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Leveraging Generative Modeling in Supply Chain Management: A Comprehensive Review

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Abstract

Generative modeling within supply chain management reveals significant potential for enhancing operational efficiency, adaptability, and resilience. Leveraging advanced AI-driven methods such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and autoregressive models, this paper investigates their role in transforming demand forecasting, inventory management, logistics optimization, and risk mitigation. By simulating complex scenarios and capturing dynamic data relationships, these models enable organizations to predict disruptions, optimize inventory levels, and streamline logistics, reducing operational costs and improving responsiveness. This study systematically examines the capabilities of generative models in addressing inefficiencies in traditional supply chains. It demonstrates how GANs mitigate stockout risks by improving demand predictions, VAEs enhance supply chain transparency through latent variable modeling, and autoregressive models forecast time-series data to refine inventory and production planning. Additionally, generative approaches integrate real-time data to dynamically optimize routing and decision-making under uncertainty. Despite their transformative potential, the paper identifies persistent barriers, including data quality issues, interpretability challenges, and integration complexities. To overcome these, it proposes leveraging federated generative models for secure, decentralized collaboration and embedding sustainability metrics into generative frameworks for eco-conscious supply chain management. This work underscores the necessity of integrating generative modeling as a core strategy to drive efficiency, agility, and resilience in modern supply chain systems.

Keywords
Supply Chain Management, Generative Modeling, Demand Forecasting, Inventory Management, AI-Driven Supply Chains

1. Introduction
In recent years, the digital transformation within the supply chain has introduced large volumes of extensively interdependent data which has increased the complexity of supply chain ecosystem and made it more vulnerable to disruption (Ivanov & Dolgui 2021; Y. Wang 2023). Traditional management approaches often fail to understand the dynamic landscape , decision makers struggle to integrate and standardize interrelation of data across various channels resulting in lost revenue, higher costs, and decreased customer satisfaction (Petrescu & Krishen et al. 2020; Wood et al. 2013) Modern management necessitates the integration of Industry 4.0 technologies that enable them to simulate complex supply chain scenarios giving a shift from reactive to proactive management (Fatorachian & Kazemi 2021; J. Wang, Zhou, et al. 2023) However, key Industry 4.0 technologies like Artificial Intelligence (AI), Machine Learning (ML), Big Data, Internet of Things (IoT), Cyber-Physical Systems (CPS), and Digital Twins are still uncommon in many supply chain sectors, creating a gap between outdated supply chain management practices and modernized manufacturing processes (Ghani et al. 2024; Raut et al. 2020; Varriale et al. 2021).

Generative model leverages advanced ML techniques to improve various drives of supply chain such as, fast souring demand forecasting, logistics optimization, resilience planning, and inventory management (Oliveira & Pereira, 2023; Pasupuleti et al. 2024; Yandrapalli 2023) Capturing historical data, generative ai produce realistic alternative scenarios allowing companies to test disruptions and evaluate alternative strategies in a virtual environment (Finkenstadt et al. 2023; Sohrabi et al. 2018) These models act as statistical tools, learning the joint probability distribution of data across demand, supply, and logistics variables, enabling highly accurate simulations that mirror real-world conditions (Amellal et al. 2024). Integrating AI into supply chain enhances capability to boost operational efficiency, enhance strategic decision-making, and improve risk management by facilitating scenario-based simulations that account for uncertainties like market shifts and supply bottlenecks (Abaku et al. 2024; Joel et al. 2024; Kulkarni & Bansal 2024).

Understanding the need for generative models in supply chain management, this study offers a comprehensive review of how advanced generative modeling techniques can transform all drives of supply chain, from demand forecasting and logistics optimization to resilience planning, inventory management, and risk mitigation (Anaba et al., 2024; Rajagopal et al., 2017)

The scope of this study encompasses:

- Defining supply chain management and its key components, with a focus on demand forecasting, inventory, logistics, and risk management.
- Outlining the fundamentals of generative modeling techniques and recent advancements relevant to supply chain management.
- Exploring the applications of generative modeling across various aspects of supply chain management.
- Examining industry-specific applications of generative modeling in supply chain management.
- Discussing the advantages and challenges of implementing generative modeling in supply chain contexts.
- Identifying future trends and research opportunities for generative models in supply chains.

By synthesizing both theoretical advancements and practical implementations of generative models in supply chain management, this review highlights the transformative potential of generative modeling for advancing modern supply chains.

2. Overview of Supply Chain Management and Optimization

Supply chain management plays a crucial role in improving competitiveness by managing cross-functional flow of materials, information, and finances from raw materials to end consumers (Chandra & Kumar 2000; Maksud et al., 2022; Raisinghani et al. 2009). In today's global competitive environment, traditional supply chain management faces numerous challenges (Figure 1) such as meeting uncertain demand variabilities while keeping the cost minimum (Manuj & Mentzer 2008) Risk of supply chain disruptions due to natural disasters and geopolitical instability is another key challenge of traditional supply chain management (Kumar J et al. 2024) Globalization has intensified these challenges, requiring companies to establish close relationships with suppliers and improve coordination of material flows to enhance competitiveness and supply chain resilience (Milovanović et al. 2017). Rising sustainability concerns have created another challenge in to force balance between responsibility and profit (Eyo-Udo et al. 2024). The complexity of global supply chains emphasizes the necessity of comprehensive risk management strategies and mitigation plans (Manuj & Mentzer, 2008). So, modern supply chain management must address increasing customer expectations for on-time delivery, skillful use of new technologies, and growing emphasis on environmental concerns (Surmacz & Szopiński 2023).

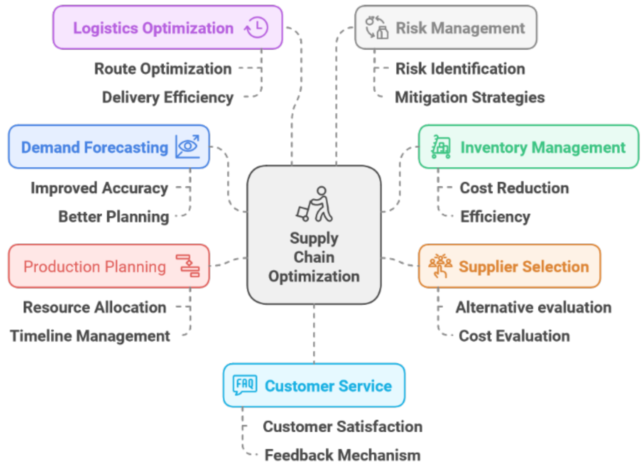

Figure 1. Challenges in modern supply chain

To address the increased complexities, smart supply chain has emerged as a prominent solution that incorporates advanced technologies to present opportunities for achieving cost reduction, enhancing efficiency

Table 1. Key intelligent technologies in smart supply chain

Technology	**Role in Supply Chain**	**References**
Machine Learning (ML)	Predicts demand patterns, optimizes inventory levels, analyzes big data and real time decision making, and mitigates risks	(Aljohani, 2023; Odimarha et al., 2024; Pasupuleti et al., 2024; Raza et al., 2023)
Artificial Intelligence (AI)	Automates decision-making, enhances process optimization and adaptability to disruption, facilitates proactive measures, analyzes key performance indicators	(Adesoga et al., 2024; Ali et al., 2024; Kumar et al., 2024; Mahi, 2024; Vatin et al., 2024)
Blockchain	Ensures secure, tamper-proof transaction tracking, reduces the need for intermediaries and minimizes cost, enhances trust, transparency, automation, traceability,	(Dutta et al., 2020; Ekwunife et al., 2024; Reddy V., 2019; Terzi et al., 2019)
Internet of Things (IoT)	Real-time asset monitoring and increases visibility, predictive maintenance, aids in proactive decision-making, improves quality control across storage conditions.	(Atlam et al., 2018; Cao, 2024; Yesodha et al., 2023)
Digital Twin	Simulates physical supply chain elements for optimization, provide a framework for digital transformation journey, improve production flexibility and scheduling,	(Bhandal et al., 2022; Freese & Ludwig, 2024; Freese Falk and Ludwig, 2021; Lugaresi et al., 2023; Maheshwari et al., 2023)
Cyber-Physical Systems (CPS)	Integrates physical and computational elements for automation and enhances efficiency by reducing cost, increases flexibility and allowing for customized responses to varying demands and conditions	(Park et al., 2021; Suárez-Riveros Erika and Mejia-Mantilla, 2021; L. Wang & Zhang, 2021; L. Yin et al., 2024)

, and promoting sustainable business practices by becoming more instrumented and interconnected (Ageeli et al. 2023; Frankowska & Nowicka et al. 2018; L. Wu et al. 2016). Table 1 highlights key intelligent technologies that play pivotal roles in smart supply chain management, including machine learning, artificial intelligence, blockchain, IoT, digital twins, and cyber-physical systems.

