Boussalham, 2024). AI systems are now being challenged to make decisions that have an immediate impact on the efficiency and profitability of supply chains. However, the general use of AI technologies creates new intricacies involving governance, accountability, and ethical considerations (Kilari, 2025).

While AI can play an important role in making people more efficient, there are also critical questions raised about responsibility in decision-making, especially when AI systems make autonomous decisions that have impact on human lives and the environment. As artificial intelligence (AI) systems are being deployed on a large scale, it is important to create a framework in which they can be used in an ethical way, and in which they are accountable and transparent, particularly in highly dynamic and interconnected fields such as supply chain management (SCM).

1.2 Adoption of AI in US Manufacturing Supply Chains

In 2026, AI adoption in U.S. manufacturing has transitioned from static predictive models to Agentic AI systems. These agents do not merely suggest actions but autonomously execute multi-step tasks such as sourcing, production balancing, and inventory replenishment without requiring a manual trigger for every step. Early 2026 reports indicate that manufacturers utilizing these agents have achieved up to a 15% reduction in unplanned downtime and significant improvements in delivery speed. However, this shift toward "agentic" autonomy necessitates a more robust governance framework, as the risk of autonomous agents mirroring human bias or making unverified decisions in high-stakes environments grows.

Furthermore, the emergence of AI-powered automation has led to concerns about the effect this has on the workforce in relation to job displacement and retention of current workers along with reskilling workforce adapt to novel technologies (Brown, 2023). Addressing these concerns inspired with a responsible mindset the way these AI systems are deployed in such a manner that they enhance productivity without trade-offs to job security and human oversight.

1.3 Challenges in the Responsible AI Implementation

Despite the potential benefits of AI in manufacturing, there are several challenges that need to be addressed in order to ensure its responsible deployment. These challenges include:

AI Governance and Accountability: It is highly important to have frameworks in place so that AI systems are utilized in a responsible manner that is also transparent. This includes regulation, ethics, and transparency in terms of accountability for A.I decision-making (Widder & Nafus, 2023).

Risk Management and Explainability: In AI systems, especially in decision making processes, that they should be explainable and auditable. Explainable AI (XAI) is fundamental to make sure that the decisions of the AI can be understood by humans, especially when they concern critical operations in manufacturing (Ejjami & Boussalham, 2024).

Human-in-the-Loop (HITL) Systems: As many of the applications that involve AI can significantly improve decision-making, it's essential to keep humans highly involved in the process. Human-in-the-loop systems can provide humans the opportunity to intervene in AI decisions that have significant ramifications on business outcomes (Meena et al., 2025).

Ethical and Legal Considerations: The integration of AI also raises ethical and legal concerns, including privacy, fairness, and accountability in decision-making. Manufacturers need to ensure that the AI systems are not only effective but also ethical, meaning they treat all stakeholders fairly and do not engage in any discriminatory practices (Dauvergne, 2022).

This paper attempts to answer these challenges by outlining a responsible AI deployment model for supply chains in the U.S. manufacturing sector with a special emphasis on setting up solid governance mechanisms, accountability for decision making, and risk management frameworks.

1.4 Research Gap and Contributions

Although prior research highlights the growing use of Artificial Intelligence (AI) in manufacturing and supply chain management, there remains a lack of integrated and operational guidance on how responsible AI principles can be implemented across the full AI deployment lifecycle in real industrial environments. Existing studies frequently discuss governance, transparency, or accountability as isolated themes, but do not sufficiently connect these concepts into a unified deployment model that manufacturing leaders can apply to manage risks, assign decision ownership, and maintain trust across multi-tier supply chain networks. In addition, the U.S. manufacturing context introduces unique requirements related to compliance expectations, workforce impacts, critical infrastructure resilience, and national competitiveness, which further strengthens the need for a responsible AI deployment model tailored to this setting.

This paper contributes in five ways:

(1) It synthesizes responsible AI governance concerns specific to U.S. manufacturing supply chains;
(2) It proposes a lifecycle-based Responsible AI Deployment Model (RAIDM) that integrates governance, accountability, transparency, and continuous improvement;
(3) It identifies practical governance mechanisms—oversight, explainability, and auditability—that can be implemented by manufacturers;
(4) It clarifies decision ownership structures and failure-handling mechanisms to reduce operational and ethical risks; and
(5) It provides managerial and policy implications to support responsible AI adoption in the United States.

1.5 Research Questions

This conceptual study is guided by the following research questions (RQs):

RQ1: What governance mechanisms are required to ensure responsible AI deployment in U.S. manufacturing supply chains?
RQ2: How can accountability and decision ownership be operationalized across the AI deployment lifecycle to prevent dislocated responsibility?
RQ3: What role do explainable AI (XAI), auditability, and human-in-the-loop (HITL) systems play in improving trust, compliance, and resilience?
RQ4: What managerial and policy actions are needed to enable scalable and ethical AI adoption in U.S. manufacturing supply chains?

2. Literature Review: AI in SCM + Lack of Governance and Accountability

2.1 AI in Supply Chain Management (SCM)

AI has become a prominent field in Supply Chain Management (SCM) because of technology's ability to increase operational efficiency and lower costs. AI-driven technologies such as predictive analytics, machine learning, and natural language processing (NLP) are increasingly used to optimize supply chain performance. These technologies help to improve demand forecasting, inventory management, and predictive maintenance which help to build more agile and resilient supply chains.

In a well-rounded review of the subject, Brintrup et al. (2023) highlighted the impact of AI in enhancing the efficiency and agility of supply chains by automating mundane duties, anticipating the demand curve, and maintaining inventory in a better manner. However, they also mentioned the existence of significant concerns about the governance structure of AI systems in supply chains, most especially the responsibility for decisions made by AI systems.

AI in SCM also has the potential to make supply chains more resilient and this is especially important at times of disruption. Wu, Liu, and Liang (2025) discussed how supply chain operations can be optimized through AI and give real-time insights to supply chain processes so companies can better navigate through disruptions such as natural disasters, pandemics, or even geopolitical conflicts. However, ethical AI deployment is a major challenge in ensuring that AI systems do not cause further inequities or biases in supply chain operations.

