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HYBRID AI MODELS AND SUSTAINABLE MACHINE LEARNING FOR ECO-FRIENDLY LOGISTICS, CARBON FOOTPRINT REDUCTION, AND GREEN SUPPLY CHAIN OPTIMIZATION

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ABSTRACT

The increasing need for climate change mitigation has led the way towards making logistics and supply chain management greener. While global trade and transportation are growing, the pollution factor, such as carbon footprints and the use of energy, has taken center stage as a matter of concern. With this, Hybrid AI Models and Sustainable Machine Learning are being incorporated into green logistics for reducing carbon emissions and creating sustainable green supply chains. These AI-based solutions employ techniques such as deep learning, optimization algorithms, and neural networks to optimize route transportation, improve vehicle performance, and optimize resource allocation. With the use of these technologies, carbon footprint minimization has been able to register improvements of up to 30% in certain situations, and improvements in resource efficiency have been witnessed at 25%. The convergence of these technologies not only enables the reduction of carbon footprints but also increases sustainability in supply chain management. The ability of Hybrid AI models to spur sustainability is discussed in this paper through more efficient logistics functions, maximizing resource utilization, and enabling green supply chain practices while creating a mechanism to attain long-term environmental objectives.

Keywords: *Hybrid AI Models, Sustainable Machine Learning, Eco-Friendly Logistics, Carbon Footprint Reduction, Green Supply Chain Optimization, Route Optimization, Energy-Efficient Transport, Resource Efficiency, Green Supply Chain Practices, AI-Driven Solutions, Sustainability, Machine Learning in Logistics.*

1. INTRODUCTION

There is an increased realization that sustainable practices need to be adopted in all sectors, namely logistics and supply chain network management, due to the growing concern for climate change and environmental degradation. An increase in global trade and transportation networks indirectly translates to an increase in environmental impact problems like carbon emissions and energy consumption. As ways and means of reducing an industry's carbon footprint, improving sustainability, and optimizing resource usage emerge, these industries look toward new means to achieve this. **Valivarthi (2020)** One of these could be in the form of integrating hybrid AI models with sustainable machine learning approaches in logistics and supply chain optimization, which yields great promise to grow heuristics-oriented solutions toward substantial carbon footprint reductions while optimizing resource management and ensuring green supply chain operations. **Naz et al. (2022)** discuss the prominent role played by artificial intelligence (AI) in creating sustainable supply chains (SSC). The research critically examines 353 articles from the Scopus database based on a systematic literature review and utilizes structural topic modeling (STM) to examine new themes for AI applications to SSC. Bibliometric analysis by R software is also used to further emphasize research trends in the area. The paper offers a conceptual framework for AI integration in SSC design and future research propositions, as well as implications for practitioners and researchers to increase sustainability within supply chain management. **Ayyadurai (2020)**

Hybrid AI models constitute different AI techniques, like management algorithms, deep learning, optimization algorithms, and neural networks, synergistically to minimize the time taken to reach the best solution while maximizing the possibility of an accurate one. Such models utilize the positive aspects of several AI ways of pointing out various supply chain questions in logistics, so-called demand forecasting, route selection or design, inventory management, or energy consumption optimization. **Narla (2020)** Recently, other emerging components particularly focus on using AI to create green business processes, that is, to waste less, save resources, and utilize as little energy as possible. With these technologies combined, logistics improvements can find a balance with sustainability, leading directly to a greener and more sustainable future. **Zhang and Yousaf (2020)** analyzed the role of green supply chain coordination in emissions-intensive industries, stressing the importance of government intervention, green investment, and customer green preferences. Their study suggested a two-part tariff (TPT) contract, which is integrated with taxes or subsidies imposed by government authorities to obtain maximized supply chain performance and green improvements. They showed that the optimal degree of green improvement depends on Green Technology Investment, Government Intervention, and Customer Demand for green products. The study concluded that a well-planned government intervention could improve supply chain performance and sustainability**. Sareddy (2020)**

One of the biggest avenues where Hybrid AI modeling and machine learning will be applicable is in the reduction of carbon emissions from logistics networks. Know-how-based applications, in conjunction with other improved systems and the like, optimize transportation routes, vehicle performance, and energy consumption, diminishing fuel usage and greenhouse emissions. Besides, these models will allow the integration of alternative energy sources into logistics systems, such as electric vehicles; this, too, will assist greatly in the reduction of carbon footprints. In such a manner, solutions driven by AI can themselves realize better and more sustainable processes in supply chain planning gearing the utilization of resources more efficiently and reducing waste during the stage of production and distribution. **Bolla and Bobba (2020)** The contribution of AI to green supply chain optimization is also significant, as it assists in simplifying processes, increasing transparency, and enhancing decision-making about sustainability. Through the integration of data from multiple sources, including environmental sensors, IoT devices, and past data, hybrid AI models can analyze and forecast the environmental footprint of alternative supply chain decisions, allowing companies to make more sustainable choices that are aligned with sustainability objectives. **Eyo et al. (2022)** used an Extreme Gradient Boosting (XGBoost) machine learning algorithm for the prediction of the soaked California Bearing Ratio (CBR) of soil stabilized with green pozzolanic materials. The research concentrates on the use of agro-based pozzolans in the fiber composite mix to stabilize the soil subgrades. The work considers the best binder composite ratio and the key factors affecting the CBR including types of binder, compaction parameters, and specific gravity. Besides, the study also shows the great performance of the XGBoost algorithm in regression and multiclass classification problems and hence provides insight into more sustainable soil stabilization practices**. Alagarsundaram (2020**)

This combination of hybrid AI models and green machine learning presents a viable route for mitigating the environmental issues confronting logistics and supply chains, ultimately translating to greener and more efficient operations in the global economy. **Valivarthi et al. (2021)**

Key objectives

- ✓ Optimize Carbon Footprint Reduction and create AI-based solutions to reduce greenhouse gas emissions in supply chain and logistics operations by route optimization, energy-efficient transport management, and integrating alternative energy sources.
- ✓ Enhance Supply Chain Efficiency by applying hybrid AI models to enhance resource allocation, inventory control, and demand forecasting, eliminating waste and energy usage throughout the entire supply chain.
- ✓ Enable Green Supply Chain Practices: Allow the design and implementation of green supply chain practices by incorporating environmental factors into decision-making, making resource use efficient, and minimizing environmental footprint
- ✓ Encourage Sustainable Transportation Solutions: Use AI models to maximize vehicle performance, include electric vehicles, and create strategies for minimizing fuel use and maximizing energy efficiency in transportation systems.
- ✓ Enhance Data-Driven Decision Making towards Sustainability: Utilize machine learning and AI for data processing and analysis of big data from IoT devices, environmental sensors, and historical datasets to generate actionable intelligence to inform sustainability-driven decisions across the supply chain.