These technologies not only increase efficiency but also help businesses respond proactively to disruptions, improving supply chain resilience (Ghani et al. 2024). Figure 2 illustrates the specific impacts of these technologies across critical supply chain functions, demonstrating how they contribute to resilience and enable proactive responses to disruptions.

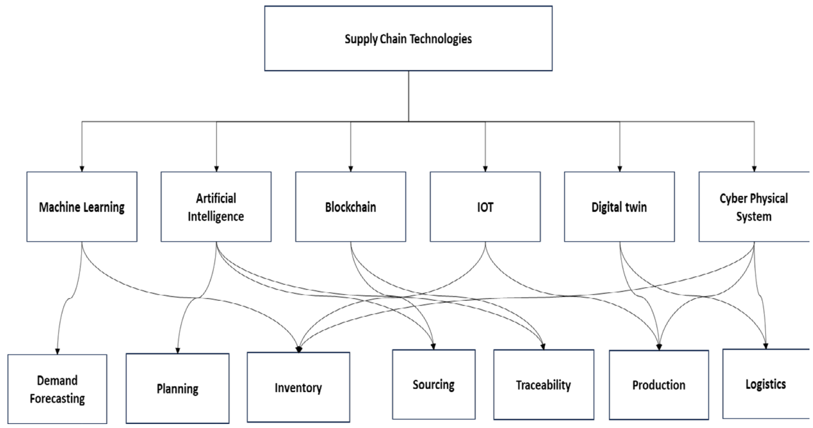

Figure 2. Technologies influencing supply chains: sector-specific impacts across key supply chain functions

3. Fundamentals of Generative Modeling

Generative models are defined as the statistical models that generate new data instances that are commonly utilized in unsupervised ML for tasks like probability estimation, data point modeling, and classification (Chen et al. 2024). Generative models aim to comprehend the joint probability distribution of input data, enabling the generation of new data points that statistically resemble the training data (Anstine & Isayev 2023). The goal of generative models is to produce realistic material that closely resembles the actual data distribution, rendering it indistinguishable from genuine data (Hiriyannaiah et al. 2020).

Deep generative models utilize deep neural networks offering greater flexibility and can handle more complex data distributions than traditional generative models (Taylor et al. 2022; Tschannen et al. 2018). Deep generative models enhance supply chain decision-making by modeling uncertainty, generating realistic demand and inventory scenarios from historical data, and improving forecasting, transparency, and efficiency in complex networks (Hosseinnia et al. 2023; Tschannen et al. 2018; Zhao & You 2020). Deep generative models can be divided into likelihood-based and implicit generative models, which gained great success as potent tools for learning data distribution through unsupervised learning (Toshpulatov et al. 2021). The principal models in this field comprise Generative Adversarial Networks (GANs), Diffusion Models, Variational Autoencoders (VAEs), and Autoregressive Models.

Generative Adversarial Networks (GANs): GANs, introduced by Goodfellow et al. (2014), are groundbreaking generative models consisting of two neural networks, a generator and a discriminator, that compete in a zero-sum game to produce realistic data samples (Dash et al. 2024; Oğuz & Ertuğrul, 2023; Remusati et al. 2024). GANs have been effectively utilized across multiple domains, especially for generating high-resolution images, and are regarded as one of the most successful generative models due to their capability to produce highly realistic outputs (Carreon et al. 2023; Goodfellow et al. 2020) GANs generate synthetic data for ML models, enhancing their resilience in supply chain management scenarios where real data is scarce or expensive (Remusati et al. 2024). Although GANs have achieved notable success, they pose unique challenges, such as mode collapse, where the generator yields limited output diversity (Kim et al. 2023).

Diffusion Generative Model: Diffusion models, a type of generative model, refine data samples by iteratively adding and removing noise, and have become popular for their capacity to generate high-quality images and 3D models (Po et al. 2024) Diffusion models operate in a two-stage process: forward diffusion, where noise is progressively added to the data over multiple steps, and reverse diffusion, which aims to reconstruct the original data by learning to reverse the noise addition process step-by-step (Croitoru et al. 2023). Diffusion models can aid in scenario planning and risk assessment by simulating various supply chain disruptions and their potential impacts, thereby supporting the development of more resilient supply chain strategies (Kassa et al. 2023).

Variational Autoencoders (VAEs): VAEs are designed to learn latent representations of data, making them valuable for tasks involving data generation and manipulation, particularly when understanding the underlying structure of the data is essential (Geng et al. 2023). VAEs are fundamental for generating new samples from learned latent spaces, with advancements aimed at reducing reconstruction error and improving generative metrics such as the Fréchet Inception Distance (FID) (Nicodemou et al. 2023) VAEs can model complex supply chain networks and forecast potential disruptions by analyzing latent variables representing various supply chain components, thereby enhancing decision-making and risk management (Kassa et al. 2023). VAEs often encounter a trade-off between reconstruction accuracy and the quality of generated samples, potentially impacting their effectiveness in specific applications (Geng et al. 2023).

Autoregressive Models: Autoregressive modeling is a ML technique for analyzing and forecasting time series data by expressing the current value of a variable as a function of its previous values (Kaur et al. 2023; Yin et al. 2023). Autoregressive models generate data by predicting each subsequent element in a sequence using prior elements, making them well-suited for time-series forecasting and sequential data analysis (Bond-Taylor et al.2022). These models are particularly effective in demand forecasting and inventory management, where accurate predictions of future demand are crucial for optimizing supply chain operations (Kassa et al. 2023). A key challenge in autoregressive modeling is maintaining model stability and addressing misspecifications, such as incorrect network connectivity, which can affect parameter estimation accuracy (Yin et al.2023).

3.1 Recent Developments

Generative models have significantly advanced supply chain management by enhancing demand forecasting, inventory management, entity recognition, cybersecurity, and process monitoring. The following table 2 highlights key developments and innovations in generative models within the supply chain context.

Table 2. Advancements of generative modeling in supply chain management

Area	**Key Developments**	**References**
Demand Forecasting Enhancements	attLSTM framework with attention mechanisms and bidirectional LSTM outperforms Seasonal Autoregressive Integrated Moving Average (SARIMA) in time series data forecasting, enhancing decision-making.	(Cui et al., 2024)
	Enhanced deep learning models emphasizing the historical data to optimize stock management and reduce overhead costs.	(Praveenadevi et al., 2023)
Entity Recognition and Knowledge Graphs	A two-stage GAN model with binocular attention-based stacked BiLSTM with CNN (BACSBN) improves entity recognition in supply chains by constructing an event logic knowledge graph (ELKG). Enhances recognition accuracy even with limited annotations.	(Deng et al., 2023)
Cybersecurity and Attack Prediction	GANs and Deep Belief Networks (DBMs) optimized with Extreme Learning Machine (ELM) and Poor and Rich Optimization (PRO) algorithms effectively predict and classify cyber-attacks in SCM systems.	(Chauhdary et al., 2023)
VAE-Based Process Monitoring	VAEs develop interpretable latent variable models for process monitoring, utilizing Taylor expansions and specific activation functions for enhanced fault impact capture.	(Pan et al., 2024)
Log Parsing with VAEs	VAEs with PVE methods parse unstructured logs into structured data, achieving an average accuracy of 0.878 in real-world datasets and improving data processing in SCM.	(Yuan et al., 2023)
Real-Time Risk Mitigation	Predictive analytics and ML models using time series analysis and anomaly detection to improve agility and risk management in supply chains.	(Aljohani et al ., 2023)

Area	Key Developments	References
Inventory Management Optimization	Deep reinforcement learning (DRL) applies near-optimal dynamic policies in real-time inventory management, outperforming traditional methods, especially in non-stationary demand environments.	(Dehaybe et al., 2024)
Backorder Prediction and Quantum Computing	QAmplifyNet framework integrates quantum-inspired techniques with classical neural networks for high-accuracy backorder prediction on imbalanced datasets.	(Jahin et al., 2023)
Model Predictive Control (MPC) for Supply Chain Optimization	Deep learning-based MPC reduces online computation time and enhances operational efficiency in real-time supply chain decision-making.	(J. Wang, Swartz, et al., 2023)