2.2 Gaps in Governance and Accountability

Despite the widespread use of AI in manufacturing and supply chains, there are still a number of gaps in the governance and accountability of AI systems. One gap of significance is that there are no clear regulations and oversight for how AI systems should be governed, especially in terms of who is responsible for decisions made, and how these could be enforced in an open and competitive environment. Widder and Nafus (2023) investigated the concept of dislocated accountability in the AI supply chain, stating that the more complex the AI systems, the more challenging it is to define who is responsible for the decision-making outcomes of AI.

Brown (2023) further said that need for ethical Artificial intelligence (AI) governance in supply chains. He argued that with AI systems assuming increasing roles in the decision-making process, manufacturers must adopt accountability mechanisms that lay out clear roles and responsibilities of all parties from AI developers to the end-users.

Moreover, the inability to explain the decision-making process in AI is a major obstacle to its widespread adoption. AI systems, especially those that rely on black box models, can make decisions that are challenging for humans to understand, and this raises the question of trust and accountability. The need for explainable AI (XAI) is critical in ensuring that AI systems can be audited and that their decisions can be explained in understandable terms especially when the decisions have a significant consequence on the supply chain operations (and business outcomes) (Kilari, 2025).

2.3 Developing Mechanisms of Governance

In the face of these challenges, governance frameworks (mechanisms) for AI in supply chains are being studied that will ensure its ethical application. These mechanisms are concerned with setting up frameworks in their regulations, including their oversight by regulators, audits and openness, and ethical decision-making. The goal is to ensure that AI systems are not only effective but also fair, responsible and accountable to all the stakeholders involved.

2.4 Methodology: Conceptual Synthesis Approach

This paper adopts a **concept-driven conceptual research design** to develop a responsible AI deployment framework for U.S. manufacturing supply chains. The study is based on structured synthesis of prior academic literature and practitioner-oriented governance discussions related to AI accountability, transparency, auditability, and ethical deployment. Rather than statistically generalizing outcomes, the goal of this research is to consolidate core responsible AI mechanisms and translate them into an actionable deployment lifecycle model for manufacturing decision environments.

A thematic synthesis approach is applied to organize the analysis into four integrated categories:

(1) responsible AI governance mechanisms (oversight, policies, and controls),

(2) accountability and decision ownership structures,

(3) risk management and failure-handling mechanisms (including HITL), and

(4) transparency and explainability mechanisms (including XAI and auditability).

These themes inform the development of the proposed Responsible AI Deployment Model (RAIDM) and its associated managerial and policy implications.

3. Conceptual Framework: Responsible AI Deployment Model (RAIDM)

3.1 Overview of Responsible AI implementation Model

The deployment of Artificial Intelligence (AI) in manufacturing supply chains must be systematic and responsible and provide for ethical practices, accountability, and transparency across the AI lifecycle. The Responsible AI Deployment Model (RAIDM), proposed in this paper, is designed to guide the manufacturers to make good use of AI Technologies by dealing with the complex challenges of governance, risk management and accountability for decision-making.

This model embraces fundamental principles of AI regulation, making sure that AI systems comply with regulatory requirements as well as ethical standards. RAIDM is a framework that is designed to ensure that AI systems in manufacturing are not just capable of optimizing operations but are also held responsible to the stakeholders and able to explain how they make their decisions. This framework is forward-thinking in establishing the requirements for ongoing monitoring, human oversight, and monitoring that is auditable, while still ensuring the integrity and resilience of the supply chain operations.

3.2 Basic Components of the Model for Responsible AI Implementation

The Responsible AI Deployment Model is based on multiple seminal components that are vital to making AI systems deployed responsibly in manufacturing supply chains.

The first key component of the model is the creation of a solid AI governance framework. This framework establishes the roles and responsibilities of every stakeholder whose involvement is involved in the deployment process of artificial intelligence to ensure that AI systems are created and operated within ethical guidelines and regulatory frameworks. The governance framework also presents mechanisms for auditability, regulatory supervision and performance monitoring, which are important for monitoring the decisions taken by artificial intelligence systems, especially during important areas of supply chain management (Brintrup et al., 2023).

One of the major aspects of the model is decision accountability. As AI systems play an increasingly larger role in making autonomous decisions within supply chains it becomes important to assign responsibility for making those decisions. The framework ensures that the entire chain of responsibility of every decision made by an AI system can be traced back to a human stakeholder or a particular component within the system, thwarting the dislocation of accountability that occurs more often than not in complex AI powered environments (Widder & Nafus, 2023). By having clear lines of responsibility, the model encourages trust and that decisions made by AI systems may be scrutinized and corrected if necessary.

In running parallel with the concept of accountability, explainability in AI systems also appears to be an important field. Manufacturing supply chains are frequently vast, interlinked systems with high operational stakes and the decisions made by AI can have a significant impact on the business outcome. Explainable AI / XAI refers to the fact that the action and decision process of AI systems be transparent and comprehensible to human beings, a key component to developing trust and rationale when decisions must be audited (Kilari, 2025). This component of the model promotes a more open approach to decision making and generates the insight needed into how the decisions of the AI systems are reached, especially when crucial decisions are required to be made such as changes in inventory levels or demand forecasting.

The RAIDM also provides for continuous monitoring and auditing. AI systems do not exist within a vacuum, and as they update themselves and learn from new data, constant oversight is necessary to ensure that the behavior of the system is aligned with the intention of the system (and ethical standards). The model urges for regular audits and performance reviews that look into the decisions made by the AI system to ensure that it is functioning as intended, free from bias, and in compliance with legal standards (Dauvergne, 2022).

Furthermore, the model also considers risk management strategies to ensure that impulsive failures or errors are managed in fear of any unexpected events during AI decision-making. While AI systems are extremely efficient in their ability to automate tasks, they are not infallible and can make mistakes or encounter other types of malfunctions. RAIDM combines the mechanisms for failure handling such as fail-safe, redundancy protocols, and human-in-the-loop (HITL) interventions for allowing human operators to explore and take control in critical cases (Meena et al., 2025). These protocols will help ensure any unexpected problems can be handled quickly and AI-driven decisions are not out of line with business purposes and ethics.

Finally, the model emphasizes the importance of stakeholder engagement and ethics in the model. Responsible AI deployment is not only about technology, but also the people that are impacted by the decisions of the system. RAIDM suggests keeping employees, customers and regulating bodies stimulated continuously in order to ensure that the deployment of AI is inclusive, equitable and aligned to larger societal goals. This engagement ensures that the deployment process takes into consideration the perspectives of those who are affected by the A.I. decisions and that ethical considerations are considered at every stage of the A.I life cycle (Wu, Liu, & Liang, 2025).

