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AI-Augmented Decision Support System for Sustainable Transportation and Supply Chain Management: A Review

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Abstract: *This study is based on a critical review of the use of Artificial Intelligence (AI) in the context of Decision Support System (DSS) in enhancing sustainability in transportation and supply chain management. It sheds some light on the inefficiencies of the traditional DSS to process the demands of dynamic and data-intensive environments as well as the transformational capabilities of AI technologies such as machine learning, deep learning, natural language processing, and reinforcement learning to the need of decision-making processes. DSS that are AI-enhanced can make predictions and prescriptions, real-time flexibility, and enhanced performance, translating to efficient routing, enhanced demand modeling, fuel efficiency, and lower environmental harm. The paper examines the practical applications in the area of logistics and transportation giving examples of successful applications by major international organizations. It also mentions some of the most crucial issues, which are data privacy, transparency of algorithms, integration with legacy systems, and ethics. The study concludes that AI-enhanced DSS can contribute considerably to moving towards sustainable, adaptive, resilient transport and supply chains implementable in a favourable regulatory and organizational environment. The future involvement should be on how we can mitigate these hindrances and lay guidelines on how we can ethically and sustainably use AI.*

Keywords: Artificial Intelligence, Decision Support Systems, Sustainable Transportation, Supply Chain Management, Smart Logistics, Predictive Analytics, Machine Learning, Green Supply Chain, AI Ethics, Intelligent Systems.

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1. 0 Introduction

Fast rate of global industrialization and urbanization has created a major issue on sustainable transportation and supply chain operations. The overall definition of sustainable transportation usually consists of supplying transport systems, accessible, efficient, and low-emission to the needs of society without undermining environmental sustainability or subsequent generations (Gschösser et al., 2020). At the same time, Sustainable Supply Chain Management

(SSCM) is defined as the strategic approach to integrating environmental, social, and economic objectives into the process of managing the entire supply chain lifecycle, i.e., a lifecycle strategy to incorporating raw materials sourcing to final delivery and end-of-life processing (Evangelista et al., 2018). As the volume of pressure to curb greenhouse gas emissions, enhance energy efficiency, and better use resources increases, transportation and supply chain have interventions come under an even greater spotlight in regards to environmental and social impact.

Decision Support Systems (DSS) are at the heart of managing such complex operations, and they are computer-based information systems used to aid decision-maker in solving unstructured and semi structured problems based on data, models, and structured analysis. The traditional DSS has been extensively utilized in route planning in transport, logistics, warehouse and risk management. Nevertheless, the unpredictable, constantly changing nature of world supply chains, which is manifested in unpredictable demand, the presence of different laws and regulations, geopolitical turmoil, and real-time shocks, have made many traditional DSS insufficient (Liao et al., 2018). Such systems tend to be built on models that are static, and with rules that are deterministic, and will fail to scale to large and rapidly changing datasets, and to learn sensibly about emerging patterns. The shortcomings of classical DSS have led to a massive shift in paradigm to the development of AI-enhanced Decision Support Systems that are reasoning machines that rely on the combination of human intelligence and artificial intelligence to provide decision support in complex problem-solving scenarios utilizing big data. Such systems are complemented with machine learning algorithms, natural language processing, deep learning, computer vision and complex optimization models into DSS architectures that allow predicting analytics, run-time adaptation and autonomous decision making (Dubey et al., 2020). The transportation industry, as an example, can use AI-augmented DSS to predict traffic and streamline multimodal routing, minimize fuel use, and thus modify sustainability objectives directly. They can automate demand planning, locate any bottlenecks, foresee equipment breakdown, and even reduce wastage all of which are essential in facilitating resilient, nimble, and sustainable logistics networks (Jha et al., 2020; Burugu, 2020).