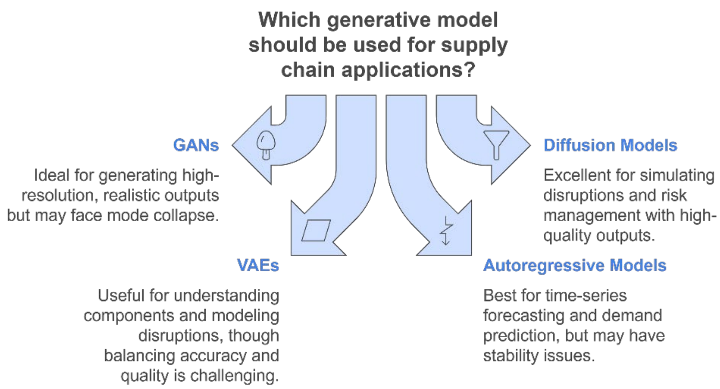

Figure 3. Generative models in supply chain applications

4. Applications of Generative Modeling in Supply Chain Optimization

4.1 Demand Forecasting

Generative modeling has found multiple applications in demand forecasting under various conditions, leveraging techniques such as GANs to effectively model uncertainty and complex data distributions, which provides optimization under demand uncertainty (Zhao & You 2020). Additionally, synthetic data generation using GANs has proven to enhance prediction accuracy, particularly in contexts like electric vehicle demand forecasting, where the accuracy of forecasts improves with synthetic data (Chatterjee & Byun 2023). At granular levels of customer sales forecasting, Recurrent Neural Networks (RNNs) and Transformers have enabled competitive performance with minimal data preprocessing (Vallés-Pérez et al. 2022). For time series demand forecasting, the attLSTM framework, which integrates attention mechanisms with bidirectional LSTM, has demonstrated superior performance and supports operational decisions within supply chains (Cui et al. 2024). The integration of LightGBM and PSO-LSTM models within big data analytics frameworks has led to improved inventory turnover and demand fulfillment rates (Tang, 2024). A novel demand forecasting framework utilizing cross-series training and advanced ML models can overcome data limitations and improve forecast accuracy (Zhu et al. 2021). For accurate demand estimation, deep learning models are applied to enhance supply chain management processes, optimizing stock management and reducing costs (Praveenadevi et al. 2023). Supply chain forecasting benefits from combining biased regression with ML techniques, underscoring the importance of integrating diverse data sources to achieve improved forecasting outcomes (C.-H. Wang & Chen 2022).

4.2 Inventory Management

Generative modeling can be applied in inventory management to address diverse challenges, with literature mentioning its usage in directly suggesting replenishment amounts from input features. Deep learning models, particularly within an end-to-end framework, are noted for bypassing traditional predict-then-optimize approaches, leading to reduced holding and stockout costs (Qi et al. 2022). Another usage mentioned is in optimizing inventory levels by determining production batches and shipping decisions, where Deep Reinforcement Learning (DRL) models significantly reduce costs in comparison to traditional methods (Stranieri et al. 2024). Model-based deep reinforcement learning, combining offline model learning with online planning, is particularly effective for managing inventories of new products with short life cycles, optimizing inventory levels and reducing lost opportunities and defective inventory (Demizu et al. 2023). Monte Carlo tree search (MCTS) techniques are another usage cited, excelling in cost reduction by optimizing order policies and inventory costs, and effectively eliminating the bullwhip effect (Preil & Krapp 2022). Furthermore, deep reinforcement learning models such as Soft Actor-Critic are documented for their role in balancing service levels and sell-through rates, contributing to a lower inventory-to-sales ratio and improved profitability (Chong et al. 2022). Quantum-inspired generative models like QAmplifyNet enhance backorder prediction accuracy, which is critical for inventory control and customer satisfaction, by handling complex datasets and dependencies, offering superior predictive capabilities compared to traditional models (Jahin et al. 2023).

4.3 Logistics and Route Optimization

Generative modeling finds diverse applications in logistics and route optimization. Multi-agent reinforcement learning models optimize vehicle routing by simultaneously considering route length and vehicle arrival times, generating routes for multiple vehicles in real-time and significantly reducing computation time compared to traditional heuristic algorithms (Ren et al. 2022). Progressive GANs, such as ProgGAN, are used in route planning to refine routes from low-resolution to high-resolution maps, enhancing the efficiency and stability of model learning and outperforming state-of-the-art methods for realistic long-distance routing (Fu & Lee 2021). Generative Inverse Reinforcement Learning (GIRL) further enhances policy learning and improves optimization methods in real-world applications, proving useful for complex routing problems like the traveling salesman and vehicle routing problems (Q. Wang et al. 2023). AI and IoT integration also optimize logistics distribution by processing real-time traffic data and historical delivery records, improving efficiency and reducing costs, thus showcasing the practical feasibility of AI-driven optimization models (Liu 2024). In dynamic pickup and delivery scenarios, data-driven approaches such as the Spatial-Temporal Aided Double Deep Graph Network (ST-DDGN) reduce vehicle usage and transportation costs, leading to substantial cost savings in logistics operations (Li et al. 2021).

4.4 Risk Management and Scenario Planning

Generative modeling techniques, such as generative AI aids in risk identification by generating novel scenarios that highlight potential disruptions, offering a practical tool to overcome resource limitations and build resilient supply chains. This approach enables optimal risk mitigation and proactive strategies (Ahmad et al. 2024). Additionally, it facilitates real-time adaptation by allowing companies to respond proactively to changing market conditions. By simulating various scenarios, generative AI enhances risk management and scenario planning through predictive analytics, enabling organizations to assess and mitigate the impact of diverse risks (Aishwarya, 2023). The integration of generative AI in scenario planning transforms traditional forecasting methods by supporting iterative refinement and developing of adaptable supply chain strategies , which is particularly useful for managing uncertainties like climate change and global conflicts (Finkenstadt et al. 2023).

5. Industrial Applicability

5.1. Fashion Industry

In the fashion industry, generative modeling can be applied across various areas of supply chain management to enhance efficiency and customization. For inventory and supply chain optimization, models like Deep Reinforcement Learning (DRL) specifically Soft Actor-Critic model optimize apparel supply chains by balancing service levels and sell-through rates, achieving lower inventory-to-sales ratios and ensuring stock availability without overstocking, which enhances demand fulfillment and maintains a competitive edge (Chong et al. 2022) Generative models can be used in sustainable fashion supply chains to optimize operations for environmentally responsible supply chain management by reducing pollution and enhancing sustainability in manufacturing and transportation (Fung et al. 2020) For fashion design and personalization, tools like Generative Attribute Manipulation, Adversarial Metric Learning, and QuitGAN enable customization by manipulating attributes, thereby improving the user experience in search and recommendation. QuitGAN specifically synthesizes compatible items to form cohesive outfits (Yang et al. 2020; Zhou et al. 2024). For consumer engagement and e-commerce, GANs and Real-Time Fashion Systems (RTFS) enhance product appeal by addressing consumer values, leading to higher willingness to pay for AI-designed items. RTFS also provides real-time customization, significantly reducing design costs and time (Lee 2021; Sohn et al. 2021).

5.2. Automotive Industry
In the automotive industry, generative modeling supports various aspects of supply chain management. For demand prediction and supplier evaluation, convolutional and recurrent neural networks, coupled with techniques like moth-flame optimization, DEA, and BWM, achieve over 90% accuracy in predicting automotive component demand, aiding in production planning (Zareian Beinabadi et al. 2024). Generative modeling also supports digital supply chains integrating Intelligent Autonomous Vehicles (IAVs), where simulation and emulation tools help design and test supply chain operations, enabling the EV industry to explore alternative configurations and maintain agility (Tsolakis et al. 2019). In circular economy and waste management context, mathematical models for reworking and recycling have been developed to handle imperfect production, extending product lifecycles, reducing waste, and optimizing costs thereby contributing to sustainable automotive supply chain (Omair et al. 2022). Agile and flexible supply chain models benefit from hybrid approaches, such as interval-valued fuzzy-rough numbers and robust goal programming, which enhance automotive supply chain agility by minimizing disruptions, defective parts, and costs, while ensuring on-time delivery and optimizing supplier and resource allocation (Hendalianpour et al. 2019). Big data warehouse and simulation models provide decision-support systems to address the complexity of automotive supply chains, allowing for scenario analysis to improve resilience and operational efficiency during potential disruptions (Vieira et al. 2019).

5.2. FMCG Industry
In the Fast-Moving Consumer Goods (FMCG) industry, generative modeling supports demand forecasting and optimization through GAN-based frameworks, applied in contexts like the biofuel supply chain, where complex data modeling enables better decision-making under uncertain demand and improves inventory management by simulating purchasing patterns (Doan et al. 2018; Zhao & You 2020). GANs and transaction sequence generators simulate customer transactions for tailored marketing, with chatbots providing personalized recommendations to enhance customer experience and engagement (Doan et al. 2018; Fosso Wamba et al., 2023; Horn et al.2024). In process automation and efficiency, generative AI is used for route optimization and automates supply chain communication, boosting efficiency and reducing manual tasks, while optimizing logistics by designing efficient routes to cut transportation costs (Fosso Wamba et al. 2023; Horn et al. 2024).