3.2.1 Research Propositions

To strengthen the conceptual contribution and enable future empirical validation, this study proposes the following research propositions:

P1 (Governance–Trust Proposition): Strong AI governance mechanisms (oversight, auditability, and policy controls) increase stakeholder trust and adoption success of AI-driven decision systems in manufacturing supply chains.

P2 (Accountability–Risk Reduction Proposition): Clear decision ownership and accountability structures reduce operational and ethical risks associated with AI-driven automation in high-stakes supply chain environments.

P3 (Explainability–Compliance Proposition): Higher explainability and transparency (enabled through XAI techniques and audit trails) improves regulatory compliance readiness and strengthens organizational confidence in AI-supported decisions.

P4 (HITL–Resilience Proposition): Human-in-the-loop intervention mechanisms improve supply chain resilience by preventing escalation of AI-driven errors during disruptions and volatile operating conditions.

3.3 AI Deployment Life Cycle Manufacturing Supply Chains

The one thing to note is that the lifecycle of AI deployment in manufacturing supply chains is an ongoing process that starts with designing and developing AI systems and continues through deployment, monitoring, and continuous optimization. RAIDM offers a standardized approach to each stage of this lifecycle to ensure responsible human AI deployment standards, avoiding irresponsible AI and ensuring that the development of AI respects the needs of both the business and society.

The first stage of the lifecycle consists of the design and development of AI systems. During this phase, AI systems are developed and trained with supply chain data to optimize supply chain processes such as predictive maintenance, inventory management, and demand forecasting. The design phase is critical for ensuring that AI systems are designed according to ethical standards and explainable and transparent. Trying to make the design ethical at this stage is critical to set the basis for responsible deployment and governance (Brintrup et al., 2023).

And once the AI system has been developed, it goes into the stage of deployment and integration. This phase consists of integrating the AI system with the existing infrastructure of the supply chain. It is essential that this integration process is done in such a way that does not disrupt ongoing operations while ensuring that the AI system is aligned to the goals of the organization as a whole. During this phase, it is necessary to have continuous monitoring to ensure that the AI system is working as it should and is not causing any unintended consequences.

After deployment, the system is in the monitoring phase, and its performance is continuously evaluated on predefined parameters such as accuracy, efficiency and cost-effectiveness. The model encourages optimization by using real-time performance tracking to make sure that AI systems are adapting as expected and that any divergent actions from the intended behavior are rectified immediately (Kilari, 2025).

Finally, the system gets to the audit and compliance phase, where its performance is closely reviewed to ensure that it complies with legal regulations, industry standards and ethical principles. Regular audits help in detecting any possible biases or failures in the AI system while ensuring that corrective measures are taken before it causes a massive problem (Brown, 2023).

3.4 Conceptual Framework Diagram

The following diagram explains the Responsible AI Deployment Model (RAIDM) and key components, showing how each phase of the AI deployment lifecycle advises the key principles of governance, accountability, and transparency. As shown in Figure 1, the RAIDM connects AI lifecycle stages with governance, accountability, and transparency mechanisms.

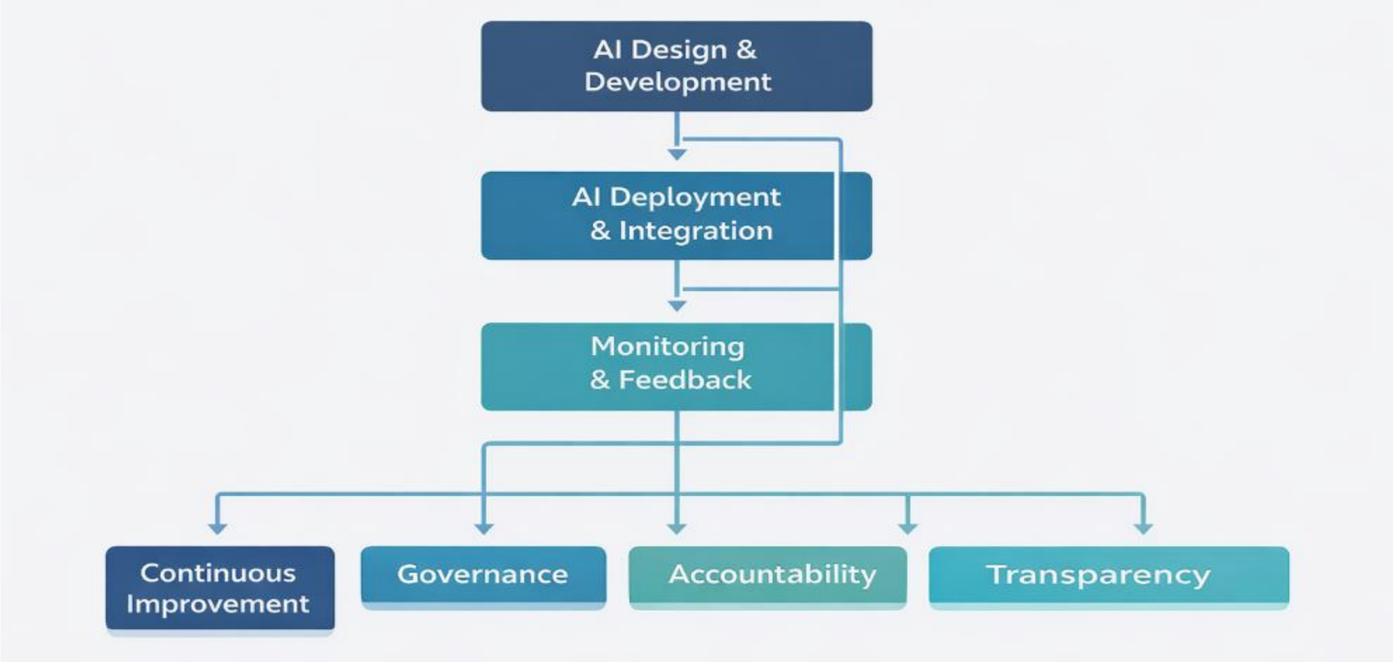

Figure 1. Responsible AI Deployment Model (RAIDM) for U.S. manufacturing supply chains.
Source: Author's own illustration.