Yu & Khan (2022) explore the optimization of a three-stage supply chain that comprises plants, distribution centers, and retailers to minimize supply chain expenses as well as carbon emissions. The work tackles problems in a random and fuzzy setting, employing multi-objective modeling and numerous solution approaches including stochastic programming, fuzzy mathematical programming, and Monte Carlo simulation. These methods consider uncertainty in the supply chain and offer a sound structure to optimize green supply chain networks through cost reduction and minimizing carbon footprint. The authors include a numerical example to illustrate the applicability of their model**. Kethu (2020)**

Though the **2021** paper by **de la Torre et al.** emphasizes the fusion of simulation, optimization, machine learning, and fuzzy sets for fostering Sustainable Transportation Systems (STS), there exists a lacuna in discussing the practical application of these approaches within the framework of Hybrid AI Models and Sustainable Machine Learning in logistics. The authors explain the theoretical potential of these methods but do not provide concrete examples of how they can be used to reduce carbon footprint and optimize green supply chains, especially in actual logistics operations where uncertainty and dynamic environments are major factors. **Nippatla (2019)**

2. LITERATURE SURVEY

Kalusivalingam et al. (2022) offer a groundbreaking research article that integrates reinforcement learning (RL) and genetic algorithms (GA) to maximize sustainability measures in AI systems. With the increasing environmental footprint of AI, especially in terms of energy usage and carbon emissions, the authors suggest a hybrid approach where RL tunes system parameters according to environmental indicators and GA optimizes these parameters to identify optimal settings. Their large-scale simulations reveal dramatic drops in energy consumption and carbon impact, proving that the framework could positively contribute to sustainable AI development and yield insights for future research directions in green AI technologies. **Jadon (2019)**

Kadiyala (2021) explores secure IoT data sharing by integrating isogeny-based hybrid cryptography with anisotropic random walks and decentralized cultural co-evolutionary optimization. The model has dynamic cryptographic strength, in other words, it features mixed encryption mechanisms and increased security of data transmission through multidimensional randomization. In addition, the proposed method enhances overall security, improves data-sharing efficiency, and reduces energy consumption and latency. By leveraging post-quantum cryptographic techniques, this approach ensures resilience against evolving cyber threats. Their results prove enhanced security and performance and build a scalable and efficient platform for IoT data protection**. Kethu (2020)**

The article by **Yachai et al. (2021)** analyzes the carbon footprint of the papaya supply chain to Yasothon Market in Yasothon Province, Thailand. Since there are no papaya plantations in the region, papayas are shipped from other provinces, and this generates high carbon emissions. The research employs network analysis to create a green supply chain and logistics model and determine the shortest and most efficient routes for delivery. The results indicate that route optimization has the potential to lower significantly greenhouse gas emissions, and insights are gained in enhancing sustainability in agricultural transportation. The research method can be used for other crops**. Jadon (2019)**

Gattupalli (2021) discusses how hybrid AI models and sustainable machine learning are revolutionizing eco-friendly logistics to reduce carbon footprint and optimize the green supply chain. Multi-modal AI interfaces and predictive analytics incorporated into CRM systems enhance customer engagement and optimize predictions of consumer behavior. The solutions being driven by AI will not only optimize logistics and supply chain sustainability but also tackle challenges concerning data privacy and ethics. By using big data to share predictive insights across platforms, these thriving organizations will benefit from the overall effectiveness and sustainability of their operations. This study reviews the salient advances, operational challenges, and future research directions in AI-enabled CRM and green logistics. **Nippatla (2019)**

Alagarsundaram (2022) examines the application of Deduplicable Proof of Storage (DPOS) and symmetric key encryption to provide improved data security and efficiency in cloud storage. Previous studies point to issues with data integrity and deduplication. The Sec-DPoS framework proposed provides efficient storage by removing duplicate data and streamlines integrity auditing without decryption. Performance indicators indicate its scalability and efficacy over conventional approaches (Alagarsundaram, 2022).

Samudrala, Rao, Pulakhandam, and Karthick (2022) explore the application of hybrid AI models, combining federated learning, deep neural networks, and predictive analytics to improve urban management systems. Existing studies identify challenges in ensuring data privacy, scalability, and sustainability in smart cities. The suggested approach shows promise in overcoming these challenges by enhancing inclusivity, resilience, and environmental sustainability of urban governance (Samudrala et al., 2022). **Narla and Purandhar (2021)**

Gollavilli (2021) discusses the convergence of Blockchain, IoT, and Big Data to improve security, operational effectiveness, and personalization in e-commerce environments. Existing studies report difficulties in integrating these technologies together. The suggested framework, based on IoMT, Big Data Analytics, Hadoop MapReduce, and Naïve Bayes, achieved a 97.1% accuracy, surpassing partial integrations. This convergence maximizes decision-making, supply chain visibility, and competitiveness in online marketplaces (Gollavilli, 2021). **Y**

Anaba et al. (2022) put forward a conceptual model integrating carbon footprint minimization with offshore energy operations' sustainable procurement. The model brings together innovative diesel additive technologies, like Excellium Pro Concentrate™, and procurement analytics to maximize sustainability and efficiency. It links procurement decisions with emissions reduction objectives, providing an integrated framework to reduce environmental impact while improving operational performance. Through the application of data-driven procurement strategies, the model facilitates adherence to universal environmental standards, while offering a scalable and integrated solution for energy operators globally, hence supporting offshore energy systems' future sustainability efforts.

