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Article

Ethics of AI-based supply chain optimization: a better balance between efficiency and fairness

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ABSTRACT

This study examines the ethical issues related to AI-driven supply chain optimization, such as algorithmic biases, the effects of automation on employment, and accountability and transparency. Given the goal of increasing efficiency, machine learning, predictive analytics, natural language processing, and artificial intelligence (AI) are being actively used in a variety of industries, including retail, healthcare, and logistics. Also, technologies are automating and improving tasks such as inventory tracking and demand forecasting. This lowers cost and increases supply chain flexibility. However, using them raises significant ethical problems, specifically the issue of making fair choices. With the presence of bias in the trained systems, there will be unfair distribution of resources and the conditions that define the consequences of decisions, such as the introduction of high-value goods over fundamental needs, and in this case, the population needs it most. Another important issue is job loss, especially in low-skilled jobs, as automation becomes the norm in the logistics industry. The study suggests that AI systems should adopt ethical principles, such as fairness, transparency, and accountability. It suggests practical steps that businesses should take to employ AI in ways that ensure everyone gets fair results. The study continues by emphasizing the need to be aware of ethical issues to use AI to improve efficiency while also promoting fairness and sustainability in global supply chain management.

1. Introduction

The global artificial intelligence (AI) market for supply chain optimization is predicted to reach 18.2 billion by 2027, underscoring the importance of AI technologies in revolutionizing supply chain processes. AI-based technologies, such as machine learning (ML), predictive analytics, and natural language processing (NLP), are increasingly being applied across companies to enhance efficiency in industries such as retail, healthcare, and logistics. One example is machine learning algorithms, which can perform predictive demand forecasting by analysing large amounts of historical data to identify future trends, thereby improving stock management. AI in the logistics industry optimizes route planning and delivery schedules, reduces fuel and delivery time costs, and enhances operational efficiency. Equally, AI systems such as real-time data analytics and demand sensing have changed supply chains in the health care sector, ensuring the delivery of necessary medical supplies is accurate and balanced. The uses of AI in supply chains are not limited to efficiency and cost reduction, as AI is now at the centre of strategic decision-making within companies. The switch to AI-driven systems is necessary to be responsive and resilient in the fast-changing global market. Companies could be applying AI to streamline processes, reduce waste, and improve resource allocation, making their supply chains more resilient to changes such as natural disasters, economic shifts, or volatile demand surges. The effect of AI on the key processes of supply chain management will only increase with the rate at which the technology is relied on. Despite the obvious positive effect of using AI to optimize supply chains, there are more than just ethical concerns about its application. The issue of bias in algorithms is one of the most urgent threats because AI systems make decisions based on information that can be shaped by existing societal biases. Research shows that a third of companies face challenges related to prejudiced AI decision-making. For example, AI systems used in hiring or credit assessment have been observed to discriminate against certain groups of

people, thereby producing unreasonable and inequitable outcomes. The biases in AI-based decision-making can take a wide range of forms in supply chains, including biased resource distribution and unequal service delivery, particularly in industries that serve diverse population groups, such as health care and retail. The other major related issue is the influence of automation on employment. The Oxford Economics study predicts that they will have completely automated the number of jobs in the logistics sector within the next 20 years. Despite the potential effectiveness of automation, people who the technology will displace, especially low-skilled workers, raise ethical concerns about job security, social fairness, and the future of the working population. These problems highlight the necessity of conducting an in-depth examination of the social consequences of introducing AI in supply chains, especially in light of the rising trend toward automation.

Since the introduction of AI as a key component of the supply chains, it is necessary to ensure such systems are reasonable, transparent, and responsible. The issue of moral AI models cannot be overstated, and they help address problems such as discrimination and irresponsibility. In a study conducted by MIT, 80 percent of AI experts believed that AI systems needed to be trained in ethical concepts to make them more acceptable and unbiased. The other fact is also significant because ethical AI systems will help protect fairness and raise the level of trust that people and stakeholders have in AI technologies. There is no ethical restriction that will prevent the reproduction of inequalities by the AI systems, and results will be achieved that will Favor certain categories of people more than others. AI systems that have not been ethically conceived can also lead to institutional discrimination, especially when they are trained on biased and unrepresentative data. For example, biased inventory management systems are why important goods become scarce in underserved communities. Discriminatory demand forecasting models can also be favourable to high-value customers and unfavourable to lower-income regions. Such concerns underscore the importance of creating AI systems that are fair, clear, and responsible, which is beyond measure.

This research aims to discuss the ethics of supply chain optimization using AI and to calculate the impact of integrating ethical AI systems on equity and risk reduction. It focuses on the debate of the trade-offs between effectiveness and equity in AI-founded systems. The study assesses the possibility of applying the ethical standards that include fairness, transparency, and accountability to AI systems, and the objective is to ensure that the moral standards advocate the even distribution of benefits to all stakeholders. The research also includes effective recommendations that businesses can implement to adopt ethical AI systems that comply with industry norms and regulations. The research equips organizations intending to implement AI in a responsible and sustainable manner with practical knowledge by analysing the ethical issues posed by AI implementation in supply chains. The size of the study also applies to sectors such as healthcare, logistics, and retail, where AI can be leveraged to achieve substantial efficiency gains, though other areas of particular ethical concern exist.

This study is organized into different chapters. It starts with a thorough literature review of existing research on the application of AI in supply chains and its ethical implications. The research methods describe the type of research design and clarify the methods used to analyse the effectiveness of ethical AI frameworks. This article presents case studies of real-world applications and highlights both the benefits and the pitfalls of applying ethical AI in practice. The experiments and results chapter will evaluate AI systems in the context of supply chain management and discuss the key results. The study also provides recommendations on how to conduct research and review best-practice recommendations for utilizing ethical AI in supply chains. The chapters build on one another to give us a detailed view of the topic, a theoretical explanation, and a solution to the issue.

1.1 Conceptual framework that connects AI algorithms, operational efficiency, fairness challenges, and ethical governance

This work proposes a conceptual framework that combines AI algorithms, operational efficiency, bias mitigation, and ethical regulation into a single closed-loop decision-making process. It aims at linking technical optimization to ethical implications. In this context, AI-based system models, such as machine learning-based demand forecasting and reinforcement learning-based allocation and optimization solvers, will be used to develop alternatives for decision-making regarding inventory, routing, delivery points, and distribution. Within the framework, AI models such as ML-based demand forecasting, RL-based allocation, and optimization solvers will create candidates for decisions like inventory, routing/delivery points, and distributions. To ensure performance improves and the supply chain becomes more flexible, these decisions are compared against operational efficiency KPIs such as cost reduction, fulfilment rate, time to delivery, utilization, and stockout rate. However, since efficiency-only goals have the undesirable consequence of prioritizing high-margin locations over underserved locations (e.g. prioritizing busy highways over rural routes), the framework must ensure fairness as a design feature rather than as a secondary issue.

A measure of fairness can be achieved through embedded constraints and multi-objective optimization: ensuring that equity measures (service parity, geographic accessibility, shortage-risk distribution) are directly incorporated into the objective function or used as constraints guarantees that optimized solutions are effective and non-discriminative. The framework is imposed by an ethical governance layer (human-in-the-loop review of important cases, e.g. shortages or medical supply prioritization), policy thresholds that define what the respective efficiency-fairness trade-offs should maintain, an audit log to support accountability, and periodic drift-detecting audit to ensure drift over time. The results of governance are fed back as constraint weights and model parameters, enabling continuous improvement without loss of responsibility or transparency.

As shown in Figure 1, AI optimization algorithms, including machine learning, reinforcement learning, and natural language processing, are used to analyze supply-chain data, which is then converted into important operational decisions such as allocation, routing, and pricing. Such decisions are intended to enhance operational efficiency by minimizing costs and lead times and augmenting forecasting accuracy. The ethical governance mechanisms that inform the decision process include audits, explainable artificial intelligence (XAI), oversight, and fairness constraints, which help ensure the process is equitable and not biased by an algorithm. Lastly, continuous monitoring and feedback assess the system's performance and provide insights to the optimization process, facilitating responsible and adaptive AI-driven decision-making.