3.5 Managerial and Policy Implications

The managerial implications of responsible deployment of AI in U.S. manufacturing supply chains are bulky. Manufacturers are and should be taking a proactive approach when it comes to design and deployment of AI systems, ensuring that they are ethical. This means that it requires leadership to prioritize transparency, accountability and governance in the implementation of AI systems. Regulatory bodies must collaborate with industry leaders in developing frameworks that will establish clear guidelines for AI ethics, compliance, and responsibility, particularly in industries that rely on the complexities of complicated supply chain networks (Elghomri, Messaoudi, & Touti, 2025).

On the policy front, governments should offer incentives to manufacturers that use ethical AI practices and such standards for AI transparency and audibility. Such policies are not going to merely focus on ensuring the judicious use of AI but will also encourage innovation in a manner that is sustainable and good for society.

4. Governance Mechanisms Oversight Explainability Auditability

4.1 Introduction to Government in the Implementation of AI

The responsible deployment of Artificial Intelligence (AI) in industrial supply chains depends greatly on good governance mechanisms. These mechanisms are crucial in ensuring that the AI systems can be deployed in a transparent, ethical, and properly done way. AI governance involves a wide practice and structure, which incorporates regulatory oversight, accountability structures, risk management, and site processes that can be audited.

Governance mechanisms, on the other hand, ensure through compliance with ethical guidelines and operation within certain boundaries, the protection of business integrity, data privacy, and stakeholder interests. In the context of manufacturing, whose decisions - AI can have immediate and widespread impacts on operations, products, and human labor - making the process requiring protocol establish structures of governance the importance of focusing on.

For example, effective governance mechanisms also assist in reducing the risks associated with AI technologies, such as bias, data mismanagement and the risks of unintended consequences. As AI systems continue to develop in terms of their capabilities and complexity, the governance model must be flexible enough to adapt to new challenges, such as new regulatory requirements or the introduction of more sophisticated AI-driven techniques in supply chain operations.

4.2 Responsible Deployment Oversight Part

Oversight is a relatively essential part of the governance framework of AI deployment. Without proper oversight, AI systems may deviate from ethical standards, introduce bias, or generate decisions that are misaligned with organizational goals and regulatory expectations. Having human oversight is key to making sure that the decisions made by AI are in line with the organization's goals and values, as well as legal guidelines.

One of the most important areas of oversight is the establishment of AI ethics boards or committees in manufacturing organizations. These boards tend to consist of high-level leadership, data scientists, ethicists and lawyers who are charged with monitoring the implementation of AI models as well as ensuring that ethical standards are met (Brown, 2023). Their responsibilities include monitoring the AI system's performance, working on concerns raised about bias and discrimination, and ensuring that the AI system works within the legal framework of an organization.

In addition to organizational boards, third-party oversight might be required. External auditors or regulatory bodies may be able to introduce independent evaluations of how AI systems are being used and whether they follow set ethical guidelines and standards. This external oversight can help to ensure that AI technologies are used in a way that is transparent and accountable to external stakeholders, and that AI systems are being used in a way that reflects public trust in AI technologies and practices.

For instance, Regulatory bodies in the U.S such as the Federal Trade Commission (FTC) and the National Institute of Standards and Technology (NIST) have started to make frameworks for Artificial Intelligence governance that can be followed by manufacturers to ensure that the safe and responsible deployment of AI technologies is ensured (Kilari, 2025).

By January 2026, the National Institute of Standards and Technology (NIST) expanded this oversight by launching two new AI Economic Security Centers. These centers, specifically the AI Economic Security Center for U.S. Manufacturing Productivity, are designed to develop technology evaluations and advancements to protect U.S. dominance in AI while reducing risks from insecure AI agents. Additionally, NIST’s AI for Resilient Manufacturing Institute (a $70 million initiative) now serves as a central hub for pairing federal standards with private-sector innovation to ensure that AI-driven supply chains remain both competitive and ethical.

4.3 Explainability for Artificial Intelligence Systems

Another important governance mechanism in the deployment of Responsible AI is explainability. As AI systems become more integrated into manufacturing supply chains, AI-driven decision-making processes based on AI must be able to be understood by human stakeholders. Explainable AI (XAI) - it is the ability of AI systems to give transparent and understandable explanations about how they make decisions. This is especially important in supply chains, where decisions made by AI can have a significant impact on the production schedule, inventory management, and the quality of the product.

In high stakes environments, such as manufacturing supply chains, AI systems must be able to offer justifications for the decisions that they make in order for those decisions to be evaluated by operators, managers, and stakeholders. Without explainability, AI systems can make decisions for which we have little to no reason, and that can contribute to distrust towards the system and a reluctance to adopt AI-driven systems (Meena et al., 2025).

For instance, if an AI system suggests a shift in the levels of inventory or optimizes the production schedule, we need to have a clear understanding behind these decisions to supply the chain managers. This will allow them to gain insight of the factors that influence the AI's decisions and to decide whether they want to accept or override the AI's recommendations.

There are several methods of improving explainability in AI systems. For example, decision trees, rule-based systems, and linear regression models are naturally more interpretable and can be used in cases where it is important to understand the AI's decision-making process. However, for more complex models such as deep learning networks, post hoc explanation methods can be applied like SHAP values (Shapley additive explanations) or LIME (Local Interpretable Model-agnostic Explanations) which can help to gain insights into how individual features contribute to the output of a model (Kilari, 2025).

4.4 Auditability in AI Systems

Auditability is another governance mechanism that is important for the responsible deployment of AI. An auditable AI system is where decisions, processes and data being used by the system can be tracked, monitored and reviewed. This has the benefit of making sure that the AI decision-making process is transparent and allows for accountability in case of errors or failures in the process.

Regular audits of the AI systems are important to identify superficial problems that may appear like bias, unfair decisions or unintentional outcomes. Auditability is also the mechanism for checking the compliance with ethical standards and regulations. This is especially important when dealing with sensitive data in the supply chains like customer information, supplier agreements, stock levels, etc.

An effective audit system should consist of mechanisms for recording all the decisions made by the AI, keeping track of the data utilized in taking decisions and making sure that the system should go off course from its intended goals, corrective actions can be taken. Audit trails can offer transparency into the AI lifecycle, including how the system involved in AI development has been developed, trained, tested, implemented, and monitored over time.