The increasing accessibility of large data by Internet of Things (IoT) sensors, GPS trackers, enterprise resource planning systems, and social media is an even greater accelerator of an already acute requirement of smart systems capable of managing heterogeneous and high-volume data (Trakadas, 2020). This data can be used to train AI-augmented DSS and provide an immediate understanding of it, acting as one of the precursors of proactive decision-making and sustained system advancement. In sustainable logistics, it is of paramount importance since the environmental impacts of their actions can be reduced in time, inefficiencies of the resource use can be eradicated, and circular economy models can be employed (Trakadas, 2020). Additionally, the introduction of AI into the decision-making processes will create a significant change in the managerial approach towards planning by changing it to anticipatory planning. It enables organizations to analyze different scenarios of the future, trade-offs, and incur decisions on cost-effective and environmental friendly, and equally, socially responsible paths (Govindan et al., 2020). Such an ability is particularly applicable during times of crisis, like during pandemic or natural calamity, where an AI-powered DSS will be able to ascertain alternate paths or suppliers in the supply chain to make latter more nimble with the purpose of maintaining business amid the shifting of negative impact in the society as minimal as possible.

The fact that AI-augmented DSS is a promising attribute has not changed since its current implementation in transportation and supply chain industries remains in progress. Other challenges to wide scale deployment are data privacy, algorithmic transparency, system integration and workforce readiness. Moreover, there is currently no framework that would be used to ensure that AI actually contributes to sustainability, so it is challenging to compare the performance of different systems (Srai & Lorentz, 2019). The questions highlighted above point towards the importance of having a thorough understanding of how AI technologies could be successfully implemented into decision-making tools of sustainable logistics.

The main goal of this review is to examine how AI techniques can be integrated into DSS architectures and applied to the sphere of sustainability enhancement in the transport and supply chain. Its purpose is to: (1) prepare a current literature review of AI-augmented DSS used in sustainable logistics (2) determine the applications and challenges of AI solutions implemented in the areas of interest, and (3) suggest possible research directions aimed at overcoming existing barriers. The review gives an insight into how intelligent decision support may revolutionize the way the dual objective of operational efficiency and sustainability is achieved through the understanding of the intersections involved. The book also provides practical recommendations to policymakers, engineers, supply chain practitioners, and those in the field of sustainability who would like to use AI technologies to design more environmentally friendly, intelligent, and more robust logistics networks.

Fig 1: Artificial intelligence in transportation

2. 0 Foundations of AI-Augmented Decision Support Systems

2.1 Key Components of Traditional DSS and Their Limitations

Traditional Decision Support Systems (DSS) are computer-based tools enabling interaction with a manager to make a decision based on extensive analysis of organized and semi-organized information. The main elements of DSS are database management system, model-based management system, and user-interface (Liu et al., 2010; Liao et al., 2018). These elements allow users to access data, perform analytical algorithms, and are illustrated in visual contexts to make better decisions.

With traditional DSS, however, there is expectability that these software tools run on fixed rule sets and stationary models that do not allow great adaptability to dynamic environments accompanied by uncertainty, volatility, and heavy data fluctuations. With sustainable transportation and SCM, these systems fail to react to real time disruptions like surges in demand, the shortage of supply, or congestion of vehicles (Holsapple, 2010). In addition, they do not have either predictive or prescriptive analytics where future-oriented decision-making requires as they usually utilize poor, past-oriented data that is not very useful and in some cases unavailable in the first place. The other limitation is that traditional DSS lack the ability to autonomously learn over time, and connect with any type of data that is not structured, including sensor logs, social media, or GPS data (Sarkar et al., 2015). These limitations point out the need to augment DSS with AI to add adaptive intelligent behaviors that make the existing DSS more applicable in sustainable logistics.