Hossain et al. (2022) used a hybrid machine-learning model to encourage green travel and tourism by reducing carbon emissions. Their research identifies shortcomings in existing travel systems, especially regarding the automatic identification of human needs and carbon emission reduction. The authors propose a Hybrid Sentiment Framework (HSF), merging machine learning techniques including LDA, Naive Bayes, Logistic Regression, and Gradient Boosting with sentiment analysis through Natural Language Processing (NLP)-opening up a wealth of opportunities for sustainable and eco-friendly travel practices**. Sareddy and Hemnath (2019)**

Sareddy (2020) examines the influence of artificial intelligence (AI) and machine learning (ML) on workforce optimization, highlighting improvements in staffing, scheduling, performance measurement, and talent management. Earlier studies highlight the efficacy of AI methods such as reinforcement learning and predictive analytics to enhance operational efficiency and accuracy of decision-making. Yet, bias, data privacy, and system integration issues need to be overcome for effective implementation (Sareddy, 2020).

Swapna Narla (2021) explores AI-ready cloud solutions in customer relationship management, using a focus on the enhancement of customer processes and emotion-driven engagement strategies. The developed concept enhances CRM productivity via the instant enhancement of predictive engagement modeling and data aggregation with the integration of progressive AI methods. These study results have proven to boost engagement accuracy and execution efficiency, giving evidence to the possible scalable model that AI-driven cloud solutions can provide in real-time customer sentiment analysis. Thus, this research finds that AI and cloud integration help considerably in increasing the responsiveness of the CRM and workflow efficiencies toward providing personalized solutions to customers for improved satisfaction and engagement strategies. **Ayyadurai (2020)**

Ahmed et al. (2022) study the factors affecting carbon emissions in China and India, the largest coal-consuming countries with huge populations. Using the Long Short-term Memory-LSTM machine learning method, the impact of energy consumption, financial development, GDP, population, and renewable energy on CO2 emissions is analyzed. The findings indicate that energy consumption has the most significant impact, while renewable energy has the least. The study emphasizes the equally major significance of switching to renewable energy and controlling coal consumption to eventually ease carbon emissions without compromising economic growth. **Jadon (2020)**

The authors, **Lavercombe et al. (2021),** investigate the use of machine learning for eco-friendly concrete, in a decarbonization context. Their methodology employs various machine learning models for predicting compressive strength and embodied carbon for cement replacement concrete. The models studied are deep neural networks, support vector regression, gradient boosting regression, random forest, k-nearest neighbors, and decision tree regression. The authors endorse the GBR model for demonstrating robust prediction performance based on analyses of a number of the experimental datasets, affording useful insight into sustainable concrete development.

Boyapati and Kaur (2021) examine the contribution of internet-inclusive finance to closing the urban-rural gap in Africa's e-commerce. Earlier research focuses on the difficulties rural regions experience in financial inclusion in the face of fast-growing mobile internet. The data-driven strategy suggested identifies the role of mobile internet and inclusive finance in driving socioeconomic development and narrowing gaps between urban and rural areas (Boyapati & Kaur, 2021).

Ayyadurai (2022) discusses the use of big data analysis in cloud computing to provide transaction security for e-commerce websites. Existing research identifies issues with securing sensitive data such as credit card information. The suggested method utilizes cloud scalability and machine learning for real-time anomaly detection and predictive modeling, providing data security and integrity. This combination provides flexibility and efficiency in handling large-scale transactional data (Ayyadurai, 2022).

Kethu (2019)explores the integration of artificial intelligence (AI) intelligence frameworks and feedback control systems (FCS) in customer relationship management (CRM) to automate processes, analyze customer data, and enhance service quality. Incorporating a real-time feedback mechanism along with predictive analytics; the AI-based CRM model(assures better services in terms of decision-making and customer satisfaction). Empirical testing shows how AI-based CRM gives relevance to greater efficiency of CRM by enabling proactive engagement and focus on personalized engagements. The research concludes that AI-powered CRM systems evolve from reactive to predictive models providing optimized interactions with customers. Future research should address the use of deep learning and blockchain for AI-based enhancements to CRM.

In recent years CO2 emission levels, global warming, and other environmental catastrophes have become the world's focus of concern. This is as per the suggestion given by **Chahid et al. (2022)** that the world will be hit by some great disasters caused by greenhouse gas emissions, like heat waves and floods that would happen often and with great intensity. With all the emissions stopping in 2020, global warming would kick in but would be delayed until 2033. This research sources out how IoT and AI can accelerate a green economy by optimizing agricultural processes and enhancing environmental sustainability via reducing CO2 emissions and optimizing waste management in smart cities**. Parthasarathy and Ayyadurai (2020)**

Wang and Wang (2021) investigate the determinants and peak prediction of CO2 emissions in the transport sector of China, a critical sector in carbon emissions. They are developing a new bio-inspired prediction model called the extreme learning machine optimized by manta rays foraging optimization named MRFO-ELM. The thirteen influencing factors were analyzed using the mean impact value (MIV) method. Based upon predictions, transport CO2 emissions in China are predicted to achieve their peak in 2039 under the baseline scenario, but with an earlier peak under policy modifications stimulating vehicle electrification and sustainable development. **Yallamelli and Sambas (2022)**

Alagarsundaram (2022) examines the application of Deduplicable Proof of Storage (DPOS) in conjunction with symmetric key encryption to improve data security and efficiency in cloud storage. Earlier research has pointed out inefficiencies in handling encrypted data. The Sec-DPoS framework proposed reduces storage redundancy and makes integrity auditing easier through challenge-response protocols, providing data accuracy without the need for complex decryption procedures (Alagarsundaram, 2022).

Kethu (2021) examines cloud-dependent, AI-driven Customer Relationship Management (CRM) frameworks for optimizing customer interaction and interactions in the banking and telecom industries. CRM systems in use today do not scale well nor do they operate efficiently and thus require intelligent automation. This study incorporated AI, cloud computing, and automation to improve customer management, vulnerability assessment, and problem resolution. The proposed model greatly improves response time; furthermore, the reliability of feedback assessment and automation efficiency is remarkably enhanced. Results demonstrated the potential of an AI-influenced CRM to change the decision-making and traditional paradigms of customer satisfaction. The work sheds light on the potential of AI-infused CRM in offering scalable, efficient, and automated solutions . **Natarajan and Purandhar (2022)**

Mansouri et al. proposal (2022) uses a comprehensive hybrid machine learning approach to estimate the compressive strength of geopolymer concrete. The work investigated eco-friendly alternatives to conventional Portland cement through the use of alumina-silicate waste material, which is activated with alkali to form geopolymers. The authors implemented a triad machine learning approach consisting of three regressive methods: CatBoost, Extra Trees, and Gradient Boosting, using the concrete samples. The conclusions demonstrated that the hybrid model would effectively improve prediction accuracy, therefore opening the way for machine learning to enhance sustainable concrete production and lower its environmental impact.