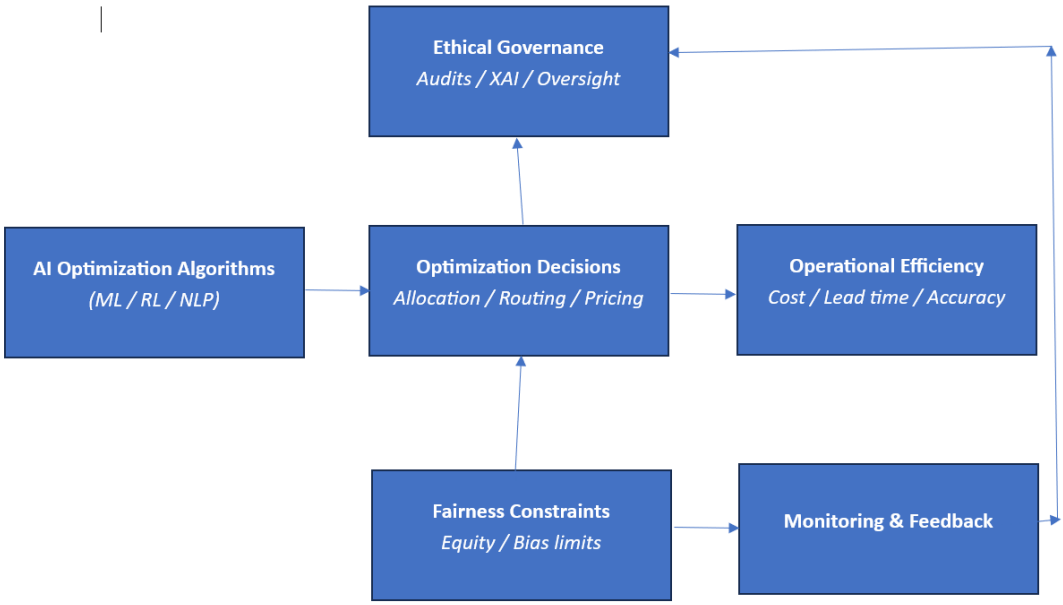

Figure 1. An ethical artificial intelligence-based optimization framework of supply chain decision-making

2. Literature review

2.1 Artificial intelligence technologies in supply chains

Artificial intelligence has transformed the way companies manage their inventory operations, demand planning, and supply chain logistics. Retailers that have adopted AI technologies have simplified their supply chains, as reported by approximately 60 percent of retailers [1]. Among the applications are demand forecasting and real-time inventory management, which generate immaterial gains in operational efficiency. The monetary gains from AI-based demand predictions will help businesses plan demand more accurately, avoid stock-outs and overstocks, reduce expenses, and manage inventory more efficiently. AI can also help retailers adopt a flexible pricing model developed in real time based on dynamic demand and competitive dynamics.

Figure 2 presents key AI deployments in supply chain and logistics, focusing on demand forecasting, inventory management, route planning, warehouse management, supplier management, and quality management, among others. They are AI processes and have changed how retailers conduct their business. Retailers will streamline their supply chains by implementing AI technologies, which will later lead to enhanced operational performance. AI-based demand forecasting strengthens the planning process by reducing the probability of stockouts and overstocks, optimizing inventory, and decreasing costs. Moreover, flexible pricing programs, aided by AI, dynamically adapt to shifts in demand and market competition, enabling companies to track competitors and become more efficient across most of the supply chain. These trends underscore the disruptive aspect of AI on supply chain management and logistics.

Significant examples of AI use in supply chain optimization include reinforcement learning (RL) and deep neural networks (DNNs). The dynamic decision-making process is governed by RL, enabling the AI system to adapt to other situations, such as interruptions caused by changes in demand or supply. An RL algorithm can be applied in logistics to construct an optimal delivery route in real time, reducing transportation costs and improving delivery time. Deep neural networks (DNNs) are used to predict product demand using large datasets. Based on these data points, DNNs can enhance the accuracy of demand predictions and refill operations, ultimately reducing costs and improving order fulfillment. These AI technologies are not only transforming the supply chain to be more efficient but also providing businesses with the flexibility to respond rapidly to market conditions and shocks.

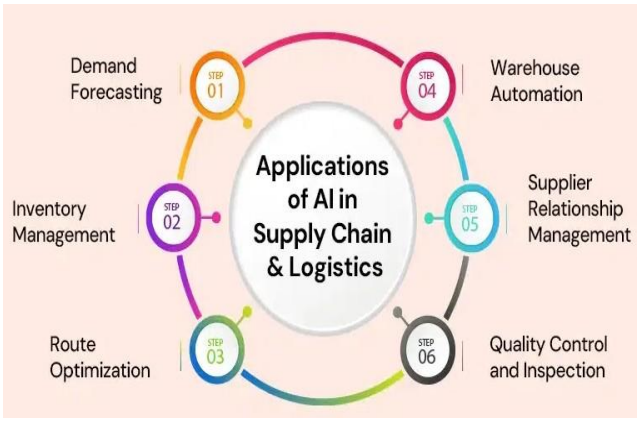

Figure 2. AI tools are used for optimizing inventory, demand forecasting, and logistics in the supply chains

2.2 Ethical concerns in artificial intelligence

Although AI implementation in supply chains has yielded positive results in terms of efficiency issues, ethical issues regarding its application cannot be neglected. Algorithmic bias is one of the key issues, where AI systems make decisions that disproportionately affect a specific group of people, usually because of biased training data. In a study on facial recognition technology, it was found that 5-10% of facial recognition systems exhibit biased results, especially when analyzing minority groups [2]. The problem is also of particular concern to supply chains, where discriminatory

algorithms may lead to unequal resource allocation or inaccurate demand forecasting, either by selectively targeting a specific group of people or a specific community.

The AI effects on jobs have also caused ethical issues. Since logistics is also largely automated by AI-based systems, this will eliminate many jobs. According to the researchers, 16 million logistics roles worldwide might be automated by 2040, and this may lead to social inequalities and the disruption of the economy of the regions that mostly rely on manual labor [3]. Even though AI has the potential to drive cost savings and efficiency, the ethical dilemma is ensuring that all people laid off due to automation are retrained or given other work. Hence, the intersectional aspects of the ethical use of AI need to take into account not only technological achievements but also the social consequences of novel technologies, especially regarding job displacement and algorithmic bias.

2.3 Frameworks for ethical AI

Multiple concepts and frameworks have been proposed to address ethical problems related to AI. The most popular models, including the IEEE and European Union models, also cover aspects of AI systems such as accountability, fairness, and transparency. The principles play a crucial role in ensuring AI technologies benefit all parties equally. The proposal of AI ethics, as stated by the EU, suggests that the algorithms must be readable and controllable to prevent unfair answers and maintain the overall view of the population regarding AI systems [4]. Fairness measures form an important aspect of ethical AI, whereby the AI systems are designed to make decisions that fairly benefit all populations. As an illustration, Google has conducted studies in which 8 out of 10 fairness audit findings indicated that 10-20 percent of algorithm-related bias was minimized after alterations to AI models. Equal opportunity and demographic parity are measures of fairness in sharing judgments among groups, ensuring that no group disproportionately suffers. These structures are important for minimizing biases in AI-aided decision-making in the allocation of demands, resource allocation, and the release of recruitments within supply chains.

2.4 Ethical AI implementation problems and constraints

While the adoption of ethical AI frameworks is necessary, most organizations face major challenges in implementing them effectively. Study indicates that 40% of organizations say that they do not understand how to make ethical AI systems come to practice [5]. This knowledge gap is usually due to the fact that AI models are quite complex, and it is difficult to evaluate and correct bias in large datasets. AI systems within supply chains, such as the examples above, must be continuously monitored and adjusted to ensure they do not act unethically. In the absence of adequate knowledge of these intricacies, organizations will not be able to reduce biases, resulting in unintended repercussions in decision-making. Figure 3 illustrates major issues organizations face in applying AI in the supply chain. Such obstacles include the high cost of training AI systems and the specialized skills required for deployment. The cost of operations is also an issue, since AI systems are expensive to run and require resources for maintenance and updates. AI models are usually complex systems, and it is challenging to control and modify them to account for ethical considerations. Another problem is scalability, as AI systems will need to be flexible to meet the demands of increased data and operational requirements. It is also essential to ensure data quality and availability, as poor data can lead to biased or even ineffective AI decision-making.