6. Advantages and Challenges of Generative Modeling in Supply Chain Management

6.1. Advantages
Generative modeling offers several advantages in SCM, enhancing decision-making processes through the application of deep learning, neural networks, and GANs, which improve both decision accuracy and reliability (Fosso Wamba et al. 2023; Han & Zhang 2021; Zhao & You, 2020). Generative AI and other AI- driven tools in logistics and supply chain management contributes to cost efficiency by enhancing process efficiencies (Fosso Wamba et al. 2023; Richey Jr. et al. 2023). Furthermore, generative models, particularly deep learning models, support improved demand prediction by providing accurate forecasting and reducing the risk of overstocking or stockouts (Bertsimas et al. 2016; Qi et al. 2022). Generative models combined with deep reinforcement learning and stochastic programming are also well-known for their capacity to lower holding and stockout costs, which enhances logistics efficiency in terms of optimal inventory and logistics (Qi et al. 2022; Stranieri et al. 2024).

6.2. Challenges
Generative modeling in supply chain management faces several challenges, particularly related to data limitations and quality issues. GANs are impacted by high missing data rates, which can degrade model performance, while incomplete or noisy data leads to unrealistic outputs (Bernal et al. 2021). Data scarcity, especially for niche products, further limits the effectiveness of model training, particularly when using neural networks (Jahin et al. 2023). Integration difficulties within existing supply chain infrastructure present another challenge, as both technological and organizational barriers hinder smooth integration of generative models, requiring significant system adaptation. This complexity can prevent organizations from adopting generative models and realizing potential benefits despite their advantages (Fosso Wamba et al. 2023; Nozari et al. 2022). Additionally, model interpretability and complexity are notable issues, as models, particularly GANs and quantum-classical neural networks, are often "black boxes" that limit interpretability and user trust (Ross et al. 2021). High complexity also demands specialized knowledge, making practical implementation challenging for organizations lacking expertise (Jahin et al. 2023; Zhao & You 2020).

7. Future Directions and Research Opportunities

7.1 Emerging Trends

Generative modeling is becoming a crucial tool for real-time adaptation in supply chains, addressing market volatility and operational disruptions with unprecedented precision (Belhadi et al. 2024). Advanced frameworks like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) drive this adaptability by enabling predictive, on-the-fly adjustments to inventory and distribution schedules based on rapid changes in demand or supply conditions (Vivekananthan et al. 2024). Emerging techniques, such as Energy-Based Models (EBMs) and Autoregressive Transformers, extend these capabilities by offering sophisticated anomaly detection and predictive maintenance (X. Wang et al. 2022) as well as anticipating complex, multistep events which are crucial in achieving resilience in high-stakes operational settings (He et al. 2024). Additionally, newer models like Diffusion and Flow-Based Models (e.g., Normalizing Flows) enhance real-time forecasting accuracy by iteratively refining data reconstructions, making them highly effective for demand and inventory forecasting in volatile environments (Strümke & Langseth 2023).

These capabilities are further amplified when generative models are combined with reinforcement learning (RL) to form hybrid solutions. By incorporating RL feedback loops, generative models continually refine strategies in response to shifting conditions, such as fluctuating demand or evolving environmental impacts, which enhances agility and resource efficiency within supply chains (Aishwarya et al. 2023) This hybrid approach underscores the trend toward adaptive, multi-stage solutions that can respond dynamically to complex and rapidly changing operational challenges.

7.2 Research Opportunities

The rapid advancements in generative models have opened new avenues for addressing complex challenges in supply chain management, with a growing focus on integrating sustainability metrics, such as carbon emissions, water usage, and energy consumption, directly into decision-making processes. By integrating these metrics, models can guide supply chain decisions toward eco-friendly options in routing and inventory management, aligning both regulatory requirements and raising consumer expectations for sustainable practices.

In addition, generative models face challenges in data quality, interpretability, and deployment, which are critical areas for future research. Models like Stochastic Variational Inference (SVI) and Implicit Generative Models (IGMs) hold potential for handling uncertain and variable-quality data (Zhang et al. 2023) while Recurrent Generative Models with memory units and Graph-Based Generative Models improve model resilience by capturing long-term dependencies and network-based risks (Wu & Wang 2022). To further support interpretability, Transformer-Based Diffusion Models and Causal Generative Models offer clearer, actionable insights, especially in scenarios where understanding cause-and-effect relationships is vital for decision-making (Y. Wang et al. 2024).

On the deployment front, Federated Generative Models are increasingly relevant, as they support decentralized data environments that emphasize data privacy and inter-organizational collaboration. Lastly, multimodal and meta-learning generative models can bring in diverse data types such as text, images, and tabular data as result creating comprehensive, cross-functional views applicable in fields like adaptive supply chains, personalized healthcare, and autonomous systems. Together, these innovations promise to position generative modeling as a fundamental resource in building supply chains that are not only resilient and sustainable but also adaptable to the demands of a complex, interconnected global economy.

7.3 Implications

This research holds significant implications for both the academia and industry practitioners. For academia, it provides a detailed synthesis of the latest advancements in applying generative modeling techniques to supply chain management. It also emphasizes potential avenues for future research, including the integration of generative models with decision-making frameworks and the investigation of their use in emerging domains such as sustainable supply chain practices. For industry professionals and policymakers, this study underscores the potential of generative modeling in supply chain domains, such as demand forecasting, inventory management, and risk management. By showcasing practical applications, this research emphasizes the advantages of leveraging generative modeling in supply chain management such as cost efficiency, improved demand forecasting, and enhanced logistical efficiency.

Furthermore, it provides valuable insights into addressing challenges, such as data quality and model deployment, thus bridging the gap between theoretical advancements and real-world application.

7.4 Limitations

The dynamic nature of generative modeling and its applications in supply chain management presents inherent limitations for this review. While this study provides a comprehensive review of established applications, it may not fully encompass the latest innovations or emergent trends that are still in the early stages. Additionally, the focus on specific industry applicability restricts the generalizability of findings, particularly for diverse supply chain environments. Moreover, this research primarily emphasizes current, well-documented applications of generative modeling in supply chain processes, such as demand forecasting and logistics optimization, potentially overlooking niche or experimental applications that could gain prominence in the future.

8. Conclusion

This review underscores the transformative role of generative modeling in modern supply chain management, showcasing its potential to improve demand forecasting, inventory optimization, logistics, and risk mitigation. Advanced techniques like GANs and VAEs enable supply chains to model complex scenarios and refine decision-making, thereby enhancing efficiency and resilience in increasingly dynamic environments. Despite these advancements, challenges remain, including data quality issues, difficulties in integrating generative models with legacy systems, and the opaque nature of many algorithms, which can limit trust and adoption. This paper contributes by synthesizing theoretical advancements and practical applications to address these challenges. It highlights the need for further innovation in integrating generative models into real-world supply chains and points to emerging solutions, such as transparent algorithm design and decentralized data-sharing approaches. By advancing understanding in these areas, the study provides a foundation for more effective and scalable applications of generative modeling in supply chain management, paving the way for systems that are both adaptive and sustainable.

References

Abaku, N. E. A., E. N. T. E., & O. N. a. C. (2024). Theoretical approaches to AI in supply chain optimization: Pathways to efficiency and resilience. *International Journal of Science and Technology Research*.

Adesoga, N. T. O., Ajibaye, N. T. O., Nwafor, N. K. C., Imam-Lawal, N. U. T., Ikekwere, N. E. A., & Ekwunife, N. D. I. , The rise of the "smart" supply chain: How AI and automation are revolutionizing logistics. *International Journal of Science and Research Archive*, *12*(2), 790–798,2024. https://doi.org/10.30574/ijsra.2024.12.2.1304

Ageeli, A. A. , Smart Supply Chain management for Sustianble Business Administrations. *Journal of Sustainable Development and Green Technology*, *3*(1), 47–55,2023. https://doi.org/10.54216/JSDGT.030105

Ahmad, K., Rozhok, A., & Revetria, R. (2024). Supply Chain Resilience in SMEs: Integration of Generative AI in Decision-Making Framework. *,International Conference on Machine Intelligence and Smart Innovation (ICMISI)*, 295–299,2024. https://doi.org/10.1109/ICMISI61517.2024.10580495

Aishwarya, Shekhar. (2023). Generative AI in Supply Chain Management. In *Article International Journal on Recent and Innovation Trends in Computing and Communication*. http://www.ijritcc.org

Ali, S. M., Rahman, A. U., Kabir, G., & Paul, S. K. , Artificial Intelligence Approach to Predict Supply Chain Performance: Implications for Sustainability. *Sustainability*, *16*(6),2024. https://doi.org/10.3390/su16062373

Aljohani, A. , Predictive Analytics and Machine Learning for Real-Time Supply Chain Risk Mitigation and Agility. *Sustainability*, *15*(20),2023. https://doi.org/10.3390/su152015088