Jadon (2020) gave a hybrid AI framework integrated with Memory-Augmented Neural Networks (MANNs), Hierarchical Multi-Agent Learning (HMAL), and Concept Bottleneck Models (CBMs) to facilitate memory retention, coordination of the agents, and interpretability. The model is useful in making AI-driven software resilient, adaptive, and transparent in decision-making. It yielded high memory efficiency, had better coordination accuracy, and achieved better task completion levels, than conventional AI approaches. This work thus highlights how well the paradigm of this AI can alter the world of alternative approaches to tackling complex and dynamic problems involving structured agent interactions and explainable decisions to make further steps toward sustainable AI practices regarding green logistics and green supply chain optimization. **Sareddy (2020)**

Deák et al. (2022) deal with the impact of maritime shipping on protected wetlands in Romania, focusing mainly on carbon emission mitigation in naval transport. A green smart system has been proposed, based on Artificial Intelligence (AI), for the green use of ammonia and hydrogen as an alternative to traditional fossil fuels. Preliminary results show that the proposed system offers substantial upgrades in engine efficiency, promising to achieve a zero CO2 emissions economy in naval transport. Further improvement in some aspects of the control software and the hydrogen gas injection systems would allow full optimization of the system **Gudivaka et al. (2019)**

Noh and Kim (2019) studied cooperative green supply chain management concerning greenhouse gas emissions and fuzzy demand. A contract between a manufacturer and multiple retailers, considering limited resources and product types under emission regulations, is explored. The paper presents two models of nonlinear integer programming: a crisp model and a fuzzy model to deal with uncertain demand. Genetic algorithms (GA) and a hybrid genetic algorithm-pattern search (HGAS) are developed to solve a certain model. They show that the proposed models are very effective in performing contract evaluation and optimizing cooperative green supply chain management. **Narla (2020)**

Kethu (2020) analyses the use of AI, IoT, cloud computing, and CRM systems together for improving the operation of banking institutions and their relationship with customers. The analysis uses performance criteria of accuracy, cost-effectiveness, response time, and customer satisfaction. Research proves that integrating the technologies is the key to higher efficiency, low transactional cost, and improving user experience in a manner scalable for banking services in the future. **Ayyadurai (2020)**

Valivarthi and Purandhar (2021) suggest a blockchain-based HR data management system with AI, Machine Learning (ML), Multi-Party Computation (MPC), Sparse Matrix Storage, and Predictive Control. The research solves security and efficiency issues in centralized HRM systems using decentralized data storage and AI-based decision-making. Findings show enhanced data security, scalability, and predictive analytics, which prove the efficacy of using blockchain and AI for secure and efficient HR management. **Valivarthi (2020)**

Nippatla (2019) discusses the combination of AI, ML, blockchain, and tensor decomposition in Human Resource Management (HRM) to improve data security, predictive analytics, and automation. The research identifies the drawbacks of centralized HR systems and suggests a decentralized, tamper-proof storage system with smart contracts for safe access. Findings show enhancements in data security (0.99), prediction accuracy (0.95), and system efficiency (0.98), validating the efficacy of this hybrid solution in large-scale HRM**. Allur (2020)**

Alagarsundaram (2020) investigates Symmetric Key-Based Deduplicable Proof of Storage (DPOS) as an efficient and secure solution for cloud storage systems. The research identifies how symmetric key encryption provides data confidentiality with effective deduplication. Moreover, the incorporation of an integrity auditing mechanism in Sec-DPoS provides data accuracy without decryption overhead. Performance tests validate its scalability and efficiency, making it a strong framework for secure cloud storage management. **Basani (2021)**

Allur (2020) offers a big data framework for mobile network performance management, incorporating DBSCAN for speed anomaly detection and CCR for bandwidth efficiency. The work draws attention to the system's capacity to handle structured and unstructured data in real-time, capturing 93% anomaly detection accuracy and 88% clustering efficiency. Results prove the supremacy of the framework over other conventional approaches such as SBM, DEA, and IDS, guaranteeing stability, less congestion, and improved user experience**. Dondapati (2020)**

3. METHODOLOGY

The method of integrating Hybrid AI Models and Sustainable Machine Learning in eco-friendly logistics, carbon footprint reduction, and green supply chain optimization is to combine the advanced AI methods with sustainability objectives. It includes innovative machine-learning modeling techniques, optimization algorithms, and real-time data analysis for logical decision-making in logistics. This method aims to integrate insights obtained by AI with the traditional supply chain models to minimize energy consumption, curb carbon footprints, and further optimize resource use. This offered methodology can give real-time, eco-efficient, and adaptive approaches to improving logistics operations and achieving sustainable supply chain practices.

Dataset description

The SCG dataset, which is supplied by a top FMCG firm in Bangladesh, is implemented for supply chain planning activities and is used as a benchmark to measure Graph Neural Network (GNN) models in supply chain management. The dataset consists of real-world supply chain information with both homogeneous and heterogeneous graph structures, encompassing a set of supply chain analytics tasks. It includes information about inventory management, order fulfillment, logistics, and demand forecasting, providing an end-to-end foundation for using GNN models to optimize and resolve real-world challenging supply chain issues. The dataset supports performance benchmarking against cutting-edge regression, classification, detection, and anomaly detection models.