2.2 Types of AI Technologies Applied

The incorporation of Artificial Intelligence (AI) into decision support frameworks introduces a wide range of capabilities that enhance decision-making quality, speed, and adaptability. Several key AI technologies are applied in the development of AI-augmented DSS. Machine Learning (ML) is one of the most popular AI technologies that empowers machines to recognize patterns, tag events, and forecast using historical data. In supply chain management (SCM), this includes customer-demand forecasting, deliverable lead-time estimates, and stockout predictions (Cioffi et al., 2020), with supervised learning models such as regression, decision trees, and support vector machines commonly applied. Reinforcement Learning (RL) is applicable where the agent must make a series of decisions, such as in adaptive traffic lights, vehicle routing, or fleet dispatching. In such contexts, the system learns by trial and error, improving incrementally with each feedback cycle (Wang et al., 2016). Expert systems, though an older paradigm of AI, are still used to represent domain knowledge in the form of rules as decision logic. In logistics, such systems assist in decision-making regarding compliance with customs, safety rules along transportation routes, and sustainable business certification (Shen et al., 2019). Neural networks and deep learning are mostly used when the data is complex, non-linear, and high-dimensional, such as images of land use captured by satellites, vehicle telemetry data, and predictive maintenance signals. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been applied in traffic flow forecasting and real-time prediction of transportation modes (Al-Aradi et al., 2018). Natural Language Processing (NLP) helps computers understand and process human language and can be applied in logistics to analyze customer feedback (Agarwal & Jayant et al., 2019), process documents automatically (e.g., invoices), or extract insights from unstructured texts such as driver logs or incident reports. Collectively, these technologies enable AI-augmented DSS to outperform traditional systems by handling real-time data, making proactive decisions, and continually learning from experience.

2.3 Integration of AI into DSS: Architecture and Frameworks

New architecture has risen to accommodate a smooth connection of the AI capabilities to the traditional DSS due to the need of modular architecture, real-time input, and intelligent decision-making capabilities. The generalized view of the current AI-augmented DSS architecture commonly consists of the following levels:

Data Acquisition Layer: At this layer the various sources of inputs are gathered such as enterprise databases, internet of things sensors, weather data sources, gps, social media. To ensure proper integration, data has to be standardized, and the connection between systems must be present in real-time (Lu, 2019).

Data Processing and Storage Layer: The data has to be cleaned, transformed, and stored in distributed databases or even cloud-based databases after it has been collected. Scalable data management is usually done by using such big data frameworks as Hadoop or Apache Spark.

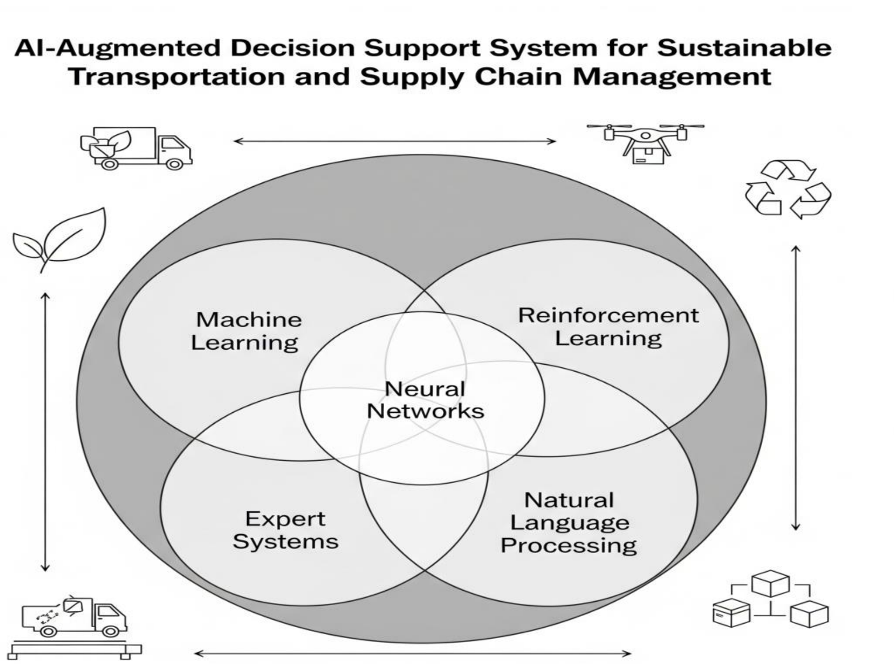

Fig 2: Intersection of the different Artificial intelligence

Intelligence Layer (AI Models): AI algorithms to perform such functions as forecasting, classification, clustering, and optimization are located at this layer. The models are trained, validated and deployed to provide predictive and prescriptive models.