Moreover, third-party auditors may become an essential part in reviewing artificial intelligence systems to make sure it complies with both its internal standards and external regulations. These independent reviews are significant for ensuring the AI system is functioning on the stated guidelines, and also ensure the ethical principles of AI transparency, accountability and fairness are upheld through the deployment process.

4.5 Integration Oversight, Explainability and Auditability

Together, the three elements of oversight, explainability and auditability are the backbone of a responsible AI governance structure. These mechanisms work in tandem to make sure that AI systems in manufacturing supply chains are deployed in an ethical manner with clear accountability for the decisions they are making and ensure that they are continually monitored to prevent or correct any issues that may arise during their operation.

In practice, organizations can follow a multi-layered approach, in which oversight can be covered by an internal AI ethics board and third-party regulators, explainability can be ensured through the use of transparent algorithms and XAI techniques, and auditability can be ensured through the development of automated auditing tools, which can track and review AI decisions in real-time.

By using these methods of governance together, the manufacturers can ensure that they will implement AI in a manner that fosters trust with stakeholders, creates compliance with ethical standards and contributes to the resilience and long-term sustainability of supply chains.

Table 1. *KPI-Based Metrics for Responsible AI Deployment in Manufacturing Supply Chains*

Responsible AI Dimension	Example KPI	How it is Measured	Why it Matters
Governance effectiveness	AI governance review frequency	# reviews per quarter	Ensures ongoing oversight
Accountability	Decision ownership traceability	% AI decisions mapped to accountable owner	Prevents “dislocated accountability”
Transparency	Model documentation completeness	% models with full model cards	Supports audit readiness
Explainability (XAI)	Explainability coverage rate	% critical decisions with XAI output	Improves trust + decision justification
Auditability	Audit trail availability	% decisions logged with timestamp + input/output	Enables investigation + compliance
Human-in-the-loop	Override rate	% AI recommendations overridden by humans	Detects weak models / risky automation
Fairness / bias control	Bias drift score	Change in fairness metric over time	Prevents discriminatory outcomes
Model reliability	Model drift detection time	Avg time to detect drift	Improves safety + stability
Security & privacy	Security incident rate	# incidents per period	Protects sensitive supply chain data
Sustainability	Carbon Avoidance Ratio	Ratio of CO2 saved (optimization) vs CO2 spent (compute)	Ensures AI supports net-zero goals.
Agentic Autonomy	Agent Reversal Rate	% of autonomous agent actions reversed by humans	Tracks if agents are exceeding safe boundaries
Compliance	Federal-State Gap Score	# of conflicting regulatory requirements addressed	Measures resilience to shifting U.S. laws.

5. Risk and Accountability: Ownership of the part of the decision, failure-handling

5.1 Introduction to the Concept of Risk and Accountability in AI Implementation

Artificial Intelligence (AI) integration in the supply chain of manufacturing brings a lot of benefits such as greater efficiency, predictive abilities, and resource management. However, such advancements come with a whole set of risks, which must be carefully managed to ensure the ethical and responsible deployment of AI technologies. As AI systems become more prevalent in making important decisions in the supply chain-from inventory management to predictive maintenance-it is important to develop clear structures for managing the risk and being accountable for one's actions.

Risk management in the implementation of AI refers to the process of identifying, evaluating and addressing the potential risks posed by the use of AI for decision-making. These risks can include bias, lack of transparency, security vulnerabilities, and unintentional consequences of AI actions. For example, if an AI model is trained on biased data, it may come to make unfair decisions, and this could result in discrimination against certain suppliers or customers. Similarly, if an AI system does not detect a possible cybersecurity threat, it can make mistakes for sensitive data and cause financial loss or damage to the reputation.

Accountability, on the other hand, refers to the process of ensuring that there is a clear ownership of decisions made by AI systems. When AI is used to making decisions that affect important facets of the manufacturing process, like supply chain optimizations or ensuring product quality, then it is important to know who is responsible for such decisions, especially when things go wrong. Establishing accountability frameworks There are many examples of AI systems operating without compliance, and in many countries the legal framework for qualifying AI systems is absent. Establish guidelines to ensure that these AI systems do not function in isolation and are supervised and subjected to the appropriate standards and may require human supervision.

5.2 Deciding Ownership and Accountability of AI System

As AI systems become more integrated into decision-making processes in manufacturing supply chains, it is becoming increasingly important to create an explicit decision ownership for both AI generated and human influenced decisions. When an AI system makes decisions autonomously, e.g. forecasting demand or optimizing production schedules, it is crucial that there is no doubt who makes the decisions.

An important challenge of the adoption of AI is the blurring of responsibility between humans and machines. AI systems, especially those involving machine learning (ML), can learn and make decisions on their own using inputs in the form of data. While these systems are highly efficient, there are also questions about who has responsibility for the consequences of their actions. If an AI system makes a mistake - let's say it orders too much inventory or optimizes production incorrectly - who should be held responsible: the developer of the AI system, the person who administers it or the manufacturer who implemented the system?

To overcome this dilemma, a new approach is therefore needed: the Responsible AI Deployment Model (RAIDM) is important in this regard because it highlights the significance of clear accountability frameworks, in which it is possible to trace back and assign specific responsibility for every decision, be it from an AI or a human. Decisional ownership can be distributed in a number of ways:

- AI Developers: In the case of AI systems that are built from scratch, the AI system developers or data scientists that were responsible for creating the model may be responsible for ensuring that the system is doing what it was intended to do, including testing for bias and errors in decision-making.
- Supply Chain Managers: While AI systems may make recommendations on what should be done, human oversight is essential in validating the decisions made by the AI system, especially in complex situations. Supply chain managers utilizing artificial intelligence systems to support decision-making should be accountable for implementing artificial intelligence recommendations.
- AI System Administrators: Individuals in charge of system maintenance and configuration of the AI system also need to take responsibility for the system's performance. They must ensure that AI tools are updated and even secured and are not stopping them from performance degradation.

The fact is that by clearly defining the ownership of decisions, organizations can prevent a situation where accountability is lost and can hinder accountabilities to be lost between human actions and machine actions (Widder & Nafus, 2023). This ensures that if an AI system makes an error or a negative outcome, the one responsible can take corrective actions.