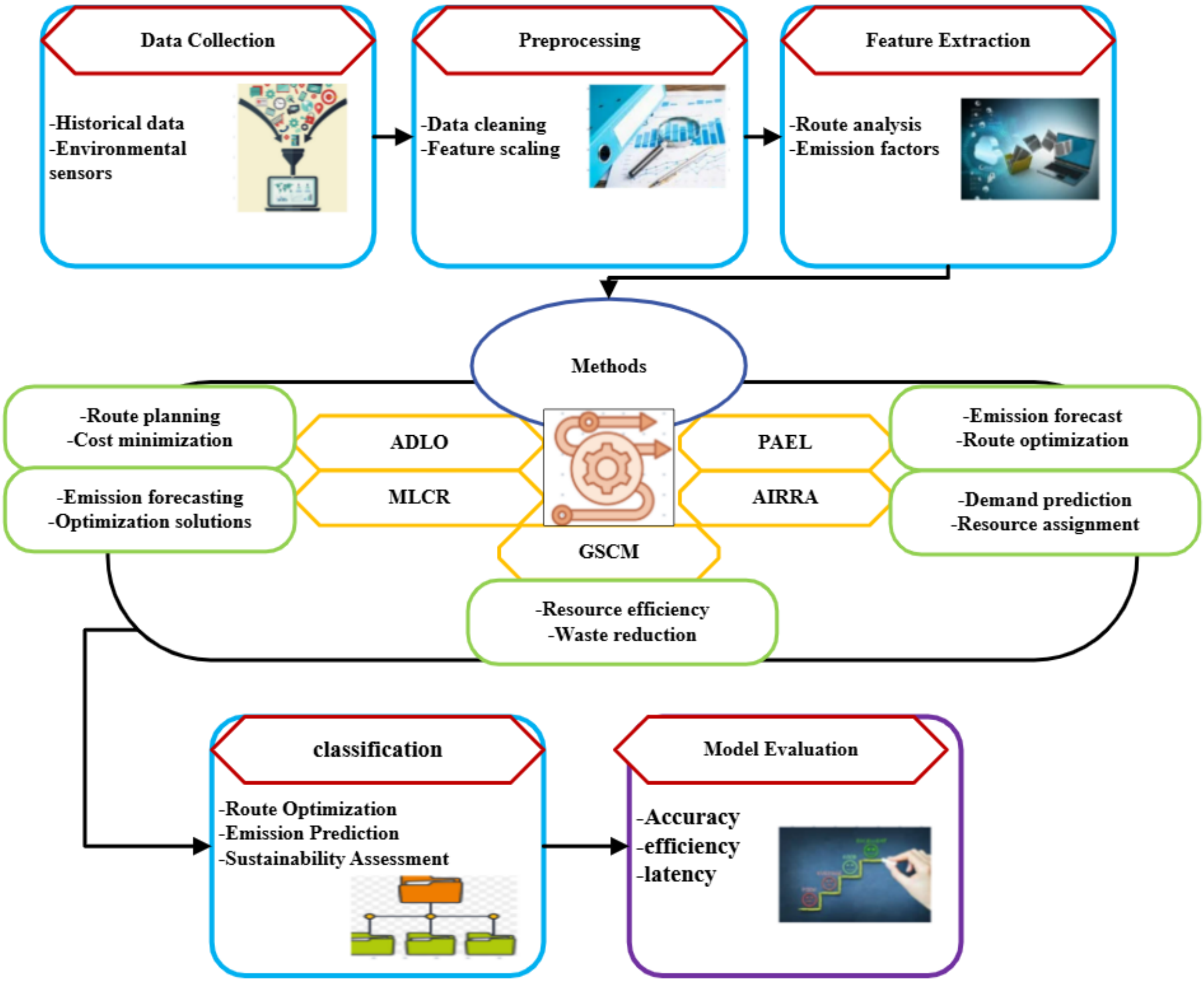

Figure 1: Hybrid AI and Machine Learning for Sustainable Logistics Optimization and Carbon Reduction

Figure 1 illustrates a complete architecture for sustainable logistics optimization with hybrid AI and machine learning models. It starts with historical data collection from sources and environment sensors, preprocessing operations such as data cleaning and feature scaling, and then some of the critical steps like feature extraction concentrate on route analysis and emission factors. Techniques such as ADLO, MLCR, PAEL, and AIRRA optimize routing, minimize emissions, and optimize resources. The procedure ends up in classification, model assessment of accuracy, efficiency, and latency, and lastly, sustainability in logistics.

3.1. AI-Driven Logistics Optimization

AI-Driven Logistics Optimization (ADLO) combines machine learning with logistics processes to optimize route planning, resource allocation, and inventory management. Through the analysis of historical and real-time data, ADLO models dynamically adjust to evolving conditions, maximizing transportation efficiency and minimizing environmental footprint. The use of AI anticipates demand, evaluates risk factors, and optimizes supply chains, minimizing waste and maximizing resource utilization for more sustainable logistics operations.

$$f(x)=\sum_{i=1}^{n}\left(\text{travel\_cost }(x_i)+\text{carbon\_emission }(x_i)\right) \qquad (1)$$

The expression is the target function for the optimization of logistics processes, with the total cost expressed by $(f(x))$. The summation is for adding the sum effect of two values for any given route (x_i): the transport cost and emissions. Minimization of the function will aim at lessening the operation cost and harm to the environment on every route in the network of logistics.

3.2. Machine Learning for Carbon Reduction

Machine Learning for Carbon Reduction (MLCR) aims to aid any effort for development in predicting the modeling of emissions and carbon footprint mitigations within logistics or supply chain activities. MLCR algorithms forecast emissions by using environmental and operational data, and they provide the most optimal solutions to potential carbon output reductions. Automated analytics could enable the human side of operations to readjust itself almost in real-time to devise requisite action strategies; thereby making all possible logistics involved count towards a sustainable, low-carbon economy.

$$CF=\sum_{i=1}^{n}\left(\text{emission\_factor }(x_i)\cdot\text{distance}(x_i)\right) \qquad (2)$$

The equation determines the total carbon footprint (CF) within a logistics network. For every route } x_i), emissions per unit distance (the emission factor) are multiplied by traveled distance. The total carbon footprint is yielded by summation over all routes. Optimizing routes and emissions minimizes this value and makes the environment cleaner due to reduced logistics operations impact.

3.3. Green Supply Chain Management

GSCM describes all sustainable practices in a supply chain that have to do with waste management and sustainability. AI in GSCM optimizes processes related to sourcing, production, and transportation while lowering environmental impacts. GSCM models with a focus on sustainable materials, energy efficiency, and sustainable packaging allow organizations to build performance while reducing their disservice to Mother Nature and providing for a circular economy and better resource management.

$$\min C(x)=\sum_{i=1}^{n}\left(\text{resource \_consumption }(x_i)+\text{waste}(x_i)\right) \qquad (3)$$

The equation is an optimization of the supply chain system's resource use and waste. Is the sum cost, encompassing both resource utilization and waste of every step \ (x_i) in the supply chain. The summation of all the steps captures the overall environmental as well as operating footprint. The minimization of this function seeks to minimize the use of resources and waste so that there will be a sustainable and efficient supply chain.