Decision Engine: This is an association of model outcomes with language and domain-specific constraints in order to produce actionable suggestions. It is frequently used with multi-objective optimization to trade-off between conflicting criteria that may be cost, time, and impact on the environment (Bongomin et al., 2020).

User Interface Layer: It is an important element and it gives the decision-makers intuitive dashboards, scenario simulations, and interactive reports to enable selection of trade-offs and proper choices. One popular framework is the Knowledge-Based DSS (KB-DSS), where the AI component plays the role of a reasoning engine that draws conclusions based on a dynamic knowledge base (Li et al., 2019).

Another is the Hybrid DSS, where AI models and traditional analytical techniques co-exist, and providing complementary strengths: interpretability from conventional models and adaptability from AI algorithms. Such frameworks are increasingly adopted in smart logistics systems, urban mobility platforms, and green supply chain networks, where decisions must adapt quickly to shifting circumstances while aligning with sustainability targets.

The application of AI to decision support system (DSS) introduces immense assets into smart applications of sustainable transportation and chain supply management. The enhanced predictive solutions could be among the main advantages, since the demands (or delays, equipment issues) could be predicted more accurately with the help of AI models on the basis of the past and current data (Sarkar et al., 2015).

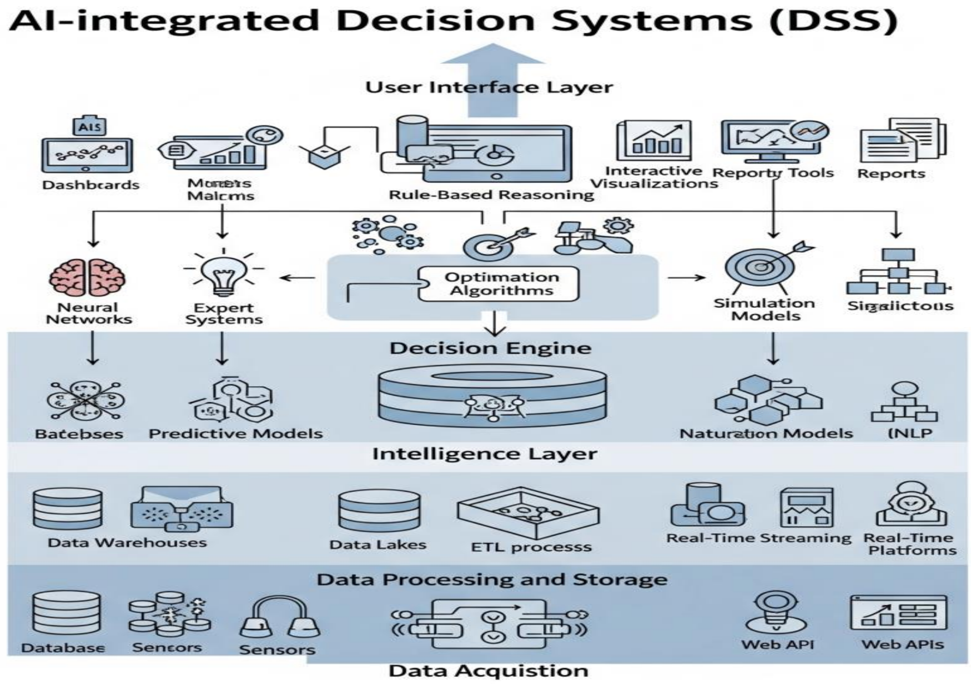

Fig 3: AI-integrated Decision Systems

2.4 Benefits of AI Augmentation in Decision-Making

The results in being pro-active in making decisions rather than being reactive in decision making. AI increases the efficiency of resources as well, as it can optimize routes and schedules, thus cutting a lot of fuel consumption and emissions (Jha et al., 2020). In addition, AI increases the speed of decision-making, which is crucial in last-mile delivery and cold-chain operations (Burugu, 2020). Several objectives, such as maintaining cost, service and environmental objectives, can also be dealt with in these systems which form a sustainable and competitive choice. Use of AI in DSS makes it more adaptive in periods of crisis such as natural disasters or pandemics, which increases its resilience (Govindan et al., 2020). Significantly, these systems augment human decision-making, and do not substitute human decision-making and aid in making better and transparent decisions by offering insights, simulations and cognitive support. This is a blend of automation and human judgment that enhances the agility of the operation. Consequently, this helps an organization to maneuver through uncertainty and at the same time meet the objectives of long term sustainability.