Amellal, I., Amellal, A., Seghiouer, H., & Rida Ech-Charrat, M. ,An integrated approach for modern supply chain management: Utilizing advanced machine learning models for sentiment analysis, demand forecasting, and probabilistic price prediction. *Decision Science Letters*, *13*, 237–248,2024. https://doi.org/10.5267/dsl.2023.9.003

Anaba, D., Kess-Momoh, A., & Ayodeji, S. , Optimizing supply chain and logistics management: A review of modern practices. *Open Access Research Journal of Science and Technology*, *11*, 20–28,2024. https://doi.org/10.53022/oarjst.2024.11.2.0083

Anstine, D. M., & Isayev, O. (2023). Generative Models as an Emerging Paradigm in the Chemical Sciences. In *Journal of the American Chemical Society* (Vol. 145, Issue 16, pp. 8736–8750). American Chemical Society. https://doi.org/10.1021/jacs.2c13467

Atlam, H. F., Walters, R. J., & Wills, G. B. (2018). Intelligence of Things: Opportunities & Challenges. *2018 3rd Cloudification of the Internet of Things (CIoT)*, 1–6. https://doi.org/10.1109/CIOT.2018.8627114

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *333*(2), 627–652. https://doi.org/10.1007/s10479-021-03956-x

Bernal, E. A. (2021). Training Deep Generative Models in Highly Incomplete Data Scenarios with Prior Regularization. *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2631–2641. https://doi.org/10.1109/CVPRW53098.2021.00297

Bertsimas, D., Kallus, N., & Hussain, A. (2016). Inventory Management in the Era of Big Data. *Production and Operations Management*, *25*(12), 2006–2009. https://doi.org/https://doi.org/10.1111/poms.2_12637

Bhandal, R., Meriton, R., Kavanagh, R. E., & Brown, A. (2022). The application of digital twin technology in operations and supply chain management: a bibliometric review. *Supply Chain Management: An International Journal*, *27*(2), 182–206. https://doi.org/10.1108/SCM-01-2021-0053

Bond-Taylor, S., Leach, A., Long, Y., & Willcocks, C. G. (2022). Deep Generative Modelling: A Comparative Review of VAEs, GANs, Normalizing Flows, Energy-Based and Autoregressive Models. In *IEEE Transactions on Pattern Analysis and Machine Intelligence* (Vol. 44, Issue 11, pp. 7327–7347). IEEE Computer Society. https://doi.org/10.1109/TPAMI.2021.3116668

Cao, J. (2024). Research on the application of Internet of Things (IoT) in supply chain management. *Applied and Computational Engineering*, *76*(1), 206–212. https://doi.org/10.54254/2755-2721/76/20240589

Carreon, A., Barwey, S., & Raman, V. (2023). A generative adversarial network (GAN) approach to creating synthetic flame images from experimental data. *Energy and AI*, *13*, 100238. https://doi.org/https://doi.org/10.1016/j.egyai.2023.100238

Chandra, C., & Kumar, S. (2000). Supply chain management in theory and practice: a passing fad or a fundamental change? *Industrial Management & Data Systems*, *100*(3), 100–114. https://doi.org/10.1108/02635570010286168

Chatterjee, S., & Byun, Y.-C. (2023). A Synthetic Data Generation Technique for Enhancement of Prediction Accuracy of Electric Vehicles Demand. *Sensors*, *23*(2). https://doi.org/10.3390/s23020594

Chauhdary, S. H., Alkatheiri, M. S., Alqarni, M. A., & Saleem, S. (2023). An efficient evolutionary deep learning-based attack prediction in supply chain management systems. *Computers and Electrical Engineering*, *109*, 108768. https://doi.org/https://doi.org/10.1016/j.compeleceng.2023.108768

Chen, H., Liu, C., Zhu, T., & Zhou, W. (2024). When deep learning meets watermarking: A survey of application, attacks and defenses. *Computer Standards & Interfaces*, *89*, 103830. https://doi.org/https://doi.org/10.1016/j.csi.2023.103830

Chong, J. W., Kim, W., & Hong, J. (2022). Optimization of Apparel Supply Chain Using Deep Reinforcement Learning. *IEEE Access*, *10*, 100367–100375. https://doi.org/10.1109/ACCESS.2022.3205720

Croitoru, F.-A., Hondru, V., Ionescu, R. T., & Shah, M. (2023). Diffusion Models in Vision: A Survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(9), 10850–10869. https://doi.org/10.1109/TPAMI.2023.3261988

Cui, L., Chen, Y., Deng, J., & Han, Z. (2024). A novel attLSTM framework combining the attention mechanism and bidirectional LSTM for demand forecasting. *Expert Systems with Applications*, *254*. https://doi.org/10.1016/j.eswa.2024.124409

Dash, A., Ye, J., & Wang, G. (2024). A Review of Generative Adversarial Networks (GANs) and Its Applications in a Wide Variety of Disciplines: From Medical to Remote Sensing. *IEEE Access*, *12*, 18330–18357. https://doi.org/10.1109/ACCESS.2023.3346273

Dehaybe, H., Catanzaro, D., & Chevalier, P. (2024). Deep Reinforcement Learning for inventory optimization with non-stationary uncertain demand. *European Journal of Operational Research*, *314*(2), 433–445. https://doi.org/https://doi.org/10.1016/j.ejor.2023.10.007

Demizu, T., Fukazawa, Y., & Morita, H. (2023). Inventory management of new products in retailers using model-based deep reinforcement learning. *Expert Systems with Applications*, *229*, 120256. https://doi.org/https://doi.org/10.1016/j.eswa.2023.120256

Deng, J., Chen, C., Huang, X., Chen, W., & Cheng, L. (2023). Research on the construction of event logic knowledge graph of supply chain management. *Advanced Engineering Informatics*, *56*, 101921. https://doi.org/https://doi.org/10.1016/j.aei.2023.101921

Doan, T., Veira, N., & Keng, B. (2018). Generating Realistic Sequences of Customer-Level Transactions for Retail Datasets. *2018 IEEE International Conference on Data Mining Workshops (ICDMW)*, 820–827. https://doi.org/10.1109/ICDMW.2018.00122

Dr. Kumar J, Dr. Skanda Moda Gururajarao, Eduardo Manuel Moran Echeverria, Crispin J Fernandez, & Mohamed Ashik Sulthan Sl. (2024). Supply Chain Resilience And Risk Management: Strategies For Mitigating Global Supply Chain Disruptions. *Educational Administration: Theory and Practice*, *30*(6), 2169–2175. https://doi.org/10.53555/kuey.v30i6.5680

Dutta, P., Choi, T.-M., Somani, S., & Butala, R. (2020). Blockchain technology in supply chain operations: Applications, challenges and research opportunities. *Transportation Research Part E: Logistics and Transportation Review*, *142*, 102067. https://doi.org/https://doi.org/10.1016/j.tre.2020.102067

Ekwunife, N. D. I., Precious, N. O. T., Rasul, N. O. A., Akinlade, N. O. F., Nwokoro, N. T. O., & Ikpe, N. V. I. (2024). Using blockchain technology to maximize supply chain and logistics management in north America. *International Journal of Science and Research Archive*, *12*(2), 854–863. https://doi.org/10.30574/ijsra.2024.12.2.1096

Eyo-Udo, N. N. L., O. N. a. C., & K. N. O. O. (2024). ETHICAL SUPPLY CHAIN MANAGEMENT: BALANCING PROFIT, SOCIAL RESPONSIBILITY, AND ENVIRONMENTAL STEWARDSHIP. *International Journal of Management & Entrepreneurship Research*, *6*(4), 1069–1077. https://doi.org/10.51594/ijmer.v6i4.985

Fatorachian, H., & Kazemi, H. (2021). Impact of Industry 4.0 on supply chain performance. *Production Planning & Control*, *32*(1), 63–81. https://doi.org/10.1080/09537287.2020.1712487

Finkenstadt, D. J., Eapen, T. T., Sotiriadis, J., & Guinto, P. (2023). *Use GenAI to Improve Scenario Planning*. https://www.hbrkorea.com/article/view/atype/di/category_id/10_1/article_no/1045

Fosso Wamba, S., Queiroz, M. M., Chiappetta Jabbour, C. J., & Shi, C. (Victor). (2023). Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence? *International Journal of Production Economics*, *265*, 109015. https://doi.org/https://doi.org/10.1016/j.ijpe.2023.109015

Frankowska, M., & Nowicka, K. (2018). Smart Supply Chain – challenges of information-driven management. *European Journal of Service Management*, *25*, 91–97. https://doi.org/10.18276/ejsm.2018.25-11

Freese, F., & Ludwig, A. (2024). A conceptual framework for supply chain digital twins – development and evaluation. *International Journal of Logistics Research and Applications*, 1–23. https://doi.org/10.1080/13675567.2024.2324895

Freese Falk and Ludwig, A. (2021). How the Dimensions of Supply Chain are Reflected by Digital Twins: A State-of-the-Art Survey. In R. and S. S. Ahlemann Frederik and Schütte (Ed.), *Innovation Through Information Systems* (pp. 325–341). Springer International Publishing.