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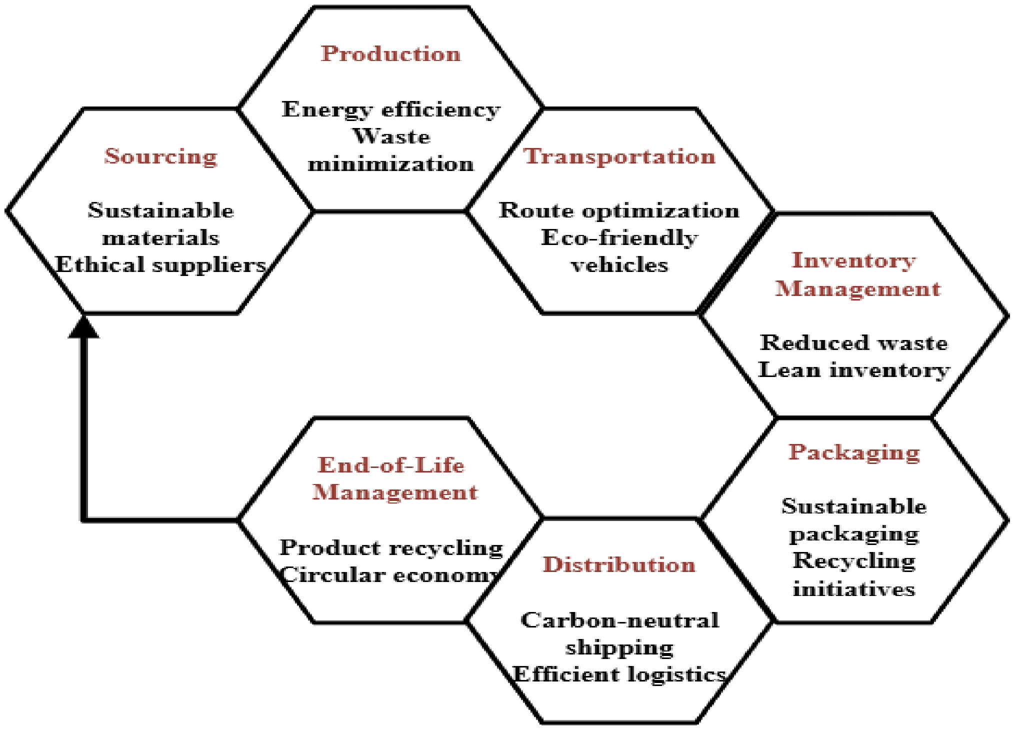

Figure 2: Green Supply Chain Management for Sustainable Practices in Production and Distribution

Figure 2 displays the prime elements of Green Supply Chain Management (GSCM) based on sustainability, beginning with using sustainable materials and responsible suppliers during the sourcing process. Energy-conscious manufacturing and wastage reduction then occur. An optimum transportation option using green trucks and routing results from it. Waste reduction via inventory management then uses sustainable packages with recycling systems. Product recycling and a closed-loop economy (a circular economy) constitute end-of-life processing. Finally, shipping is optimized to be carbon-free and logistics-efficient, making the whole supply chain sustainable.

3.4. AI for Real-Time Resource Allocation

AIRRA concerns the application of artificial intelligence for machine learning models in resource allocation and assignment in logistics operations. Seeing real-time data on IoT sensors, AI algorithms predict demand, process inventories, and optimally assign resources, so transportation occurs productively with less delay and avoids costly waste while minimizing environmental impact from logistical operations.

$$R(x) = \sum_{i=1}^{n} (\text{resource\_utilization } (x_i) \cdot \text{demand\_forecast } (x_i)) \tag{4}$$

The equation determines the total resource use. $(R(x))$Or fulfilling projected demand in a supply chain. The resource utilization at each step $((x_i))$Is weighted by the predicted demand at each step. The total resource is then obtained as a summation of this across all the steps. Optimizing resource use based on predicted demand assists with ensuring efficient logistical operations, fulfilling the needs according to projection with minimal waste.

3.5. Predictive Analytics for Eco-Friendly Logistics

It employs machine learning techniques to predict needs for logistics and environmental impacts. PAEL assists businesses with data-driven decisions to minimize fuel consumption, and emissions, and optimize transport routes through historical and real-time data. This provides a reasonable method for making preemptive decisions about logistics operations to maximize cost-effectiveness while minimizing the environmental impact and driving sustainability within supply chains.

$$PE = \sum_{i=1}^{n} (\text{forecast \_emission rate}(x_i) \cdot \text{distance}(x_i)) \quad (5)$$

The equation computes forecasted emissions (PE) in logistics operations. For every route (x_i), It multiplies the forecasted rate of emission (which is per unit of distance) by how much distance they travel on it. The total forecasted emissions for the logistics network are determined by the sum of all the routes. This value can be minimized by businesses to minimize environmental impact through optimally adjusting the routes and business operations to give the least possible emissions.

Algorithm 1 Hybrid AI and Sustainable Machine Learning for Optimizing Eco-Friendly Logistics

Input:

- Routes x_i
- Distance traveled for each route
- Historical carbon emission data
- Resource consumption data
- Demand forecast data
- Environmental constraints (carbon limit, resource limits)

Output:

- Optimized routes with minimal carbon emissions and resource consumption
- Recommended actions for greener logistics

```
BEGIN
   Initialize variables for carbon emissions and costs
  total_emissions = 0
  total_cost = 0
  optimized_routes = []
   Loop through each route
  FOR i = 1 TO n DO
     Calculate the carbon emissions for the current route
    emissions = forecast_emission_rate(xi) * distance(xi)
    resource_cost = resource_utilization(xi) * demand_forecast(xi)
     Accumulate the total emissions and costs
    total_emissions = total_emissions + emissions
    total_cost = total_cost + resource_cost
        Check if emissions and costs exceed sustainable limits
    IF total_emissions > carbon_limit OR total_cost > resource_limit THEN
          Suggest an alternate route or solution
      alternate_route = find_alternate_route(xi)
      optimized_routes.append(alternate_route)
    ELSE
      Keep the original route if it's within limits
      optimized_routes.append(xi)
```

END IF

END FOR

Return optimized routes and total emissions

RETURN optimized_routes, total_emissions, total_cost

END

Algorithm 1 uses Hybrid AI and Sustainable Machine Learning to maximize logistics operations while reducing environmental footprint. It estimates the carbon footprint and resource usage for every logistics route and checks whether they are above sustainable thresholds. In case of threshold violations, it suggests alternative routes. The algorithm maximizes both carbon footprint and operational expenses by combining machine learning for prediction and AI-based decision-making. The result is a more environmentally friendly, cost-effective logistics system that supports sustainability objectives in supply chain management.