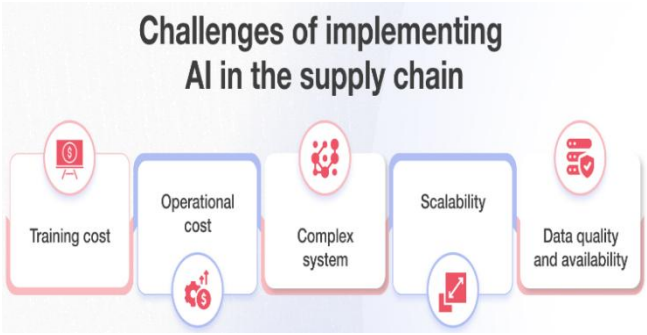

Figure 3. An overview of challenges in implementing ethical AI

Another critical limitation in the application of ethical AI is the technical challenge of training AI models on diverse, representative datasets. Data in the supply chain in most real-world settings can be incomplete, outdated, or biased, leading to AI models that exacerbate existing inequality. The absence of fairness-conscious learning methods, including debiasing algorithms, may prevent the application of AI in supply chain scenarios on equal terms. Since AI systems tend to be trained on historic data, they may enforce and not rectify past biases and therefore aggravate biases like discrimination or unequal distribution of resources [6]. To ensure ethical use of AI systems, it is important to address these technical shortcomings. For example, in the study [7], the authors failed to provide an overall measure of fairness, but they showed a substantial quantitative reduction in inequity. The positive prediction rate in the comparison between the protected and unprotected groups was reduced from 20-40% to 5-10% with an adversarial debiasing experience on the Adult and COMPAS benchmark datasets, but accuracy did not decrease significantly. which, at times, requires massive research and development investments to develop strong learning approaches that consider fairness.

2.5 Limitations and gaps of the existing literature

Although much work has examined the ethical aspects of AI in the supply chain, the existing literature still has limitations and gaps. A substantial part of the research is dedicated to general ethical frameworks and offers no specific, practical guidance for implementing them in the concrete context of supply chain management. Additional research is needed on the pitfalls of AI implementation in sectors such as retail, healthcare, and logistics, where the impact of biased algorithms can be far-reaching. The current body of literature pays little attention to the intersection of ethical AI and human control in supply chain management. Although AI systems are significant for optimization, the role of human judgment in promoting fairness and accountability has not been well researched. The next step to address the issue of AI system development is to research how to incorporate human supervision without compromising the effectiveness and speed of automation. Several other studies also do not examine the long-term effects of the widespread adoption of AI on society, including the economic impact of job losses and the potential for greater workforce inequality. The additional implications of AI are still developing, and it is necessary for researchers to explore them and for policy and business executives to act on them [7].

Table 1 indicates significant gaps in current research on AI in supply chains, including a lack of attention to ethical responsibility, equity, transparency, and societal impacts in AI-based decision-making processes. Such gaps indicate that research frameworks combining ethical governance, bias mitigation, and responsible AI practices should be incorporated into supply chain optimization.

Table 1. Gaps in the literature review

Literature	Research Gaps
Oosthuizen et al. 2021 [1]	Makes no judgment as to whether AI-driven pricing, inventory, or customization is affecting customer groups or geographic regions.
Chadha, 2025 [2]	Mentioning AI decision safety and accuracy without any responsibility stated on the cases of wrong decisions taken by AI.
Nyati, 2018 [3]	Disregards ethical issues such as employee monitoring and privacy.
Tsamados et al. 2022 [4]	Never has shown how fairness and transparency can be operationalized in actual supply chain decision systems.
Bonthu & Goel 2025 [5]	Fails to consider the unsuitability of AI selection of supplier as detrimental to small or developing-region suppliers.

3. Methods and techniques

3.1 AI algorithms in supply chain optimization

The implementation of AI in supply chain optimization relies on a number of robust algorithms capable of handling complex operations, such as order delivery, inventory management, and demand forecasting. Demand was estimated using a Random Forest model (maximum depth = 12, minimum split size = 5) that had 200 trees. This model follows group-based retail forecasting methods, which balance the trade-off between overfitting and management. Inventory prediction was performed with a Gradient Boosting model (300 estimators, learning rate 0.05, maximum depth 6), configurations that are frequently employed when the relationship between demand and costs is nonlinear. The sequential operational decision-making was selected using a Reinforcement Learning technique, specifically the Deep Q-Network (DQN) framework. The state space entailed inventory level, predicted demand, supplier lead time, backlog quantity, and transportation cost, whereas the action space entailed order quantity adjustment, supplier selection, safety stock modification, and selection of delivery route. The reward functions maximize service level and minimize holding costs, stockout penalties, and transportation costs. To facilitate understanding of the concept, the pseudocode blocks in the Appendix summarize how each method is used in practice.

Some of the best algorithms include random forests (RF), Gradient Boosting Machines (GBM), and reinforcement learning (RL). Random Forests and Gradient Boosting Machines are highly useful in predictive analytics and categorization, as they can handle large datasets and non-linear correlations between variables. The algorithms have also been useful in demand forecasting, enabling programs to predict future product demand using past sales records, consumer patterns, and economic conditions.

Reinforcement learning (RL) has recently emerged as an attractive method for optimizing sequential decision-making in supply chain systems operating under uncertain, dynamic demand conditions. Unlike traditional optimization or forecasting models, RL agents provide adaptive learning policies for non-stationary environments by interacting with the environment and receiving rewards and penalties as feedback. The RL has been shown to be more efficient than traditional base-stock and heuristic policies in inventory management problems by minimizing long-term operational costs rather than single-period prediction errors [8]. For example, with fixed multi-period horizons of approximately 1,000-10,000 demand steps, experiments using Deep-Q-Network-based warehouse replenishment reduced the combined holding and shortage costs by 21-30 percent compared to conventional planning approaches [9]. Similarly, compared with conventional statistical demand-forecasting techniques, RL-based demand forecasting and replenishment decisions, evaluated using multi-year retail data, performed worse in terms of Mean Absolute Percentage Error (MAPE) and improved fill-rate characteristics [10]. These results indicate that RL can dynamically adjust delivery options and quantities in real time to reduce stock-outs and improve operational performance and responsiveness. Such adaptive policy skills are associated with the broader digital revolution in the supply chain, and profitability is increasingly tied to continuous real-time policy optimization rather than immediate planning models.

3.2 Data collection and analysis

AI-based optimization of supply chains depends on the quality and variety of data used to train its machine learning models. It uses large amounts of data, including transactions, customer behavior, and supply-and-demand data. The sales and inventory details tracked in the transaction logs provide insight into product movement and sales rate [11]. Data on customer behavior, such as browsing and purchase behavior, and customer feedback, can also be leveraged to make requirement forecasting more precise by providing more detail on consumer preferences. The information needed to optimize supply chain activities is demand-supply figures that track inventory levels, supplier performance, and demand trends.

Walmart's sales forecasting platform is one of the most successful uses of AI. The company developed an AI system that correlated real-time transaction statistics with demand, and it has been capable of making sales predictions with high accuracy, at 90 percent [12]. This level of accuracy can enable Walmart to optimize stock levels so that stock wastage is minimal and customers' needs are met without extra supplies, which would incur unexplained storage costs.

Table 2 shows the key categories of data used in AI supply chain solutions. Proper predictions rely on high-quality, reliable, and complete data; thus, AI can revert to inaccurate demand and inventory selection. The completeness and representativeness of data are the key elements of AI-based supply chain optimization. An incomplete or biased history can compromise forecasting accuracy and introduce allocation bias, driven by unreliable data on demand patterns in rural areas or by abnormal stockout events. As a result, mitigation methods must be used prior to model training. Statistical imputation of incomplete demand data may be obtained by either deriving with mean/median replacement statistical imputation, KNN statistical imputation, or time-series statistical imputation. These methods are computationally efficient yet can

minimize sensitivity to extreme events and regularize volatility. SMOTE (Synthetic Minority Oversampling Technique) can increase classification recall by generating synthetic samples from minority observations to counteract class imbalance (e.g., rare disruptions or stockouts). Nonetheless, SMOTE does not preserve complex temporal relations but presupposes linear ones.

Table 2. The major Data types and challenges of AI-based supply chain optimization

Data Type	Description	Example	Challenges
Transaction Data	Sales and inventory records provide information about product flow and sales.	Real-Time transaction data Sales prediction system at Walmart.	This will lead to inaccurate predictions due to incomplete or biased data.
Customer Behavior Data	Browsing history, buying history, and customer reviews.	Gives information to use in forecasting demand as per consumer preferences.	Information should not be biased to make distorted demand forecasts.
Demand-Supply Data	Keeps track of inventory, supplier performance, and demand trends.	The AI models follow inventory to make demand predictions and streamline the supply chain.	The lack of data integrity or incomplete data might result in wasted resources.
Data Quality and Integrity	Gives correct estimates with the help of high-quality and representative data.	Critical to the AI models to predict demand.	The process of data collection must be extensive and objective

Sophisticated methods generate natural synthetic demand or disruption conditions using Generative Adversarial Networks (GANs). GANs can be used to stress-test RF, GBM, and RL models in unusual yet high-impact scenarios, as they are better suited to nonlinear and multidimensional interactions. GAN-based supplementation, which is computationally resource-intensive, is more resilient and fairer than more simplistic methods of oversampling. Imputation, imbalance correction, and synthetic data generation are beneficial for AI-based supply chain optimization, enabling better generalization, reduced bias propagation, and improved model stability.