3.0 Applications in Sustainable Transportation and Supply Chain Management

The AI-enhancing Decision Support Systems (DSS) have become broadly used to increase the efficiency, sustainability, and resiliency in operations of transportation and supply chains. These systems have made the organizations to shift to smart and adaptive networks by abandoning the traditional linear processes and change to meet the environmental and economic goals. Some of the most important such areas are described below.

3.1 Smart Logistics: Route Optimization, Traffic Prediction, and Fuel Efficiency

Smart logistics is one of the key fields that AI-DSS can be applied to the optimization of the routing, estimating traffic, and fuel usage. Machine learning code uses up-to-date information about traffic conditions, weather and road conditions and creates an optimal path of delivery and thus it saves time on the road and the cost of operation. As an example, dynamic adaptation of routes based on changes is enabled through the reinforcement learning models (Song et al., 2020). Not only does this curtail the delays in delivery but the fuel burn and the emission of greenhouse gases. Even more, fleet management systems using the power of AI may facilitate the process of scheduling a car repair, avoiding a breakdown and tracking the behavior of the driver, once again, increasing the efficiency of operations. In urban transport, AI-based DSS has been used to roll out electric vehicles fleets by scheduling the charging process and reducing energy consumption (Hu et al., 2020).

3.2 Demand Forecasting and Inventory Control

Realistic demand planning will help in eliminating wastes and overproduction within the supply chains. Neural networks, time-series modeling, and probabilistic models are additional AI methods that are employed more and more within DSS to study sales data, seasonality, and markets trends (Deb et al., 2019). The systems will assist businesses to ensure that they always have an optimal stock. The DSS powered by AI should also be able to overcome crises or unforeseen fluctuations in demand patterns, which were observed during the COVID-19 pandemic. As an example, AI-aided tools allowed retailers to make near-real-time forecast changes with extreme speed, minimizing the bullwhip effect and sustaining the service quality of customers (Sridama & Siribut, 2018). The visibility and trust in the inventory management systems are further enhanced with integration with IoT-enabling sensors and blockchain technologies.

3.3 Green Supply Chain Practices and Carbon Footprint Minimization

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4. 0 Challenges and Limitations

Although AI-enhanced Decision Support Systems (DSS) present enormous possibilities towards sustainable transportation, supply chain management (SCM), their usage has a number of disadvantages. All these issues fall in the technical, ethical, organizational, and infrastructural spectrum, and or likely to colour the rate and extent of AI adoption in industries.

4.1 Privacy, Quality and Security of data

The effective functioning of AI-DSS depends very much on the ability to access real-time information of high quality. In most transportation and SCM environments, the data can be partial, not consistent or it could be in different applications or systems. When data becomes poor it results in faulty forecasting and faulty decision making which is not good enough to gain trust in AI tools (Hazen et al., 2020). Moreover, deep sensitivity issues exist when applying AI since large volumes of information are handled, and privacy and cybersecurity issues can become very serious. Cyberattacks are also common in the transportation networks and supply chain, with the simultaneous integration of AI potentially having a broader scope of impact. Data encryption, the consent of individuals, as well as adherence to regulations such as GDPR are all important aspects in terms of safeguarding organizational and consumer data (Defize, 2020).