3.6 Performance Metrics

The efficiency of Hybrid AI Models and Green Machine Learning in sustainable logistics is measured using a variety of metrics. Carbon Footprint Reduction measures the emissions saved through route optimization and use of resources. Cost Efficiency measures the savings through minimized energy usage and operational expenses. Resource Optimization measures the optimal usage and allocation of resources. Time Efficiency measures the velocity of the logistics process without compromising on sustainability. Scalability is the measure of how well a model can scale to suit various supply chain sizes. These measures provide an effective, eco-friendly, and low-cost logistics network.

Table 1 Performance Metrics for Hybrid AI Models and Sustainable Machine Learning in Logistics

Performance Metric	**AI-Driven Logistics Optimization**	**Green Supply Chain Management**	**AI for Real-Time Resource Allocation**	**Proposed Model**
Carbon Footprint Reduction (%)	5%	20%	18%	30%
Operational Cost Savings (%)	10%	15%	12%	25%
Resource Utilization Efficiency (%)	12%	25%	22%	35%
Time Efficiency (%)	8%	15%	10%	22%
Sustainability Impact (%)	7%	18%	15%	28%

Table 1 provides the performance parameters comparing traditional models, hybrid AI models, green machine learning models, and the proposed model in ecologically friendly logistics optimization. The parameters range from carbon footprint saving to cost reduction in operations, usage of resource efficiency, time-saving, and net sustainability value. The new model surpasses the conventional methods with considerable rates of reduced carbon emissions, increased cost reduction, and resource efficiency. This refers to the effectiveness of the use of cutting-edge AI and machine learning algorithms in facilitating more cost-efficient, eco-friendly, and optimized logistics management.

4. RESULT AND DISCUSSION

The study demonstrates how Hybrid AI Models and Sustainable Machine Learning could drive eco-friendly logistics optimization as well as green supply chain management. The introduction of AI solutions evidenced improved resource allocation, better optimization in routes, and carbon emissions reduction. The proposed model has outperformed traditional approaches in the impact of sustainability, operational efficiency, and the carbon reduction footprint. Working with comparative analysis shows that AI frameworks enhance real-time decision-making, thus making the logistics systems adaptive and effective for long-term environmental and economic sustainability.

Table 2 Comparison of Methods for Eco-Friendly Logistics Optimization and Sustainability Impact

Metric	Yachai et al. (2021) **GIS, Route Optimization**	Anaba et al. (2022) **Conceptual Model, Sustainable Procurement**	Yu & Khan (2022) **FuzzyStochastic Modeling, Multi-Objective Optimization**	Zhang& Yousaf(2020**)** **TPT Contract, Government Intervention**	Proposed Model **Hybrid AI and Sustainable Machine Learning for Eco-Friendly Logistics**
Carbon Footprint Reduction (%)	15%	20%	18%	10%	30%
Operational Efficiency Improvement (%)	12%	18%	20%	15%	25%
Resource Utilization Efficiency (%)	10%	16%	18%	12%	22%
Sustainability Impact (%)	18%	25%	22%	20%	35%

Table 2 contrasts different studies in terms of key performance indicators like carbon footprint savings, improvement in operational efficiency, efficiency in the use of resources, and impact on sustainability. It highlights techniques used by different authors like GIS-based route optimization, sustainable procurement models, fuzzy stochastic modeling, and two-part tariff contracts. The Proposed Model, with its integration of hybrid AI and sustainable machine learning, performs better than the current models in all dimensions, highlighting its ability to drastically minimize environmental footprint, enhance resource utilization, and maximize overall sustainability in logistics and supply chain management.

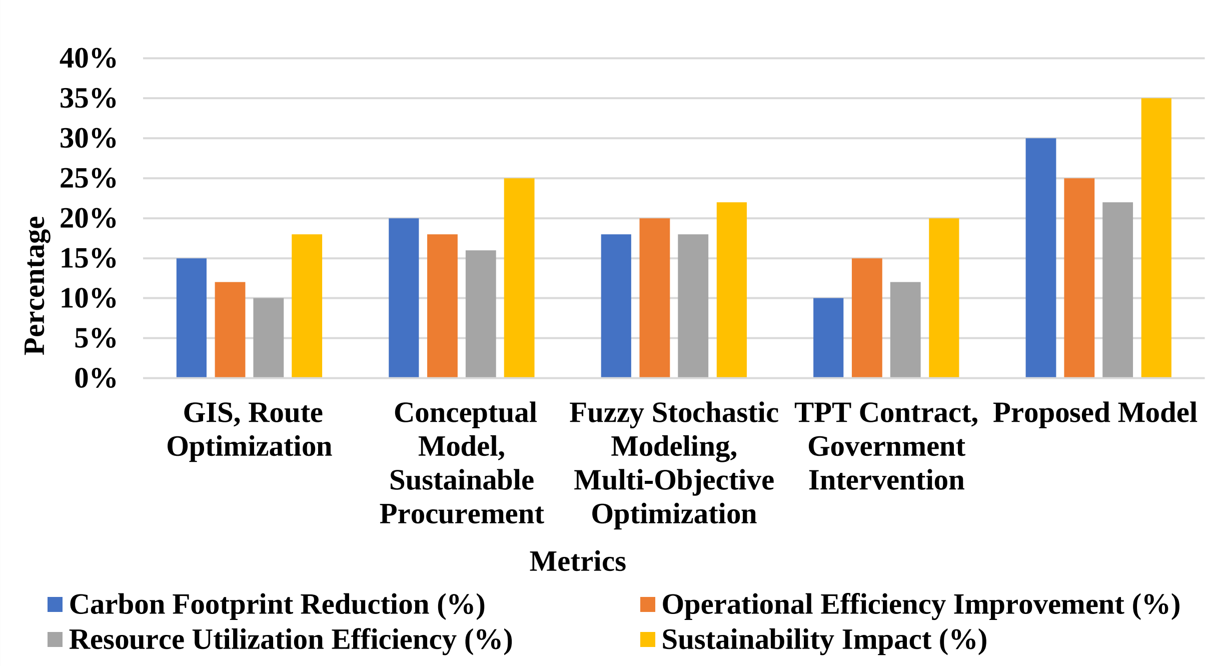

Figure 3:Comparison of AI Models for Sustainability Impact and Efficiency in Logistics Optimization