5.3 AI System failures

5.3.1 Handling Failures in AI Systems

Despite all of the benefits of AI systems, there are guaranteed to be failures. Whether it's because of bugs in the software, inaccurate inputs of data into the system or unexpected external factors, AI systems can go wrong or generate wrong outputs. In the case of manufacturing supply chains, these failures can have severe consequences, including delays in the production process, inaccurate inventory levels, or damage to the quality of the products.

To help mitigate the risks of AI failures, the Responsible AI Deployment Model includes a series of failures handling mechanisms that ensure that AI systems can recover from failures without having a dramatic effect on business operations. These mechanisms focus on detecting issues before they get out of control and allowing for intervention from human stakeholders at a rapid rate, when necessary.

One of the important failures in handling mechanisms is the introduction of redundancy systems. In the case of AI-driven manufacturing systems, systems are used to back up the AI's decision-making process that has been redundant.

For instance, if any AI model is not able to optimize the inventory management, the backup models will be triggered and can be used to carry on the operations without any disruption. Failover mechanisms make sure that the manufacturing supply chain can keep going even when one component stops.

Additionally, the model calls for Human-in-the-Loop (HITL) systems. In HITL frameworks, AI systems are continually monitored by humans who would be able to intervene in case of failure. For example, if an AI system makes a demand forecast that is wrong, a supply chain manager can override the recommendation and adjust the decision manually to conform to real-time market conditions. HITL systems are useful to ensure that the human being is ultimately responsible for decisions, especially when AI systems are making complex and high-risk decisions (Kilari, 2025).

Another important failure in handling mechanism is continuous monitoring. AI systems need to be measured periodically on performance metrics in order to spot deviations from the realized outcomes. Continuous monitoring ensures that the failure is quickly identified and corrected instead of AI errors leading to a larger system-wide failure. Auditability done (the topic was previously addressed) plays an important role in this process as it enables organizations to track and review the decisions made by AI systems, in order to present failures caused by those decisions, in time.

5.4 Risk Mitigation Strategies

Managing the risks associated with AI in manufacturing means taking a proactive approach to identify any potential risks and taking strategies to mitigate these risks. These strategies can be divided into a number of key areas:

Bias and Fairness AI systems, in particular, which are trained based on past data can introduce bias in decision-making. In terms of manufacturing supply chains, this bias can result in unfair treatment of suppliers, customers or employees. Risk mitigation strategies consist of using diverse data sets for training AI models, as well as using regular bias audits to make sure that AI systems are making decisions based on fair and representative data (Brintrup et al., 2023).

Data Privacy and Security: The AI systems of supply chain deal with a large amount of sensitive data and provide customer data, supplier contracts, inventory data, etc. Securing this data is extremely important so that it is not accessed or misused by these people. Risk management in this area includes data encryption, secure communication channels and adherence to data privacy rules, such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA).

Operational Failures: It is important for AI systems to be robust and resilient in manufacturing supply chain operations to minimize any downtime and ensure that any disruptions do not result in significant financial losses. Redundancy systems, failover strategies, and real-time monitoring are essential risk management tactics to provide the assurance that AI failures will not stop operations and that manufacturing processes will run unabated when they are not interrupted by AI failures.

Regulatory Compliance: As more people adopt AI, there is also more need for regulatory compliance. Manufacturers need to ensure that AI systems comply with the industry-specific and the general AI regulations. This includes making sure that AI systems are ethical and compliant with legal requirements, such as fairness, explainability and transparency.

Sustainability and ESG Accountability: In 2026, sustainability is no longer an optional disclosure but an "operating system" for resilient supply chains. AI systems are now tasked with calculating Scope 3 emissions and automating up to 90% of ESG reporting. However, a core risk in "Responsible AI" is the energy intensity of the AI models themselves. Responsible deployment must include metrics for energy intensity per inference and ensure that AI-driven route optimizations (which can reduce fuel consumption by 12–15%) are not offset by the carbon footprint of massive computational training.

5.5 Role of Accountability in Risk Management

Accountability is not only a governance issue; it is also a key part of good risk management. AI making decisions in these systems, it is necessary to know who is responsible for the decisions they make and especially when something goes wrong. Clear accountability structures make it easy for manufacturers to quickly know who is responsible in case of failure and take corrective actions.

The setting up of AI accountability is critical in ensuring that AI-driven choices have been made with due diligence and that properly mitigating the risks. Whether by clear decision ownership, audit trails or oversight by third parties, the principles of accountability ensure that all stakeholders, including AI developers, system operators and managers, are aware of their responsibilities and can be held accountable for the performance of AI systems.

6. Managerial and Policy Implications (U.S. Specific).

6.1 Managerial Implications to Deploy AI

The use of AI technologies within manufacturing supply chains is simply very powerful in terms of the potential for greater efficiency, cost reduction, and resilience that could be achieved. However, with the promise of AI adoption comes a set of managerial responsibilities with the goal of ensuring ethical and effective deployment of AI. Manufacturers need to overcome several critical challenges to be certain that AI systems are used responsibly while taking advantage of their potential.

6.1.1 Ethics of AI Implementation:

One of the important managerial issues is the ethical use of AI systems. Supply chain managers should not just manage the technical performance of AI systems but can also be responsible for ensuring that these systems function in a way that is consistent with the values and ethical principles of the organization. This includes ensuring fairness and transparency and no discrimination is being made in an AI-determined decision. For example, in the context of using AI for demand forecasting, managers need to consider ensuring that the data used to train the system is representative of all customer segments, in order to avoid bias, which could have negative consequences for marginalized groups, or advantage for others (Brintrup et al., 2023). To address these ethical concerns, there are AI ethics boards or advisory panels that can be set up in organizations to monitor AI activities and ensure that they follow ethical standards.

The following mechanism is Human-in-the-Loop (HITL):

Another managerial implication is the need to include human oversight in the decision-making process of AI systems, particularly when AI systems are implemented in complex and high-risk environments. The Human-in-the-Loop (HITL) model is one of the governance tools needed to ensure that human decision-makers can intervene when AI systems make decisions that have large implications for the operations of the supply chain. This model is especially relevant in cases where the decisions made by AI systems have an impact on employees, customers or important business outcomes. For instance, while Artificial Intelligence is capable of optimizing inventory management or deciding on suppliers, decision making regarding strategic actions must be made with human-led stakeholders, to take into account different contextual factors that the AI might miss in its considerations, such as relationships with suppliers or supply chain disruptions (Kilari, 2025).