3.3 Techniques for detecting algorithms' fairness and bias

There has been considerable speculation about the ethical concerns related to bias and fairness at the outset of applying AI to optimize supply chains. To ensure that AI systems make unbiased decisions, several bias detection methods have been developed. Fairness through Unawareness is an approach in which algorithms are designed to make decisions regardless of sensitive factors such as race, gender, or socioeconomic status. Although this method might be effective in reducing some bias, it might not account for the correlations necessary to achieve equity in some situations. Adversarial Debiasing is a more sophisticated method. To assess the influence of protected characteristics on the first model's predictions, a second model is trained. The first model is adjusted to reduce bias if the second model identifies it as such. For example, the study by Zhang et al. [13] found that adversarial debiasing substantially reduced bias in decision-making models while preserving nearly the same prediction accuracy. This shows that there are methods to minimize bias in AI systems without incurring severe performance consequences.

In addition to these approaches, statistical measures of fairness are used to compare the fairness of AI systems' work. Two widely applied aspects of supply chains, statistical parity and disparate impact, are used to determine whether an algorithm will make discriminatory decisions based on group membership. Bias measurements were determined using statistical parity and disparate impact to formalize count fairness. Let A denote a protected group (e.g., region category) and $\hat{Y} = 1$ represent a favorable outcome, such as resource allocation or product stock. The statistical parity difference was defined as $SPD = P(\hat{Y} = 1 \mid A = 1) - P(\hat{Y} = 1 \mid A = 0)$, where values close to zero indicate fair treatment. The disparate impact ratio was defined as $DIR = \frac{P(\hat{Y}=1|A=1)}{P(\hat{Y}=1|A=0)}$. Under the standard fairness principles, fairness was accepted when the ratio met the 80% rule ($0.8 \leq$ DIR ≤ 1.25). The example experiment used a debiased AI model with a DIR of 0.92 and an SPD of approximately zero, whereas the traditional rule-based system had a DIR of 0.71 and disproportionately allocated high-demand zones. Such measures will have been critical in providing a degree of assurance that AI models are being constructed in a non-willing fashion, such as a lack of centralization in the distribution of inequality or discriminatory demand prediction.

3.4 Assessment standards of AI systems

Key Performance Indicators (KPIs) should focus on balancing the performance of operations with fairness because they need to evaluate the effectiveness and fairness of AI models used in the optimization of supply chains. Cost savings, reduced processing time, order fulfillment accuracy, and inventory optimization are effective KPIs for evaluating the AI system's success in improving logistics operations. An example is the AI-controlled healthcare logistics system, which has demonstrated 15% greater operational efficiency and faster delivery [14]. Nevertheless, relying on efficiency indicators as the sole measure of performance is dangerous, as it masks differences in outcomes across areas or demographic groups.

To further operationalize fairness, fairness-related KPIs need to be included in the assessment framework. Equal Opportunity Difference (EOD) and Disparate Impact Ratio (DIR) measures are used to assess the extent to which AI-supported decisions, such as resource allocation, supplier selection, or distribution priorities, are distributed across a demographic or geographic region. As an illustration, EOD would ensure that qualified parties across all groups have an equal opportunity to benefit from AI-based decisions, whereas DIR would determine whether underprivileged regions have equitable access to medical supplies. The concept of fairness must be embedded in the very concept of optimization, not merely an audited factor.

This can be achieved through AI systems that simultaneously optimize efficiency and fairness within a multi-objective framework. This strategy has two goal functions: one is the maximization of operational performance (such as cost reduction), and the other is the minimization of discrepancy (such as SPD reduction or maintenance of DIR at a specified level). The resulting solutions can be analyzed using Pareto front analysis, which identifies the best trade-offs when efficiency gains do not substantially reduce fairness. Alternatively, to ensure that efficiency gains are achieved without violating equity standards, it may be possible to directly incorporate fairness constraints (e.g. DIR ≥ 9.85) into the optimization model.

Transparency is an important element of evaluation in this paradigm. With explainable AI tools and audit processes, decision-makers can understand how predictions are made and ensure that fairness requirements are met. To make fairness a measurable and implementable design specification in AI-assisted supply chain systems, organizations quantify fairness by incorporating it into optimization formulations and systematically evaluating the trade-offs. This combined assessment system provides fair and accurate outcomes, as well as performance benefits.

4. Ethics of AI in practice case study and application

The case studies in this section rely on secondary data from published industry reports, academic research, and official technical documentation, rather than the primary organizational exploration by the authors themselves. Contextual explanations of the ethical consequences of AI implementation in supply chains are provided using real-life examples from Pfizer, Amazon, the Cleveland Clinic, and Walmart. The performance measures, such as cost reduction, delivery accuracy, and stockout reduction, were not audited or tested independently, as was done in this research, but were instead reported as indicated in the cited sources. New market applications, including drone-based medical supply distribution systems operated by Zipline in Rwanda and Ghana, and AI-based demand forecasting and inventory optimization projects in Reliance Retail's Indian ecosystem, are also reviewed in this analysis. It is in these ways that AI-driven logistics can enhance the efficiency of final-mile delivery and raise new questions about equitable access for disadvantaged or rural groups. The case studies complement information on ethical trends observed across various industries, as they are used as explanatory and comparative tools rather than for empirical validation.

4.1 AI in MedTech logistics

In the MedTech industry, AI is instrumental in streamlining medical supply chains, ensuring medical products are delivered to their destinations in a timely and efficient manner. It has been demonstrated that AI systems reduce stockouts by up to 40%, which is critical in healthcare facilities, where delays in medical supplies can have a severe impact on patient care. For example, Pfizer adopted an AI-based system that optimized delivery routes, saving the company 15% in costs by creating more efficient approaches to delivering goods and minimizing wasted resources [14]. These performance numbers are not based on independent empirical measurements but rather on interpretive analysis and are derived from published implementations across the industry. Such systems would be less rigid in responding to changes in demand and supply, better able to anticipate demand, and therefore increase supply chain resilience. As shown in Figure 3, AI has been of great importance across various areas of MedTech, including product development, supply chain management, sales, and customer service. AI systems are used in the MedTech logistics industry to streamline operations and minimize stockouts by up to 40%, a key factor in the timely and efficient delivery of patient care. The AI-driven systems that Pfizer has deployed improve demand prediction and resource management, resulting in 15% cost savings. These applications enhance efficiency and increase the resilience of medical supply chains to variations in demand and supply.

Ethical issues also play a crucial role in the application of AI to Med Technologies logistics. The AI algorithms are biased toward high-value items, which are delivered on time, whereas lower-value or less significant items may receive less consideration. Such practice may lead to unfair service provision of healthcare, more so where underprivileged communities are involved, and the resources they need are not necessarily well-known, but can still be relevant to the well-being of their patients [15].

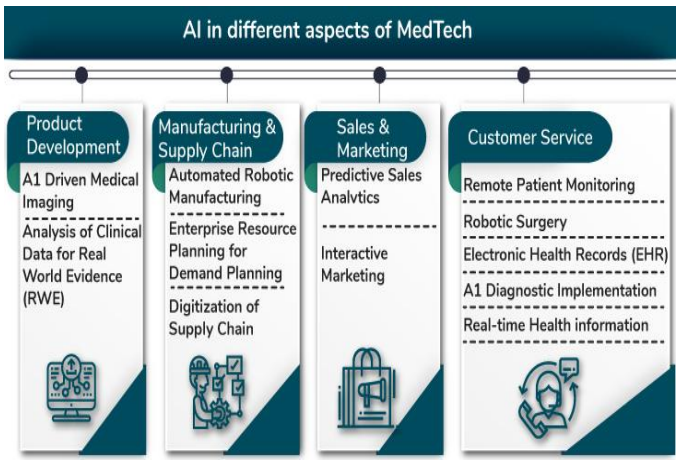

Figure 3. AI in MedTech: Supply chain, product development, and customer service

As an example, AI systems in the possession of major pharmaceutical companies can prioritize large-fit drugs for well-timed urban areas and leave rural or under-invested locations with stockouts of primary resources. Such unfairness shows the importance of ethical concerns in the design and deployment of AI systems in healthcare logistics.