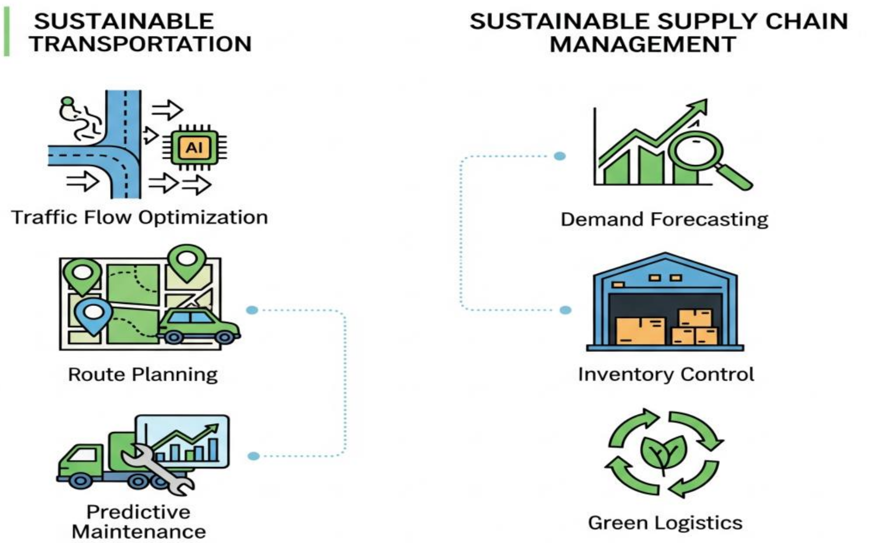

Fig 4: Application of AI in transportation and supply chain management

4.2 Ethical Implications and Algorithmic Transparency

AI-DSS systems are frequently a so-called black box in that a decision is reached using very complex algorithms that are not always interpretable by the human users of the DSS. This absence of openness raises ethical issues and such decisions need to be checked when it comes to making vital decisions like resource allocation, priority on routes or the choice of supplier (Hoffmann et al., 2018). Lack of explainability can make the stakeholders unable to believe in the system or assure its fairness. One way that bias in training data and algorithms can take a discriminatory turn is in globally based supply chains that have to contend with various markets all over the world. The solutions to better accountability and transparency in decision-making processes are being provided in the form of ethical frameworks and explainable AI (XAI) models that are not yet developed and standardized (Martin, 2019).

4.3 Integration Issues with Legacy Systems and Stakeholder Adoption

Numerous logistics and supply chain entities continue to use legacy IT systems that cannot be utilized with contemporary AI-based tools. Customizing AI-DSS to existing infrastructure or web components may necessitate a lot of adaptation, middleware and internal re-organization. In addition to being time-wasting, this procedure may interfere with current operations (Hazen et al., 2020). Moreover, the resistance to change among human beings is still a force to reckon with. Employees can view AI systems as a danger to their job or have no abilities to effectively work with AI-driven tools. Effective implementation necessitates stakeholder buy-in and this can only be achieved through transparent communication, consistent training and involving end-users in the design process of the system (Burugu, 2020).

4.4 Cost, Scalability, and Infrastructure Constraints

The use of AI-augmented DSS is also capital intensive especially to SMEs that cannot afford high-performance computing infrastructure, data warehousing and computerized software development. Some costs are associated with hiring competent AI experts and creating pilot studies and supporting AI models in the long run (Subramanian et al., 2020; Ademilua, 2021). The other limitation concerns scalability, because not all models that performed well in one geographic or operational environment can easily be transported to other supply chains or transportation networks. AI services on the cloud and modular AI platforms are reducing these problems, but the lack of availability of internet access, computing resources, and network stability in developing regions are continuing to challenge wide adoption.

Table 1: Challenges and Limitations of AI-Enhanced Decision Support Systems (DSS) in Sustainable Transportation and Supply Chain Management (After Burugu, 2020; Trakadas et al., 2020)