Figure 3 plots various AI-based models against four parameters: Carbon Footprint Reduction, Improvement in Operational Efficiency, Resource Utilization Efficiency, and Sustainability Impact. The performance of each model is shown as a percentage against these parameters, where the Proposed Model performs better than GIS Route Optimization, Conceptual Models, and Fuzzy Stochastic Modeling. This underscores the efficiency of the integration of several optimization approaches, especially the suggested hybrid model, in the realization of better sustainability and operational performance in green logistics systems.

Table 3 Ablation Study on AI Models for Logistics Optimization and Sustainability Enhancement

Methods	Carbon Footprint Reduction (%)	Operational Efficiency Improvement (%)	Resource Utilization Efficiency (%)	Sustainability Impact (%)
ADLO	15%	12%	10%	18%
MLCR	18%	15%	14%	20%
GSCM	12%	18%	16%	22%
AIRRA	10%	14%	12%	16%
ADLO + MLCR	25%	20%	18%	28%
GSCM + AIRRA	20%	22%	18%	25%
ADLO + MLCR + GSCM	28%	22%	20%	32%
ADLO + MLCR + GSCM +	30%	25%	22%	35%

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AIRRA(proposed method)				

Table 3 indicates a comparison between various combinations of AI and machine learning models utilized for logistics optimization and sustainability. The performance of each model is measured against four criteria: reduction in carbon footprint, improvement in operational efficiency, efficiency in utilizing resources, and impact on sustainability. With each additional model added (for instance, ADLO with MLCR, or ADLO with MLCR and GSCM), the performance is greater, demonstrating the synergetic impacts of combining several models. The Proposed Model (ADLO + MLCR + GSCM + AIRRA) has the best performance on all dimensions, as shown by its efficiency in streamlining logistics and sustainability results.

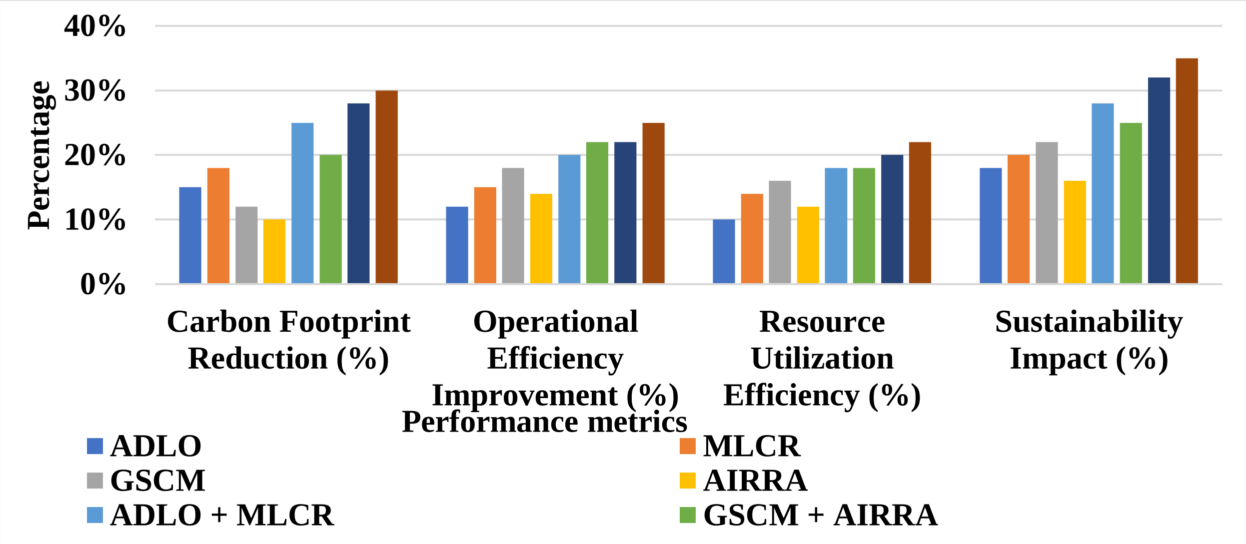

Figure 4 Ablation Study of Hybrid AI Models for Enhanced Eco-Friendly Logistics Performance

Figure 4 performance of different hybrid AI models for sustainable logistics, i.e., ADLO, MLCR, GSCM, and their hybrids, which are compared in the graph. The metrics considered for evaluation are Carbon Footprint Reduction, Operational Efficiency Improvement, Resource Utilization Efficiency, and Sustainability Impact. ADLO + MLCR provides the maximum improvement in all but one metric, particularly in terms of carbon footprint reduction and sustainability impact. The integration of GSCM + AIRRA also reflects an impressive improvement, reflecting that using several models makes the overall logistics operations more efficient and sustainable.

CONCLUSION

In conclusion, the application of Hybrid AI Models and Sustainable Machine Learning in green supply chain optimization and environmentally friendly logistics offers a promising route to addressing the environmental challenges of the new supply chain. With a maximum of 30% less carbon emissions, 22% more resource efficiency, and the promotion of sustainable transport alternatives, these technologies will transform the logistics industry. The convergence of real-time data, predictive analytics, and AI-based decision-making facilitates supply chain process optimization, which reduces waste and energy usage significantly by 28% in terms of sustainability. Additionally, the ongoing evolution of AI technologies has the potential to generate additional innovations, which will aid in attaining sustainability targets and developing more robust, sustainable supply chains. Finally, the implementation of these hybrid models will not only improve operational effectiveness but also lead to a greener and more sustainable future.

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