4.2 AI in retail and E-commerce

Artificial intelligence-based retail and e-commerce systems rely on dynamic pricing, inventory optimization, and demand forecasting to make logistics more efficient. Research results indicate that, when adjusted for price elasticity and demand patterns, algorithmic price optimization can increase firms' revenues by an average of 5-10 percent [16,17]. Nevertheless, the study of digital markets and algorithmic pricing also demonstrates that when behavioral or geographic proxies are positively correlated with demographic traits or income, personalized pricing can generate quantifiable outcomes across customer groups [18,19]. The ethical trade-off that models' fairness constraints, e.g. constraining price differences between regions, or that it must be at least a given Disparate Impact Ratio (e.g.≥0.85), can be quantitatively measured using the opposite to analysis to show that it can considerably lower price differences between groups and revenue gains by an

estimated 1-3%. This means that retailers may strike a balance between profitability and ethical obligations in AI-oriented supply chains by incorporating fairness-based constraints into pricing algorithms, thereby minimizing inequity at relatively low economic cost.

4.3 AI in the healthcare supply chain

The field of AI in healthcare is not limited to logistics but also to optimizing resource distribution during critical events, such as pandemics or natural disasters. During the COVID-19 pandemic, the U.S. healthcare system implemented AI to monitor patients' needs and ensure the equitable distribution of healthcare products. AI systems also enabled healthcare providers to make deliveries based on real-time information about patients' conditions, available hospital space, and supply availability. This helped minimize the risk of shortages and ensured that priority was given to the areas where resources were most needed, thereby making the process of providing healthcare in a crisis more efficient.

Ethical issues in AI applications in healthcare supply networks are also quite challenging. Medical supply prioritization may be biased at times due to the setting of medical supply rules and regulations by the AI algorithms, particularly in places with limited access to equitable healthcare facilities [20]. For example, AI systems that prioritize hospitals in more affluent areas may exacerbate health disparities, placing underrepresented groups at a disadvantage. An example is a Cleveland Clinic case study that demonstrates this difficulty. Although an AI algorithm to optimize inventory proved an efficient method, leading to a 12% increase in supply chain efficiency, it was criticized for an apparent imbalance in resource allocation. Hospitals in rich locales received medical supplies much faster than those in poorer locales, which took longer to receive them. This raises a few critical ethical issues regarding the use of AI to promote fairness and equity, especially when a life is at stake, and the healthcare system is involved.

4.4 Lessons learned on real-world applications

The case studies identify the most hazardous ethical pitfalls that are to be avoided at the organizational level during the implementation of AI in the supply chain. Bias, lack of transparency, and lack of responsibility are the most important problems to address.

AI algorithms, particularly those trained on past data, can reinforce existing biases, leading to biased solutions. In the context of healthcare logistics, AI systems will be able to deliver products based on historical trends, thereby meeting the needs of wealthier localities while neglecting poorer ones. In retail, AI-based models used to set prices can unintentionally discriminate against lower-income consumers by charging more, basing their decisions on purchasing behavior or geographic location. Table 3 describes typical ethical issues in AI supply chains, such as bias, lack of transparency, skin-deep accountability, and inadequate monitoring, and proposes best practices, such as fair practices, explainable AI, human supervision, and ongoing monitoring, to ensure responsible use of AI. These problems should be addressed by adopting industry best practices in the industry. Some of the practices to be undertaken include the creation, openness, interpretation, and explanation of AI models.

Transparency ensures that AI decision-making processes can be audited and that stakeholders are aware of the process and its rationale. Bias-sensitive learning mechanisms can also be added that could be utilized in detecting and deterring AI-based prejudices [21]. For example, adversarial debiasing and unawareness-based fairness can be applied to reduce discrimination in predictive models. Having human oversight in the development of critical decisions helps ensure that ethical concerns are considered when implementing AI systems at scale. The real-world monitoring and evaluation of AI systems' performance are crucial for companies that must continually assess them. Real-time tracking will help identify any bias or inefficiency that may arise after deployment or ensure that AI models do not conflict with ethical values over the long term. These best practices enable organizations to employ AI to create a more just, open, and efficient supply chain, mitigate the risk of harm, and distribute the advantages of AI fairly across all stakeholders.

5. Experiments and results

5.1 Experimental methodology and set-up

The entire experiment aimed to compare the performance of traditional supply chain management (SCM) models with AI-based technologies in logistics processes, such as demand forecasting and warehouse automation.

Table 3: Major ethical traps and pitfalls in introducing AI in the supply chain

Ethical Pitfalls	Description	Examples	Best Practices
Bias	AI algorithm, particularly when it is being trained by historical evidence, can be used to strengthen the current biases	Within the field of healthcare logistics, AI can be biased towards an affluent district, disregarding less privileged regions	Enhance bias-sensitive learning, e.g. adversarial debiasing and fairness
Absence of Transparency	The absence of transparency in AI systems may deny the stakeholders the chance to learn decision-making processes.	The use of AI in retail prices can also discriminate against the less affluent unintentionally.	Construct explainable, interpretable and generate clear AI models.
Accountability	The use of AI can also cause unfair outcomes and unintended consequences when there is no accountability	Artificial intelligence applying prejudiced actions in prices, deliveries, or stocks.	Make sure that there is human control over main decision-making and establish systems of accountability.
Monitoring and Evaluation	To identify biases and inefficiencies after the AI systems are deployed, it is necessary to constantly monitor the AI systems	The applications of AI models can develop new biases due to lack of control	Introduce real time monitoring of problems by detecting and rectifying post deployment.

The research was conducted as a pilot study in which several organizations operated in real-world supply-chain environments. The effect of implementing the supply chain optimization solutions was tested A/B on 20 companies that were in the process of implementation. The companies were divided into two groups, namely, Group B (treatment) and Group A (control). Group B implemented AI-based approaches, including machine learning and reinforcement learning models, while Group A continued with their conventional supply chain functions, such as manual forecasting and rule-based inventory management. For a basic comparison, companies were selected based on industry and size, then randomized using selective randomization. The experiment lasted about three months and was divided into an active testing period and a brief observation period. The participating organizations represented the retail, e-commerce, manufacturing, pharmaceutical, and food supply industries and allowed for their assessment under a variety of operational conditions.

The data set used in the study comprised operational transaction records collected during the three-month trial stage and from the previous 12 months. The dataset consisted of several hundred thousand transaction entries with characteristics such as product ID, order quantity, price, inventory level, lead time, seasonality indicators, and customer demand patterns. Before the model was trained, duplicate records were removed, categorical variables were encoded, and numerical values were uniformized. The missing values were handled using mean imputation for numerical attributes and forward-fill for time-series demand data. The data were divided into training and testing subsamples in an 80:20 ratio, so that the people could be split into two parts, ensuring reliable performance analysis.

AI models in the experiment also focused on routing decisions, inventory optimization, and demand forecasting, all of which are crucial to supply chain management. The demand forecast was generated using algorithms such as random forests and gradient boosting machines to predict future product demand by modeling real-time consumer behavior, seasonality patterns, and past sales. As a direct result of the capacity of the AI models to process large amounts of data and detect very complicated patterns that would be difficult to detect using a more manual approach, the demand-related operational cost performance was improved by the AI-based systems by approximately 15-30 per cent compared to traditional approaches [22].

The experiment also focused on automating the warehouses. AI-controlled robots were compared to rule-based and human-controlled automation processes using computer vision and reinforcement learning. The systems were also tested on their capacity to pick and pack orders, as well as on their inventory and warehouse layout features. The results revealed that AI-driven warehouse solutions outperformed traditional automation methods in terms of speed and operational efficiency.

5.2 Results of AI integration in supply chain optimization

The outcomes of implementing AI in supply chain operations were striking in all respects. The AI-based system was found to achieve 20-50% accuracy in order fulfillment, significantly reducing mistakes caused by manual processing and traditional forecasting models. This enhancement was more pronounced in high-demand-variability industries, including the retail sector and e-commerce, where exact inventory levels are paramount to satisfy customer demand. In addition to making the order more accurate, AI systems were found to significantly reduce costs. Warehouse automation, routing optimization, and improved demand prediction cut logistics costs by 15-20%. The possibility of AI predicting surges in demand and modifying inventory management policies ahead of time (preventing either overstocking or understocking), which can result in unnecessary expenses [23]. As shown in Table 4 and Figure 5 below, AI systems in warehouse management could respond to and forecast supply chain disruptions faster than conventional systems, resulting in a 10-18% reduction in labor and transportation costs. Figure 5 shows that customer satisfaction also increased by one-fifth among the firms that implemented AI-based systems. Better inventory management largely fueled this, along with shorter delivery times and fewer stockouts. The test customers were found to be much more satisfied with the timeliness of their deliveries, as AI systems facilitated refined order fulfillment and tracked orders in real time.