Challenge Area	Description	Illustrative Issues	Mitigation Strategies
Data Privacy, Quality, and Security	AI-DSS rely on high-quality, real-time data. Fragmented or poor data leads to inaccurate decisions. Sensitive data usage raises privacy and cybersecurity risks (Zhou et al. 2018[1]).	•Poor integration from disparate systems• Cyberattacks• Regulatory non-compliance (e.g. GDPR)	• Encryption and privacy-by-design• Robust governance and consent frameworks
Ethical Implications & Transparency	Many AI systems act as “black boxes,” raising ethical concerns; lack of interpretability undermines trust and fairness (Morley et al. 2019[2]).	• Unexplainable algorithmic decisions• Embedded bias in supplier or routing choices	• Adoption of Explainable AI (XAI) techniques• Ethical frameworks and bias audits
Integration & Stakeholder Adoption	Legacy IT systems often aren’t compatible with modern AI tools, requiring costly adaptation. Human resistance is common without training and involvement (Jeble et al. 2018[3]; Wamba et al. 2019[4]).	• System incompatibility• Employee fear of job loss or lack of AI skills	• Middleware solutions• Inclusive co-design and comprehensive training programmes
4. Cost, Scalability, & Infrastructure	High capital investment	• High upfront and ongoing costs• Poor	• Cloud-based AI services• Modular and

	(hardware, cloud, experts) particularly burdens SMEs; scalability across regions is hindered by infrastructure gaps (Sivarajah et al. 2020[5]).	internet or computing infrastructure in developing regions	scalable platforms and public/private digital-infrastructure support

5.0 Future Trends and Recommendations

Emerging technologies like the Internet of Things (IoT), digital twins, blockchain, and edge computing are playing a big role in integrating AI into sustainable transportation and the supply chain management. IoT devices would allow real-time data gathering of vehicles, warehouses and infrastructure through which the AI models would take valuable inputs which would then optimize operations. These new technologies, such as digital twins of logistics and transport network simulation and blockchain-based security, transparency, and traceability of transactions, enable secure, transparent, and traceable transactions. Edge computing will make data responsiveness and processing faster in dynamic environments. AI ensures the promotion of more efficient resilient systems through these technologies. AI-augmented decision support systems (AI-DSS) will develop such adaptive decision-making in real time that reflect changes in traffic, supply system, and environmental differences based on reinforcement learning and feedback systems even in the future. It is important in mobility in cities, just-in-time delivery and emergency management. Nevertheless, AI should also be implemented in a sustainable manner, and this means that policy frameworks and standards need to be identified to safeguard its ethical utilization, data confidentiality, and interoperability within systems. The governments and regulators are advised to offer aid to sustainable AI projects by creating legislation and incentives. As much as this has occurred, research gaps still exist particularly in aspects of AI fairness, explainability, and coupling with the pursuit of green goals. Academia and industry must work collaboratively to fill & treat those gaps, promote innovation, and make sure that intelligent and scaleable AI tools become ethical, environmentally sound.

6.0 Conclusion

This review surveyed on the application of Artificial intelligence (AI) in Decision Support System (DSS) to make transportation and supply chains more sustainable in management. The results demonstrate that it is quite possible to out-compete the traditional DSS with by more or less AI-augmented ones as they have the potential to process data in real-time, conduct predictive analytics, have an adaptive learning capacity, and make autonomous decisions, which is beneficial in terms of emissions, logistics structure, and demand prediction, and resource optimization. Machine learning, natural language processing and reinforcement learning are some of the technologies enabling such systems to tackle dynamic challenges in the areas of smart logistics, inventory management and carbon footprint reduction. The effectiveness and benefits of their application are proved in real practice by such companies as DHL, Amazon, Unilever, and others. Nevertheless, obstacles to adoption of this type of AI include issues such as data privacy and algorithm transparency, seamless compatibility with existing systems, and more. Ethics and the absence of unified models of sustainable AI are also of an upmost concern. Much should be done by policymakers, researchers, and industry stakeholders to optimize the opportunities of AI-augmented DSS. This partnership will make sure that these smart systems are deployed ethically, safe and in an effective way towards achieving resilient and environmentally sound transportation and supply chains.

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Declaration

Consent for publication

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Availability of data

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Not applicale

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Authors' Contributions

Samuel Omefe conceptualized and directed the study. Simbiat Atinuke Lawal gathered literature and case studies. Sakiru Folarin Bello analyzed AI algorithms. Itunu Taiwo examined strategic and ethical aspects. Kevin Nnaemeka Ifiora addressed technical integration. All authors contributed to writing, reviewing, and finalizing the manuscript on AI-enhanced DSS for sustainable transportation and supply chains.