6.1.2 Responsibilities for Failure and Accountability:

Managers must also ensure that there are clear accountability frameworks in place to figure out who is accountable for decisions made by AI systems. AI can enable autonomous decision-making based on learned data patterns, however, when the decisions lead to failures or unintended consequences, responsibility has to be ensured to corrective action. In the case of an AI system for optimizing demand forecasting that ends up resulting in overstocking, it is important for managers to be able to know whether the algorithmic model, the data used to train the model, or the AI governance process contributed to the failure. This clarity in accountability is critical in reducing the risks associated with failures in AI systems and ensuring that the organization can learn from its mistakes to improve its AI systems (Widder & Nafus, 2023).

6.1.3 Data privacy and security Management:

AI systems in supply chains are frequently known to be data-intensive, and it is up to managers to ensure that data privacy and security are preserved. Sensitive information, like customer orders, supplier information, and logistics information, should be prevented from being accessed by unauthorized parties. Managers must provide data encryption methods and set up data access rules that provide enough protection to keep sensitive data private while ensuring that AI systems will have access to the data, they need to address problems and make informed decisions. Additionally, compliance with data protection regulations such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA), are of utmost importance which, in case of non-compliance, could result in financial penalties and damage to the company's reputation (Meena et al., 2025).

6.2 Implications for the Policy of AI Deployment

On the policy front, it seems the U.S. government and regulatory bodies will need to collaborate with the private sector to develop and implement policies that will help to ensure the responsible and ethical deployment of AI in manufacturing supply chains. This includes developing a strong regulatory body that not only supports the adoption of AI but also ensures that the deployment of AI in question meets the wider objectives of sustainability, equity and public safety.

Determining Artificial Intelligence Governance Standards:

One of the most important policy implications is to have clear AI governance standards. As AI systems grow more involved with supply chain decision-making, it's important for the government to set rules regarding AI transparency, accountability, and performance monitoring. Agencies like the National Institute of Standards and Technology (NIST) and the Federal Trade Commission (FTC) can create guidelines that can make sure that AI systems in manufacturing fall in line with ethical standards. These guidelines would discuss important aspects of AI deployment, such as explainability and bias mitigation, as well as auditing, to ensure that AI technologies are used responsibly and with minimal negative societal impacts (Kilari, 2025).

Providing Incentives to EPS: Ethical AI Practices:

Governments can promote healthy uses of AI by providing financial incentives or tax benefits to manufacturers which implement reasonable AI deployment patterns. Such incentives could motivate businesses to put AI governance, data privacy, and transparency at the forefront of their adoption of AI in their operations. This might be especially effective in trying to get small and medium-sized manufacturers to embrace AI sensibly, as they may not have the resources to build up robust internal governance structures around their use of AI.

Promoting the Education of AI and Making Workforce Transition:

As AI adoption grows, there is bound to be a rising requirement of a skilled workforce that could manage and oversee these technologies. Policymakers will need to also concentrate on offering more AI education programs and worker re-skilling efforts for manufacturing industry workers. As we continue to integrate AI into society, having the necessary skills to work with AI will not only promote the ethical use of AI and exercise a positive impact on society, but also may mitigate the potential negative impacts on jobs and employment (Brown, 2023). Workforce transition programs will be required to enable employees to adapt to changes brought about by AI including new roles in AI oversight and AI-driven decision support.

Ethical AI in global Supply Chains:

As the supply chains for manufacturing are quite frequently maritime, policymakers need to deal with the ethical implications of the implementation of AI in different countries and regions, too. The U.S. can play a structural role in defining international norms for AI governance, making sure that AI systems that are utilized in global supply chains comply with ethical and legal norms. This includes promoting AI standards that consider the environmental impact of AI, as well as its potential to increase or reduce social inequalities (Dauvergne, 2022).

Artificial Intelligence vs. Sustainability Policies:

AI can play a key role in driving sustainability for supply chains as well, but it has to be used in a manner that does not contribute to environmental destruction. Policy frameworks should support AI systems that support sustainable supply chain practices, such as waste reduction, reduction of carbon footprints and resource optimization. Policymakers can offer incentives to AI solutions that are in line with environmental, social, and governance (ESG) objectives and support the transition to a circular economy (Orenuga, Oyeyemi, & John, 2024).

On the policy front, the U.S. landscape in early 2026 is defined by a significant conflict between state-level "AI Bills of Rights" and federal authority. While states like California and Texas have enacted rigorous transparency acts (effective January 1, 2026) that mandate training data disclosures and content detection, a new Federal Executive Order issued in January 2026 seeks to preempt these "onerous" state laws to create a uniform national policy. For manufacturers, this creates a period of regulatory uncertainty, requiring an agile RAIDM that can comply with both high-risk state classifications and shifting federal standards for economic security.

6.3 The Collaboration of the Industry and Government

For the responsible use of AI to succeed, there should be a strong partnership between industry and government. Industry leaders can share their insights into the practical challenges of implementing AI in manufacturing supply chains, while the government can ensure that AI systems are implemented in a way that is fair and considers public interests. Public-private partnerships can be beneficial in creating standards around AI, protocols for sharing data and regulations for dealing with AI, ensuring the responsible implementation of AI, and driving the rise and innovation in manufacturing technologies.

7. Conclusion and Possible Future Research

7.1 Conclusion

The use of AI technologies in manufacturing supply chains in the US comes with multiple benefits such as increased efficiency, cost savings, and greater supply chain resilience. However, the implementation of AI involves a structured approach towards making it ethical, responsible and transparent. This paper has proposed the Responsible AI Deployment Model (RAIDM) as a way to help manufacturers unwind the complexities involved in AI adoption but addresses concerns surrounding AI governance, accountability and risk management.

RAIDM focuses on key principles, including AI governance frameworks, decision ownership, and ongoing auditing that all focus on ensuring that AI systems function in a responsible manner. By built-in mechanisms like explainability, human oversight etc., the model promotes trust while minimizing the risks of bias, data privacy, and unintended consequences.