Changes were statistically assessed by comparing weekly KPI values across the intervention period (α = 0.05) between Group A (control) and Group B (treatment) using two-sample t-tests (or Mann-Whitney U tests when the conditions of normality were not met). The results were reported using Cohen's d effect sizes, 95% CIs, and p-values. The study's findings showed that the changes were statistically significant and unlikely to have occurred by chance. A statistical analysis of conventional SCM systems and AI-based systems showed that AI achieved significantly higher results than traditional systems across all metrics considered. Although conventional systems were often constrained by past trends and historical data, AI systems use real-time data, making predictions more dynamic and precise. This implied that AI-powered supply chains could respond more quickly to changes in demand and supply, thereby enhancing resilience and reducing operational costs. The results should not be viewed as generally applicable across all operational scenarios, even though the suggested AI-based supply chain optimization showed continuous benefits. Depending on the industry's features, performance varies.

Table 4. The integration of AI in supply chains: improved accuracy, cost cuts, and customer satisfaction

Metric	Typical Improvement Range
Order Fulfillment / Forecast Accuracy	20–50% improvement [24]
Logistics Cost Reduction	15–20% [25]
Inventory Management	20–30% reduction in inventory levels [26]
Customer Satisfaction / Service Levels	Up to ~65% increase [27]

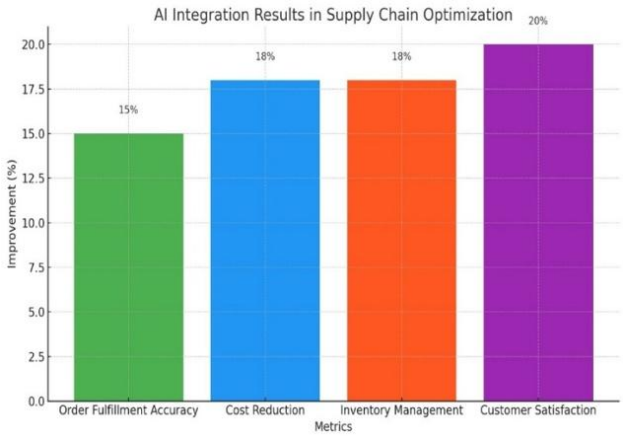

Figure 5. An overview of AI integration results in the supply chain

5.3 Challenges encountered in the experimentation process

Despite the positive outcome, a number of issues arose during the experiments that were fundamental to understanding the applicability of AI in the real world of supply chain management. One of the greatest problems encountered was data consistency. In other regions, particularly more isolated or distant locations, the data input into AI models was not as vast or all-encompassing. AI systems rely heavily on large, homogeneous datasets to make accurate predictions, and regions that lack such data find it challenging to achieve the same level of accuracy as regions with abundant data. For example, AI models in rural areas may be unable to simulate demand trends, resulting in lower efficiency in logistics processes. Such a problem is the issue that less-populated locations are not adequately supplied with data infrastructure to enable AI capabilities to their full extent.

Other methods, such as federated learning and transfer learning, are applicable for minimizing data shortages in low-infrastructure zones or rural areas. Federated learning, whose main idea is to enable multiple supply chain partners to collaborate and jointly train an AI model without sharing raw data, enhances prediction accuracy in distributed networks whilst ensuring anonymity [28,29]. Transfer learning can bridge the performance gap caused by distributional differences by optimizing models trained on large datasets from dense urban areas for sparsely recorded rural areas [30,31]. The strategies are used to increase generalization in regions with limited local data and to help artificial intelligence systems remain useful across diversified supply chains.

The main concern was bias in the algorithms of AI systems. Although the overall outcomes were positive, there was bias in some applications, especially in the resource allocation models. These models showed that AI systems make decisions based on past trends that may be biased towards society. For example, a case study on AI-driven healthcare supply chain logistics systems showed a 5-10% difference across demographic groups. The allocation of resources, including medical supplies, was the area where AI systems primarily served wealthier regions and better-equipped hospitals, which was an unfavorable situation since marginalized communities were disadvantaged [32]. The latter is potentially due to biased training data or the lack of fairness-sensitive learning methods, necessitating continuous monitoring and bias correction of AI systems.

The experiment also indicated that AI systems displayed outstanding performance in large-scale, data-intensive settings but tended to deteriorate when operating on small datasets or in areas characterized by a wide variety of cultural and demographic conditions, as well as economic statuses. This difficulty indicated that AI systems, despite their high effectiveness, should not be regarded as an all-purpose solution. Indigenizing AI to fit local contexts and localities is a critical issue that organizations should consider before adopting AI in global supply chains. The general conclusions indicate that AI can be effectively used in supply chain optimization. The experiment confirmed that AI can make processes more efficient, cheaper, and more likely to boost customer satisfaction. It also stressed the need to consider issues such as data consistency and algorithmic fairness to ensure that AI systems can be adopted equitably across markets and contexts.

6. Discussion

6.1 Balancing efficiency and fairness

The rapid uptake of AI-driven automation in supply chains, enabled by predictive analytics, real-time information processing, and resource distribution, has significantly enhanced operational responsiveness. Understanding the intersection of efficiency gains and justice considerations is more important than merely mentioning efficiency gains. To achieve the highest performance, AI systems place a greater priority on high-value, high-demand segments, disproportionately prioritizing them based on wealth or data density. This results in a systemic conflict between maintaining equal distributions and increasing efficiency, particularly in underserved or impoverished localities.

Supply chain optimization ought to be conceptualized using the efficiency-fairness frontier framework. This method compares decisions made by AI using two equally important aims: distributive fairness (e.g. equitable distribution within regions or between demographic groups) and operational efficiency (e.g. minimizing costs, maximizing service level). Solutions can then be studied in terms of Pareto-optimal trade-offs and evaluated in terms of potential effects on equity vs. cost or speed, as shown in Figure 6. Adding fairness requirements, such as proportional allocation constraints or minimum service requirements for neglected areas, transforms the optimization process from strictly profit-maximizing objectives to ethical design.

Figure 6 demonstrates the connection between equity and AI system efficiency. A reduction in unfair decisions will increase the efficiency loss. That is, organizations must strike a balance between fairness and performance to arrive at an optimal solution. To establish a middle ground between efficiency and fairness, companies are advised to design AI systems evenly to ensure that they not only optimize supply chains but also allocate resources equitably. This makes it necessary to integrate fairness into the decision-making process by incorporating fairness tools that emphasize inclusivity and operational performance. The trade-off between reducing costs and maintaining fairness should also be reconsidered. The advantages of AI for cost-cutting should not be based on marginalized populations [33]. The goal of companies is to develop AI systems that equitably allocate resources across demographics to enhance efficiency throughout the supply chain without exacerbating existing inequalities.

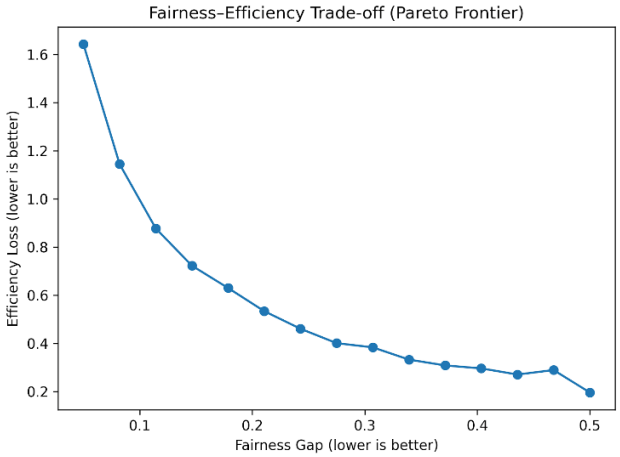

Figure 6. Pareto trade-off diagram (fairness vs efficiency)

6.2 Impact of ethical AI on workforce employment

The adoption of AI in supply chain processes brings many transformations to the workforce. According to the World Economic Forum's Future of Jobs (2025) report, more than half of businesses predict job cuts due to AI's ability to automate work, particularly manual and routine tasks. Conversely, by 2030, technology is expected to create approximately 170 million new jobs worldwide in data, analytics, and human-AI collaboration, with an estimated 92 million jobs lost, resulting in a net gain of 78 million jobs over the decade. Although automation can significantly improve efficiency and reduce costs, there is also an ethical issue concerning job displacement and its social implications. Migration of the labor force, especially low-skilled workers, may lead to even greater economic inequality and unemployment in some areas.