Fu, T., & Lee, W.-C. (2021). ProgRPGAN: Progressive GAN for Route Planning. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 393–403. https://doi.org/10.1145/3447548.3467406

Fung, Y.-N., Choi, T.-M., & Liu, R. (2020). Sustainable planning strategies in supply chain systems: proposal and applications with a real case study in fashion. *Production Planning & Control*, *31*(11–12), 883–902. https://doi.org/10.1080/09537287.2019.1695913

Geng, C., Wang, J., Chen, L., & Gao, Z. (2023). Solving the reconstruction-generation trade-off: Generative model with implicit embedding learning. *Neurocomputing*, *549*. https://doi.org/10.1016/j.neucom.2023.126428

Ghani, A. S. (2024). Revolutionizing Supply Chains: A Comprehensive Study of Industry 4.0 Technologies (IoT, Big Data, AI, etc.). *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*, *08*(04), 1–5. https://doi.org/10.55041/ijsrem30037

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative Adversarial Nets. In Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, & K. Q. Weinberger (Eds.), *Advances in Neural Information Processing Systems* (Vol. 27). Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2014/file/5ca3e9b122f61f8f06494c97b1afccf3-Paper.pdf

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2020). Generative adversarial networks. *Commun. ACM*, *63*(11), 139–144. https://doi.org/10.1145/3422622

Han, C., & Zhang, Q. (2021). Optimization of supply chain efficiency management based on machine learning and neural network. *Neural Computing and Applications*, *33*(5), 1419–1433. https://doi.org/10.1007/s00521-020-05023-1

He, J., Dong, Z., & Huang, Y. (2024). Multivariate Time Series Anomaly Detection with Adaptive Transformer-CNN Architecture Fusing Adversarial Training. *2024 IEEE 13th Data Driven Control and Learning Systems Conference (DDCLS)*, 1387–1392. https://doi.org/10.1109/DDCLS61622.2024.10606841

Hendalianpour, A., Fakhrabadi, M., Zhang, X., Feylizadeh, M. R., Gheisari, M., Liu, P., & Ashktorab, N. (2019). Hybrid Model of IVFRN-BWM and Robust Goal Programming in Agile and Flexible Supply Chain, a Case Study: Automobile Industry. *IEEE Access*, *7*, 71481–71492. https://doi.org/10.1109/ACCESS.2019.2915309

Hiriyannaiah, S., Srinivas, A. M. D., Shetty, G. K., G.M., S., & Srinivasa, K. G. (2020). Chapter 4 - A computationally intelligent agent for detecting fake news using generative adversarial networks. In S. Bhattacharyya, V. Snášel, D. Gupta, & A. Khanna (Eds.), *Hybrid Computational Intelligence* (pp. 69–96). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-818699-2.00004-4

Horn, Z., Magee, L., & Munster, A. (2024). Lost in the logistical funhouse: speculative design as synthetic media enterprise. *AI & SOCIETY*. https://doi.org/10.1007/s00146-024-02038-3

Hosseinnia Shavaki, F., & Ebrahimi Ghahnavieh, A. (2023). Applications of deep learning into supply chain management: a systematic literature review and a framework for future research. *Artificial Intelligence Review*, *56*(5), 4447–4489. https://doi.org/10.1007/s10462-022-10289-z

Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, *32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Jahin, M. A., Shovon, M. S. H., Islam, Md. S., Shin, J., Mridha, M. F., & Okuyama, Y. (2023). QAmplifyNet: pushing the boundaries of supply chain backorder prediction using interpretable hybrid quantum-classical neural network. *Scientific Reports*, *13*(1), 18246. https://doi.org/10.1038/s41598-023-45406-7

Joel, O., Oyewole, A., Odunaiya, O., & Soyombo, O. (2024). LEVERAGING ARTIFICIAL INTELLIGENCE FOR ENHANCED SUPPLY CHAIN OPTIMIZATION: A COMPREHENSIVE REVIEW OF CURRENT PRACTICES AND FUTURE POTENTIALS. *International Journal of Management & Entrepreneurship Research*, *6*, 707–721. https://doi.org/10.51594/ijmer.v6i3.882

Kassa, A., Kitaw, D., Stache, U., Beshah, B., & Degefu, G. (2023). Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research. *Computers & Industrial Engineering*, *186*, 109714. https://doi.org/https://doi.org/10.1016/j.cie.2023.109714

Kaur, J., Parmar, K. S., & Singh, S. (2023). Autoregressive models in environmental forecasting time series: a theoretical and application review. *Environmental Science and Pollution Research*, *30*(8), 19617–19641. https://doi.org/10.1007/s11356-023-25148-9

Kim, S., Song, Q., & Liang, F. (2023). *A New Paradigm for Generative Adversarial Networks based on Randomized Decision Rules*. http://arxiv.org/abs/2306.13641

Kulkarni, N., & Bansal, S. (2024). Transforming Supply and Value Chains The Impact of Artificial Intelligence. *International Research Journal of Modernization in Engineering Technology and Science*. https://doi.org/10.56726/irjmets48972

Kumar, N. P., Choubey, N. D., Amosu, N. O. R., & Ogunsuji, N. Y. M. (2024). AI-enhanced inventory and demand forecasting: Using AI to optimize inventory management and predict customer demand. *World Journal of Advanced Research and Reviews*, *23*(1), 1931–1944. https://doi.org/10.30574/wjarr.2024.23.1.2173

Lee, Y. K. (2021). Transformation of the Innovative and Sustainable Supply Chain with Upcoming Real-Time Fashion Systems. *Sustainability*, *13*(3). https://doi.org/10.3390/su13031081

Li, X., Luo, W., Yuan, M., Wang, J., Lu, J., Wang, J., Lü, J., & Zeng, J. (2021). Learning to Optimize Industry-Scale Dynamic Pickup and Delivery Problems. *2021 IEEE 37th International Conference on Data Engineering (ICDE)*, 2511–2522. https://doi.org/10.1109/ICDE51399.2021.00283

Liu, Q. (2024). Logistics Distribution Route Optimization in Artificial Intelligence and Internet of Things Environment. *Decision Making: Applications in Management and Engineering*.

Lugaresi, G., Jemai, Z., & Sahin, E. (2023). *Digital Twins for Supply Chains: Current Outlook and Future Challenges*.

Maheshwari, P., Kamble, S., Belhadi, A., Venkatesh, M., & Abedin, M. Z. (2023). Digital twin-driven real-time planning, monitoring, and controlling in food supply chains. *Technological Forecasting and Social Change*, *195*, 122799. https://doi.org/https://doi.org/10.1016/j.techfore.2023.122799

Mahi, R. (2024). OPTIMIZING SUPPLY CHAIN EFFICIENCY IN THE MANUFACTURING SECTOR THROUGH AI-POWERED ANALYTICS. In *International Journal of Management Information Systems and Data Science* (Vol. 1, Issue 1).

Maksud, N. M. , A. M. N. , H. M. , A. M. , & T. A. C. (2022). Strategies to Mitigate Uncertainty Impact on Livestock Industries and Its Supply Chain. . *Supply Chain Insider* .

Manuj, I., & Mentzer, J. T. (2008). GLOBAL SUPPLY CHAIN RISK MANAGEMENT. *Journal of Business Logistics*, *29*(1), 133–155. https://doi.org/https://doi.org/10.1002/j.2158-1592.2008.tb00072.x

Milovanović, G., Milovanovic, S., & Radisavljević, G. (2017). Globalization: The key challenge of modern supply chains. *Ekonomika*, *63*, 31–40. https://doi.org/10.5937/ekonomika1701031M

Nicodemou, V. C., Oikonomidis, I., & Argyros, A. (2023). RV-VAE: Integrating Random Variable Algebra into Variational Autoencoders. *2023 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 196–205. https://doi.org/10.1109/ICCVW60793.2023.00027

Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the Challenges of Artificial Intelligence of Things (AIoT) for the Smart Supply Chain (Case Study: FMCG Industries). *Sensors*, *22*(8). https://doi.org/10.3390/s22082931

Odimarha, N. a. C., Ayodeji, N. S. A., & Abaku, N. E. A. (2024). MACHINE LEARNING'S INFLUENCE ON SUPPLY CHAIN AND LOGISTICS OPTIMIZATION IN THE OIL AND GAS SECTOR: A COMPREHENSIVE ANALYSIS. *Computer Science & IT Research Journal*, *5*(3), 725–740. https://doi.org/10.51594/csitrj.v5i3.976

Oğuz, A., & Ertuğrul, Ö. F. (2023). Chapter 1 - Introduction to deep learning and diagnosis in medicine. In K. Polat & S. Öztürk (Eds.), *Diagnostic Biomedical Signal and Image Processing Applications with Deep Learning Methods* (pp. 1–40). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-323-96129-5.00003-2

Oliveira, E. e., & Pereira, T. (2023). A New Generation? A Discussion on Deep Generative Models in Supply Chains. In E. Alfnes, A. Romsdal, J. O. Strandhagen, G. von Cieminski, & D. Romero (Eds.), *Advances in Production Management Systems. Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures* (pp. 444–457). Springer Nature Switzerland.