What's more is that given the significant potential benefits of AI for human well-being, the paper emphasizes the importance of managerial and policy frameworks to support the responsible adoption of AI, including clear regulations, financial incentives and workforce development initiatives. Ensuring that AI systems are deployed ethically will require a collaboration between industry and government to create

AI standards and a fair and transparent environment for AI-driven innovation.

7.2 Future Research Directions

While the adoption of AI in manufacturing supply chains has been shown to show great promise of success, there are areas that require further research:

Global Governance Standards: Research is required on how to establish AI governance standards that can be applied across the globe, to a global supply chain, which must maintain consistency of ethical standards and compliance.

Explainability: Future work should include focusing on improving the techniques of explainable AI (XAI), particularly for complex models that are being used in supply chains, to improve transparency in decision making processes.

AI and Sustainability While examining the role of AI in advancing sustainable practices within the manufacturing supply chains is of paramount importance, potential research here involves exploring AI's role in cutting the amount of waste and energy used.

Workforce Adaptation: Research should be conducted on the adaptation implications of AI integration in the workforce and ways to upskill workers to handle AI systems and adapt to new roles.

Ethical AI Deployment: Researching ways to address the bias in AI models and limiting this bias in the supply chain's decisions will be an important focus for further research.

7.3 Final Thoughts

Responsible deployment of AI is paramount to realizing the benefits of AI technology in manufacturing supply chains while reducing the risks of using AI technologies. By following the RAIDM, focusing on governance, accountability and transparency organizations can ensure that AIs contribute to operational success and ethical outcomes.

References

1. Brintrup, A., Baryannis, G., Tiwari, A., Ratchev, S., Martinez-Arellano, G., & Singh, J. (2023). Trustworthy, responsible, ethical AI in manufacturing and supply chains: synthesis and emerging research questions. *arXiv preprint arXiv:2305.11581*. https://doi.org/10.48550/arXiv.2305.11581.
2. Ejjami, R., & Boussalham, K. (2024). Industry 5.0 in manufacturing: Enhancing resilience and responsibility through AI-driven predictive maintenance, quality control, and supply chain optimization. *International Journal For Multidisciplinary Research*, 6(4).
3. Widder, D. G., & Nafus, D. (2023). Dislocated accountabilities in the "AI supply chain": Modularity and developers' notions of responsibility. *Big Data & Society*, 10(1), 20539517231177620. https://doi.org/10.1177/20539517231177620.
4. Wu, H., Liu, J., & Liang, B. (2025). AI-driven supply chain transformation in Industry 5.0: Enhancing resilience and sustainability. *Journal of the Knowledge Economy*, 16(1), 3826-3868.
5. Meena, R., Sahoo, S., Malik, A., Kumar, S., & Nguyen, M. (2025). Artificial intelligence and circular supply chains: framework for applications and deployment from the triple bottom line model perspective. *Annals of Operations Research*, 1-31.
6. Elghomri, B., Messaoudi, F., & Touti, N. (2025). The Role of AI in Driving Accountability and Transparency in Global Supply Chains: The Fragmented Bridge Between Research and Practice. *Operations and Supply Chain Management An International Journal*, 275-287.
7. Brown, I. (2023). Allocating accountability in AI supply chains. *Ada Lovelace Institute*.
8. Kilari, S. D. (2025). The Impact of Artificial Intelligence on Automated Manufacturing and Supply Chain Systems: Advancements, Challenges, and Future Prospects. *Challenges, and Future Prospects* (March 23, 2025). https://dx.doi.org/10.2139/ssrn.5204723.
9. Dauvergne, P. (2022). Is artificial intelligence greening global supply chains? Exposing the political economy of environmental costs. *Review of International Political Economy*, 29(3), 696-718. https://doi.org/10.1080/09692290.2020.1814381.
10. Orenuga, A., Oyeyemi, B. B., & John, A. O. (2024). AI and Sustainable Supply Chain Practices: ESG Goals in the US and Nigeria. https://doi.org/10.54660/IJFEI.2024.1.1.127-137.
11. Zhang, W., Li, H., & Xu, Y. (2025). Enhancing AI-driven Decision Support Systems for Sustainable Supply Chain Practices. *Journal of Sustainable Supply Chain Management*, 17(2), 50-68.
12. Kumar, S., & Gupta, P. (2023). Leveraging AI for Supply Chain Optimization: Challenges and Opportunities. *International Journal of Industrial*

Engineering and Operations Management, 32(1), 99-112.

13. Walker, S. P., & Lee, T. (2024). Governance Models for AI in Manufacturing: Exploring Policy Implications. *Manufacturing & Policy Review*, 8(1), 55-72.

14. Ankit Sharma. (2019). Effect and Impact of IoT (Internet of Thing) on Supply Chain Management. https://doi.org/10.56975/jetir.v6i1.195290

15. Singh, P., & Jackson, R. L. (2025). Understanding the Role of AI in Decision-Making within Manufacturing Supply Chains. *Journal of Business Decision Analysis*, 34(2), 121-137.

16. Brown, T., & Davis, R. (2024). Ethical AI: Frameworks for Governance in Manufacturing. *International Journal of AI and Ethics*, 22(4), 200-214.

17. Ankit Sharma. (2024). Cognitive AI for Autonomous Supply Chain Disruption Management: Architecture, Implementation, and Evaluation. *Journal of Computational Analysis and Applications (JoCAAA)*, *33*(05), 3436–3459. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/4604

18. Shah, S., & Gupta, M. (2024). The Role of AI in Managing Risk and Enhancing Resilience in Supply Chains. *Risk Management Journal*, 12(3), 112-124.

19. Garcia, H., & Gonzalez, J. (2023). AI Integration in Manufacturing: Opportunities and Challenges. *Journal of Manufacturing Science and Technology*, 45(6), 1129-1139.

20. Ankit Sharma. (2020). Beyond cryptocurrency – More to blockchain. Ankit Sharma. (2020). https://doi.org/10.13140/RG.2.2.24976.23049

21. Lee, M., & Thompson, K. (2025). Responsible AI Adoption in the U.S. Manufacturing Sector: A Case Study. *Global Supply Chain Journal*, 20(1), 82-98.

22. Ankit Sharma, Priyanshi Joshi. (2024). Artificial Intelligence Enabled Predictive Decision Systems for Supply Chain Resilience and Optimization. *Journal of Computational Analysis and Applications (JoCAAA)*, *33*(08), 7460–7472. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/4715