The application of AI tactics that prioritize ethics is essential in eliminating the issue. The critical aspect in implementing these strategies is ensuring that employees are kept in check so they can be relocated to new areas of the evolving supply chain. It has been estimated that half of logistics employees will be forced to change jobs due to automation, implying that reskilling programs will be part of AI adoption strategies. To be competitive in the labor market, companies will be forced to invest in training that equips workers with the skills they will use to work alongside AI systems [34]. It is also possible to use AI to help organizations create employment not only by streamlining their logistics but also by creating opportunities in areas such as data analytics, building AI models, and fixing their systems, rather than automating most jobs. The social effects of AI on the working population should be mentioned. The ethical practices of AI should be designed to mitigate the negative impacts of automation and maximize AI's potential for businesses and laborers. This will ensure that AI implementation is used to bring positive change to the workforce rather than being a disruptive factor.

6.3 The accountability and transparency in AI

The foundation for building trust in AI systems is accountability and transparency; in particular, in the domain of supply chain management, the results of decisions directly impact many stakeholders. It has become known that 80 percent of consumers are more assured by a company with clearly established AI systems, indicating that such systems should be discussed clearly and understandably. Transparency may be interpreted as the ability to make AI models and decision-making processes visible to end users and stakeholders. It may be deployed with the support of Explainable AI (XAI) frameworks, enabling the company to explain why AI systems operate in particular ways and to understand how specific decisions are made. Transparent AI can also help alleviate the biases that accompany black-box algorithms by instilling confidence and reducing fear of collaborating with AI. When AI processes are made more visible, companies can more quickly identify potential bias in models used for supply chain decisions, such as inventory allocation or demand prediction. In addition, transparency can increase accountability in decision-making, as AI systems will operate in compliance with ethical standards and regulations. Integrating responsibility into AI systems would mean businesses have systems to audit AI decisions. This allows the AI system's output to align with corporate culture, laws, and interests. Periodic audits and feedback loops, which include human participation, can help identify opportunities to optimize AI models and eliminate biased or unfair decisions that could affect customers or employees. Figure 7 presents the most crucial aspects of the Transparency Framework in AI. This model emphasizes that transparency is necessary in AI systems to instill confidence and responsibility, particularly in domains such as supply chains. The Dynamic Transparency Model can be designed as three layers, having a Data Transparency Layer that would implement bias checks and transparency in the input data, a Model Explainability Layer that would decode the allocation and routing and use XAI tools such as SHAP and LIME, and a Decision Governance Layer that will allow human oversight of fairness thresholds.

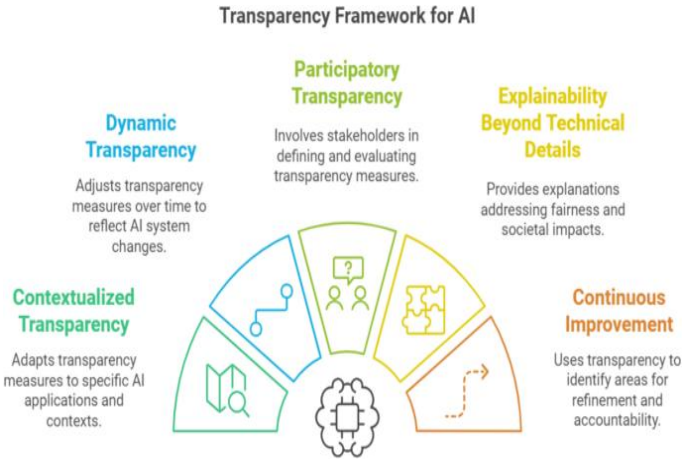

Figure 7. An overview of key elements of AI transparency

Transparency is not added to the report after deployment, as in this layered approach. Supply chain AI is therefore operationally sound, equitable, and audit-friendly. Dynamic Transparency will evolve over time as AI systems develop, whereas Participatory Transparency will involve stakeholders in determining the transparency effort [35]. Justification outside the Internalities will be fair, and the implications for society will be discussed. Contextualized Transparency can make transparency application-specific for AI apps, and Continuous Improvement enables regular audits and self-feedback to improve, hold oneself accountable, and overcome biases in decision-making.

6.4 Practical difficulties while applying ethical AI

Although the benefits of AI in the supply chain are self-evident, several practical dilemmas complicate the ethical application of AI. One of the most significant concerns is the hindrance of organizations to the introduction of ethical AI models. Research shows that 45% of executives report that implementing ethical AI systems results in significant operational changes and is met with resistance within the organization due to the complexity of AI designs and the opposition these systems may pose to traditional processes [36]. This resistance will have to be overcome by educating the stakeholders about the benefits of ethical AI, including improved decision-making, improved customer relations, and operational efficiencies. Another concern is the lack of cohesive policies on the ethical use of AI. Empirical methods may also be applied, including, but not limited to, XAI and fairness-conscious learning, though their use is more common in some industries and areas than in others. The absence of standards for ethical AI is also evident and might lead to differences in methods, making it difficult to compare AI activity across companies or sectors. The companies should also aim to address those challenges by forming a coalition to establish tough company-specific guidelines to ensure the ethical application of AI in the supply chain. It would not only help balance business goals and moral conduct but also ensure compliance with regulatory norms.

Constant surveillance is also used to ensure that AI systems remain ethical in the long run. The review of AI models must be performed regularly after implementation to assess performance, fairness, and accountability. The monitoring process should involve obtaining feedback from human operators and end users to address any bias or ethical concerns that may arise after implementation [37]. By doing so, organizations will be able to ensure the advancement of AI systems in a way that positively influences all stakeholders and is just and open-minded in the long run. Through traditional implementation of AI development along with ISO/IEC 23894 (AI risk management) and ISO 42001 (AI management systems), companies can exercise concrete governance. Businesses can also implement a Supply Chain AI Ethics Scorecard to track such measurable variables as human oversight rates, explainability coverage (e.g., SHAP adoption), data audit frequency, and fairness metrics (DIR/SPD). These tools can help bring ethical AI from theory to organizational practice by providing auditable benchmarks.

7. Future consideration

7.1 AI breakthroughs in supply chain optimization

The future of AI in supply chain optimization will continue to be delighted with innovation at the frontier, especially in quantum computing. Using quantum mechanics, quantum computing may assist companies in optimizing routes, timetables, and stock levels with much greater precision, enabling more cost-effective resource allocation [38]. AI fairness can also be improved through quantum computing, as it could enable more complex algorithms that consider more variables, thereby eliminating biases in decision-making. An important algorithm is the Quantum Approximate Optimization Algorithm (QAOA), a variational quantum model for solving combinatorial problems commonly known as NP-hard graph optimization problems, including scheduling, vehicle routing, and warehouse allocation. A comparison of QAOA and traditional methods. Restricted to EAs or simulated annealing, quantum-assisted optimization of solution spaces has a higher effective solution space search capacity because objective functions are encoded into a parameterized quantum circuit, which is then solved. Even with the available constraints in noisy-intermediate-scale quantum (NISQ) simulations, D-Wave quantum annealers and IBM quantum processors have achieved better convergence when used for both simulated last-mile delivery and port scheduling tasks. It has also been possible to formulate logistics routing and distribution planning as a Quadratic Unconstrained Binary Optimization (QUBO) problem.

Besides quantum computers, the field of hybrid AI with human-in-the-loop (HITL) systems has the potential to transform decision-making in the supply chain. Hybrid models will focus on integrating AI computational power with human intuition and ensuring that people with experience and context supervise the most important decisions and make moral judgments. For example, where AI can be used to make decisions about inventory or distribution based on large amounts of information, human beings could intervene to alter the AI system's decision in specific situations when it could be prejudiced or unjust. This solution will ensure that automation does not fully replace human judgment but is instead enhanced, making AI-enabled decision-making more ethical and practically valuable [39].