Omair, M., Alkahtani, M., Ayaz, K., Hussain, G., & Buhl, J. (2022). Supply Chain Modelling of the Automobile Multi-Stage Production Considering Circular Economy by Waste Management Using Recycling and Reworking Operations. *Sustainability*, *14*(22). https://doi.org/10.3390/su142215428

Pan, Z., Wang, Y., Cao, Y., & Gui, W. (2024). VAE-Based Interpretable Latent Variable Model for Process Monitoring. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(5), 6075–6088. https://doi.org/10.1109/TNNLS.2023.3282047

Park, K. T., Son, Y. H., & Noh, S. Do. (2021). The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. *International Journal of Production Research*, *59*(19), 5721–5742. https://doi.org/10.1080/00207543.2020.1788738

Pasupuleti, V., Thuraka, B., Kodete, C. S., & Malisetty, S. (2024). Enhancing Supply Chain Agility and Sustainability through Machine Learning: Optimization Techniques for Logistics and Inventory Management. *Logistics*, *8*(3). https://doi.org/10.3390/logistics8030073

Petrescu, M., & Krishen, A. S. (2020). The importance of high-quality data and analytics during the pandemic. *Journal of Marketing Analytics*, *8*(2), 43–44. https://doi.org/10.1057/s41270-020-00079-3

Po, R., Yifan, W., Golyanik, V., Aberman, K., Barron, J. T., Bermano, A., Chan, E., Dekel, T., Holynski, A., Kanazawa, A., Liu, C. K., Liu, L., Mildenhall, B., Nießner, M., Ommer, B., Theobalt, C., Wonka, P., & Wetzstein, G. (2024). State of the Art on Diffusion Models for Visual Computing. *Computer Graphics Forum*, *43*(2), e15063. https://doi.org/https://doi.org/10.1111/cgf.15063

Praveenadevi, D., Sreekala, S. P., Girimurugan, B., Krishna Teja, K. V. R., Naga Kamal, G., & Chandra, A. C. (2023). An Enhanced Method on Using Deep Learning Techniques in Supply Chain Management. *2023 International Conference on Disruptive Technologies (ICDT)*, 210–213. https://doi.org/10.1109/ICDT57929.2023.10151338

Preil, D., & Krapp, M. (2022). Artificial intelligence-based inventory management: a Monte Carlo tree search approach. *Annals of Operations Research*, *308*(1), 415–439. https://doi.org/10.1007/s10479-021-03935-2

Qi, M., Shi, Y., Qi, Y., Ma, C., Yuan, R., Wu, D., & Shen, Z.-J. (Max). (2022). A Practical End-to-End Inventory Management Model with Deep Learning. *Management Science*, *69*(2), 759–773. https://doi.org/10.1287/mnsc.2022.4564

Raisinghani, M. S., & Raisinghani, M. S. (2009). Leveraging Supply Chain Management in the Digital Economy. In *Encyclopedia of Information Communication Technology* (pp. 526–531). IGI Global. https://doi.org/10.4018/978-1-59904-845-1.ch069

Rajagopal, V., Prasanna Venkatesan, S., & Goh, M. (2017). Decision-making models for supply chain risk mitigation: A review. *Computers & Industrial Engineering*, *113*, 646–682. https://doi.org/https://doi.org/10.1016/j.cie.2017.09.043

Raut, R. D., Gotmare, A., Narkhede, B. E., Govindarajan, U. H., & Bokade, S. U. (2020). Enabling Technologies for Industry 4.0 Manufacturing and Supply Chain: Concepts, Current Status, and Adoption Challenges. *IEEE Engineering Management Review*, *48*(2), 83–102. https://doi.org/10.1109/EMR.2020.2987884

Raza, S. A., Govindaluri, S. M., & Bhutta, M. K. (2023). Research themes in machine learning applications in supply chain management using bibliometric analysis tools. *Benchmarking: An International Journal*, *30*(3), 834–867. https://doi.org/10.1108/BIJ-12-2021-0755

Reddy V., V. P. V. (2019). Enhancing supply chain management using blockchain technology. *International Journal of Engineering and Advanced Technology*, *8*(6), 4657–4661. https://doi.org/10.35940/ijeat.F9141.088619

Remusati, H., Le Caillec, J.-M., Schneider, J.-Y., Petit-Frère, J., & Merlet, T. (2024). Generative Adversarial Networks for SAR Automatic Target Recognition and Classification Models Enhanced Explainability: Perspectives and Challenges. *Remote Sensing*, *16*(14). https://doi.org/10.3390/rs16142569

Ren, L., Fan, X., Cui, J., Shen, Z., Lv, Y., & Xiong, G. (2022). A Multi-Agent Reinforcement Learning Method With Route Recorders for Vehicle Routing in Supply Chain Management. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 16410–16420. https://doi.org/10.1109/TITS.2022.3150151

Richey Jr., R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *Journal of Business Logistics*, *44*(4), 532–549. https://doi.org/https://doi.org/10.1111/jbl.12364

Ross, A., Chen, N., Hang, E. Z., Glassman, E. L., & Doshi-Velez, F. (2021). Evaluating the Interpretability of Generative Models by Interactive Reconstruction. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445296

Sohn, K., Sung, C. E., Koo, G., & Kwon, O. (2021). Artificial intelligence in the fashion industry: consumer responses to generative adversarial network (GAN) technology. *International Journal of Retail & Distribution Management*, *49*(1), 61–80. https://doi.org/10.1108/IJRDM-03-2020-0091

Sohrabi, S., Riabov, A., Katz, M., & Udrea, O. (2018). An AI Planning Solution to Scenario Generation for Enterprise Risk Management. *Proceedings of the AAAI Conference on Artificial Intelligence*, *32*(1). https://doi.org/10.1609/aaai.v32i1.11304

Stranieri, F., Fadda, E., & Stella, F. (2024). Combining deep reinforcement learning and multi-stage stochastic programming to address the supply chain inventory management problem. *International Journal of Production Economics*, *268*, 109099. https://doi.org/https://doi.org/10.1016/j.ijpe.2023.109099

Strümke, I., & Langseth, H. (2023). *Lecture Notes in Probabilistic Diffusion Models*. http://arxiv.org/abs/2312.10393

Suárez-Riveros Erika and Mejia-Mantilla, Á. and J.-S. S. and J. J.-F. (2021). Cyber-Physical Systems in Logistics and Supply Chain. In T. and L. P. and J. J.-F. and M.-T. J. R. Trentesaux Damien and Borangiu (Ed.), *Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future* (pp. 260–271). Springer International Publishing.

Surmacz, T., & Szopiński, W. (2023). Overview of supply chain management challenges. *Scientific Papers of Silesian University of Technology. Organization and Management Series*, *2023*(174), 315–322. https://doi.org/10.29119/1641-3466.2023.174.22

Tang, W. (2024). *Improvement of Inventory Management and Demand Forecasting by Big Data Analytics in Supply Chain*. https://doi.org/10.2478/amns-2024-2213

Terzi, S., Zacharaki, A., Nizamis, A., Votis, K., Ioannidis, D., Tzovaras, D., & Stamelos, I. (2019). Transforming the supply-chain management and industry logistics with blockchain smart contracts. *Proceedings of the 23rd Pan-Hellenic Conference on Informatics*, 9–14. https://doi.org/10.1145/3368640.3368655

Toshpulatov, M., Lee, W., & Lee, S. (2021). Generative adversarial networks and their application to 3D face generation: A survey. *Image and Vision Computing*, *108*, 104119. https://doi.org/https://doi.org/10.1016/j.imavis.2021.104119

Tschannen, M., Agustsson, E., & Lucic, M. (2018). *Deep Generative Models for Distribution-Preserving Lossy Compression*. http://arxiv.org/abs/1805.11057

Tsolakis, N., Bechtsis, D., & Srai, J. S. (2019). Intelligent autonomous vehicles in digital supply chains. *Business Process Management Journal*, *25*(3), 414–437. https://doi.org/10.1108/BPMJ-11-2017-0330

Vallés-Pérez, I., Soria-Olivas, E., Martínez-Sober, M., Serrano-López, A. J., Gómez-Sanchís, J., & Mateo, F. (2022). Approaching sales forecasting using recurrent neural networks and transformers. *Expert Systems with Applications*, *201*, 116993. https://doi.org/https://doi.org/10.1016/j.eswa.2022.116993

Varriale, V., Cammarano, A., Michelino, F., & Caputo, M. (2021). Sustainable Supply Chains with Blockchain, IoT and RFID: A Simulation on Order Management. *Sustainability*, *13*(11). https://doi.org/10.3390/su13116372

Vatin, N. I., John, V., Nangia, R., Kumar, M., & Prasanna, Y. L. (2024). Supply Chain Optimization in Industry 5.0: An Experimental Investigation Using Al. *BIO Web Conf.*, *86*, 1093. https://doi.org/10.1051/bioconf/20248601093

Vieira, A. A. C., Dias, L. M. S., Santos, M. Y., Pereira, G. A. B., & Oliveira, J. A. (2019). Simulation of an automotive supply chain using big data. *Computers & Industrial Engineering*, *137*, 106033. https://doi.org/https://doi.org/10.1016/j.cie.2019.106033

Vivekananthan, S. (2024). *Comparative Analysis of Generative Models: Enhancing Image Synthesis with VAEs, GANs, and Stable Diffusion*. http://arxiv.org/abs/2408.08751

Wang, C.-H., & Chen, T.-Y. (2022). Combining biased regression with machine learning to conduct supply chain forecasting and analytics for printing circuit board. *International Journal of Systems Science: Operations & Logistics*, *9*(2), 143–154. https://doi.org/10.1080/23302674.2020.1859157

Wang, J., Swartz, C. L. E., & Huang, K. (2023). Deep learning-based model predictive control for real-time supply chain optimization. *Journal of Process Control*, *129*, 103049. https://doi.org/https://doi.org/10.1016/j.jprocont.2023.103049

Wang, J., Zhou, H., Sun, X., & Yuan, Y. (2023). A novel supply chain network evolving model under random and targeted disruptions. *Chaos, Solitons & Fractals*, *170*, 113371. https://doi.org/https://doi.org/10.1016/j.chaos.2023.113371

Wang, L., & Zhang, Y. (2021). Linear approximation fuzzy model for fault detection in cyber-physical system for supply chain management. *Enterprise Information Systems*, *15*(7), 966–983. https://doi.org/10.1080/17517575.2020.1791361

Wang, Q., Hao, Y., & Zhang, J. (2023). Generative inverse reinforcement learning for learning 2-opt heuristics without extrinsic rewards in routing problems. *Journal of King Saud University - Computer and Information Sciences*, *35*(9), 101787. https://doi.org/https://doi.org/10.1016/j.jksuci.2023.101787

Wang, X., Tu, S., Zhao, W., & Shi, C. (2022). A novel energy-based online sequential extreme learning machine to detect anomalies over real-time data streams. *Neural Computing and Applications*, *34*(2), 823–831. https://doi.org/10.1007/s00521-021-05731-2

Wang, Y. (2023). Digital Transformation and Resilience in Global Supply Chains: A Comprehensive Review and Future Directions in the Post-COVID-19 Era. *Advances in Economics, Management and Political Sciences*, *51*(1), 140–145. https://doi.org/10.54254/2754-1169/51/20230649

Wang, Y., Yan, Y., Mo, Q., & Li, Y. (2024). Research on Interpretable Language Generation Model Based on Granger Causal Analysis. *2024 5th International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT)*, 275–278. https://doi.org/10.1109/AINIT61980.2024.10581601

Wood, J. (2013). Coping with the data deluge. In D. Shorley & M. Jubb (Eds.), *The Future of Scholarly Communication* (pp. 75–88). Facet. https://doi.org/DOI: 10.29085/9781856049610.008

Wu, J., & Wang, P. (2022). *Graph Learning based Generative Design for Resilience of Interdependent Network Systems*. http://arxiv.org/abs/2207.00931

Wu, L., Yue, X., Jin, A., & Yen, D. C. (2016). Smart supply chain management: a review and implications for future research. *The International Journal of Logistics Management*, *27*(2), 395–417. https://doi.org/10.1108/IJLM-02-2014-0035

Yandrapalli, V. (2023). Revolutionizing Supply Chains Using Power of Generative AI. *International Journal of Research Publication and Reviews*, *4*(12), 1556–1562. https://doi.org/10.55248/gengpi.4.1223.123417

Yang, X., Song, X., Han, X., Wen, H., Nie, J., & Nie, L. (2020). Generative Attribute Manipulation Scheme for Flexible Fashion Search. *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 941–950. https://doi.org/10.1145/3397271.3401150

Yesodha, K. R. K., Jagadeesan, A., & Logeshwaran, J. (2023). IoT applications in Modern Supply Chains: Enhancing Efficiency and Product Quality. *2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA)*, 366–371. https://doi.org/10.1109/ICIDeA59866.2023.10295273

Yin, H., Safikhani, A., & Michailidis, G. (2023). A General Modeling Framework for Network Autoregressive Processes. *Technometrics*, *65*(4), 579–589. https://doi.org/10.1080/00401706.2023.2203184

Yin, L., Li, T., Li, G., Besklubova, S., Zhong, R. Y., & Zhao, S. (2024). Cyber-physical internet based intelligent operation platform for off-site construction supply chain management. *Enterprise Information Systems*, *18*(6), 2346743. https://doi.org/10.1080/17517575.2024.2346743

Yuan, W., Ying, S., Duan, X., Cheng, H., Zhao, Y., & Shang, J. (2023). PVE: A log parsing method based on VAE using embedding vectors. *Information Processing & Management*, *60*(5), 103476. https://doi.org/https://doi.org/10.1016/j.ipm.2023.103476

Zareian Beinabadi, H., Baradaran, V., & Rashidi Komijan, A. (2024). Sustainable supply chain decision-making in the automotive industry: A data-driven approach. *Socio-Economic Planning Sciences*, *95*, 101908. https://doi.org/https://doi.org/10.1016/j.seps.2024.101908

Zhang, Y. (2023). *Uncertainty Quantification using Generative Approach*. http://arxiv.org/abs/2310.09338

Zhao, S., & You, F. (2020). Distributionally robust chance constrained programming with generative adversarial networks (GANs). *AIChE Journal*, *66*(6). https://doi.org/10.1002/aic.16963

Zhou, D., Zhang, H., Yang, K., Liu, L., Yan, H., Xu, X., Zhang, Z., & Yan, S. (2024). Learning to Synthesize Compatible Fashion Items Using Semantic Alignment and Collocation Classification: An Outfit Generation Framework. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(4), 5226–5240. https://doi.org/10.1109/TNNLS.2022.3202842

Zhu, X., Ninh, A., Zhao, H., & Liu, Z. (2021). Demand Forecasting with Supply-Chain Information and Machine Learning: Evidence in the Pharmaceutical Industry. *Production and Operations Management*, *30*(9), 3231–3252. https://doi.org/10.1111/poms.13426

Biographies

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Rifat Faruk Zitu, an Industrial and Production Engineering graduate from Shahjalal University of Science and Technology (SUST), Sylhet, has demonstrated academic excellence throughout his undergraduate journey, earning multiple scholarships in recognition of his achievements. As a corresponding member of The Human Factors and Ergonomics Society (HFES), he brings a spirit of enthusiasm and dedication to his work, continuously striving to simplify complex problems and deliver seamless solutions. Proficient in both experimental and theoretical research, he is skilled in utilizing advanced tools such as Python, R, and SPSS. His research interests focus on the integration of digital tools into industrial domains, with a particular emphasis on leveraging technologies like Physics-Informed Neural Networks (PINNs) and optimization techniques to drive innovation and efficiency.

Nadim MD Maksud is an Industrial and Production Engineer with expertise in waste management, consumer behavior, and supply chain optimization. He holds a B.Sc. in Industrial and Production Engineering from Shahjalal University of Science and Technology and currently works as an SAP Specialist at PwC, focusing on Production Planning, Quality Management, and Plant Maintenance. Previously, he worked as a Business Technology Analyst at Eitekh ERP Limited, where he designed and configured SAP solutions. Nadim has conducted research on consumer technology adoption, waste management, and supply chain resilience, with publications and accolades in supply chain case competitions. His work emphasizes advancing sustainable and efficient industrial solutions.

Arpita Chakraborty Tropa is an Industrial and Production Engineer with a B.Sc. from Shahjalal University of Science and Technology. Currently, she works as a Trainee Engineer - Production at PRAN-RFL Group, where she focuses on process optimization and reducing rejection rates. Arpita has a strong interest in the circular economy and its potential to achieve sustainable supply chains, alongside a keen focus on human factors in industrial settings. She has experience in multidisciplinary research and has actively contributed to leadership roles during her undergraduate studies, playing a key part in several student associations. Her academic excellence has earned her multiple scholarships throughout her degree. Arpita is passionate about combining her technical expertise with her leadership experience to drive improvements in industrial processes and contribute to sustainable practices in manufacturing.