7.2 Ethical artificial intelligence rules and standards

With the continual transformation of supply chain management by AI, it has become increasingly critical to have transparent, standardized ethical regulations for AI in place. European Union governments and the United States are actively developing frameworks to provide a fair and transparent approach to AI systems. The intended purpose of the EU's Artificial Intelligence Act is to establish a unified set of regulations governing AI applications across different fields, including supply chains. In this regulation, it is anticipated that there will be several provisions to ensure that AI systems used in logistics, inventory management, and demand forecasting are fair, transparent, and free of bias [40]. The Interim Measures for the Management of Generative AI Services (2023) and the broader scope of algorithmic regulations in China demonstrate that accountability, security, and transparency are equally important when using AI outside the EU AI Act and new U.S. government guidelines. The same can be said of the other strategies mentioned: China focuses on state surveillance and compliance; the U.S. has sector-specific governance and executive direction; and the EU's approach to regulation is risk-based. It is projected that the timeline for regulatory convergence will demand greater global alignment in risk classification, transparency requirements, and auditing standards for high-impact AI systems, such as supply chain applications, by 2030.

Figure 8 illustrates the key ideas of Ethical AI to consider in future AI development for supply chain management. These values include Fairness, Accountability, Transparency, Privacy, Harm Prevention, and Trust-Building. These principles are important because even the European and United States governments are developing frameworks and regulations to ensure that AI systems in areas such as logistics, inventory management, and demand forecasting are impartial, predictable, and free of prejudice. The aim of these standards is to provide standard and ethical principles for AI implementation across industries.

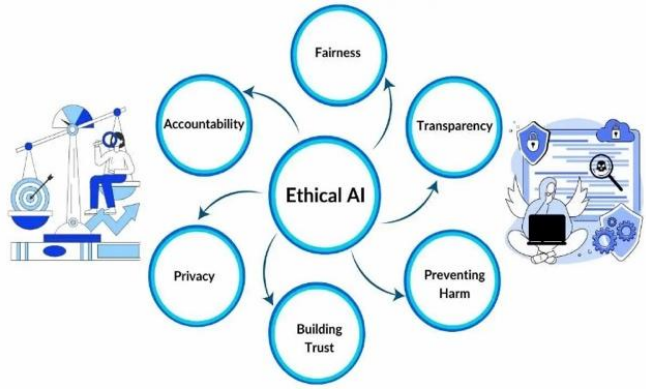

Figure 8. An illustration of key principles of ethical AI

Beyond regulatory policies, there is also a growing demand for an industry-wide certification system for ethical AI. This certification would provide a framework for organizations intending to adopt AI in their supply chains, ensuring that the AI-based systems they introduce meet accepted standards of fairness, accountability, and transparency. Third parties may accredit such systems and provide consumers, regulatory bodies, and firms with a useful guide to whether an AI system is ethically responsible. As AI usage by all parties continues to rise, this certification might be essential for enhancing trust and the accountable use of AI throughout the supply chain industry [41].

7.3 Human oversight in internalizing AI systems

Having human control in AI systems is vital to ensure there is a moral balance between automation and decision-making. The efficiency of AI systems is not matched by the refined knowledge that humans can provide in difficult ethical scenarios. In the logistics sector, AI can prioritize the least expensive routes, which unintentionally exclude rural or low-income localities. Human control will ensure that such unwanted consequences are identified and addressed before they affect the rest of the supply chain [42]. Human-in-the-loop systems also offer the ethical checks needed to ensure they do not perpetuate biases that could harm marginalized communities or exacerbate systemic disparities. In the future, it will be necessary to create hybrid AI systems that blend human intelligence with AI capabilities to promote even-handed decision-making. Such hybrid systems would enable dynamic interaction between humans and AI, whereby the latter will handle routine, data-driven tasks and the former will handle more intricate, value-laden choices. Integration will help organizations create more ethical AI that can navigate the complexities of supply chains while meeting the principles of fairness. Further developments in AI ethics will also include tools that enable both AI and human decision-makers to work harmoniously, ensuring efficiency and fairness throughout the supply chain.

7.4 Research recommendations

As AI continues to influence supply chain operations, new studies in the field should address some of the areas discussed, such as ethical concerns and the overall performance of AI systems. The methods for bias detection and mitigation should be further developed and improved. Although it has been noted that the issue of algorithmic bias in AI models has been significantly improved, much more must be done to make the models truly fair. Future studies should examine more advanced fairness-conscious algorithms and strategies to assess their effects on various population groups across multiple settings [43]. This will be especially relevant since AI is increasingly used in decision-making processes that influence the population's health, resource distribution, and employment rates. The field of human-AI cooperation is under-researched. A research publication should aim to develop hybrid models that incorporate AI decision-making alongside human input when needed. This might involve creating AI systems that can be modified in real time by human supervisors when ethical issues arise and ensuring that the AI systems are effective and responsive to society's cultural values. The long-term consequences of AI use in supply chains should also be measured through longitudinal research [44]. These studies should be capable of establishing not only operational effectiveness but also the social and economic externalities at a larger scale, including the effects on employment and income inequality. Such research would provide important expertise on how to manage the use of AI responsibly and equitably, so that the advantages of AI can be realized in a righteous manner within society.

8. Conclusion

The work shows that AI-based supply chain optimization can deliver measurable operational improvements, including a 20-50% increase in order fulfillment hits, a 15-20% reduction in logistics costs, and a 65% increase in customer satisfaction under the conditions studied. Nevertheless, the results also show a certain ethical risk: when information is incorrect or biased, different allocations are given to different groups, and a 5-10% service-level deviation is expected in sensitive processes such as healthcare logistics. The theoretical novelty of this manuscript is the transparent organization of supply chain streamlining as an efficiency-fairness trade-off issue, in which operational KPIs are measured against fairness measures as a governance requirement. The study transcends the usual cost-minimization reportage and establishes ethical concerns by incorporating quantifiable design constraints, bias identification, disclosure, human authority, and accountability into the optimization process. In practice, the findings provide an operational roadmap for implementing AI in supply chains across logistics, retail, and healthcare: introduce fairness audits, maintain high-quality data management, exploit explainability and logging, and implement human-in-the-loop regulatory measures for workforce and allocation decisions that have a crucial impact. With the implementation of these steps, efficiency will be maintained, and equity, trust, and readiness to adapt to evolving AI governance standards will improve. Further research needs to be conducted to concentrate on (i) multi-objective maximization techniques that maximize efficiency and equity (ii) longitudinal research which considers workforce outcomes and equity on a long-term basis (iii) analytically validate the approach on a regional or more akin dataset (iv) practical observational frameworks which trace fairness drift in its execution. The supply chains will be more transparent, accountable, socially sustainable, and efficient with the help of such movements within the areas.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to

publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement
The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest
The authors declare no potential conflict of interest.

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Appendix

Pseudo Code: Random Forest (RF) of Demand Forecasting.

INPUT: history of sales + demand information.
SET numberoftrees = 200

FOR each tree from 1 to 200:

- select training data (randomly, with replacement).

- construct a single decision tree (terminate when the depth = 12 or the splits are too small).

- store that tree

PREDICT demand for new data:

- predict with every tree object

or stored tree

- take the forecast of each stored tree.

Avoid uncertainties and ambiguities in salary determination by setting clear targets. <|human|>- overall prediction = mean of all tree predictions.

OUTPUT: predicted demand

The model predicts the demand by taking an average of several decision trees that have been trained using past sales data.

Pseudo Code: Gradient Boosting (GBM) Inventory Prediction.

INPUT: inventory, demand and cost related data.

SET numberofmodels = 300

SET learningrate = 0.05

begin with a crude basic initial forecast (such as average inventory requirement).

FOR model = 1 to 300:

- compute error = (actual currentprediction)<|human|>- errors =(actual currentprediction).

- use a small decision tree to fit these errors (depth = 6)

- update prediction:

currentprediction = currentprediction + learningrate asinolute prediction

The model optimizes forecast of an inventory by using a simple estimate and as time goes by, improves the accuracy of the forecast by progressively refining the mistake of the model by using many small decision trees.

Pseudo Code: DQN Reinforcement Learning of Supply Chain Decisions.

INPUT: environment displaying the state of the supply chain on a daily/step basis.

DEFINE state = inventory, predicteddemand, leadtime, backlog, transportcost.

define actions = [change order qty, select supplier, change safety stock, select route].

REPEAT for many episodes:
reset environment

WHILE not finished:
- observe current state
- choose action: random action Sometimes explore. elsewhere exploit (optimal solution of the nervous system)
- apply action and get: reward and nextstate
- birth (state, action, reward, nextstate) into memory
- generate training: train neural network with saved experiences:
easy actions which yield greater long term reward.
- move to nextstate

OUTPUT: learned action (optimal actions in the long *run)*

It is within this model that the most suitable actions in the supply-chain are learned by the repeated execution of alternative actions (such as varying order quantity, supplier) and rewards of the same to perform better alternative actions over time.