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Article

Revolutionizing Automotive Supply Chain: Enhancing Inventory Management with AI and Machine Learning

Vishwanadham Mandala

Data Engineering Lead in the Department of Analytics and AI, Cummins, Inc, USA

*Correspondence: Vishwanadham Mandala (vishwanadh.mandala@gmail.com)

Abstract: Consumer behavior is evolving, demanding a wide range of products with fast shipping and reliable service. The automotive aftermarket industry, worth billions, requires efficient distribution systems to stay competitive. Manufacturers strive to balance growth with product and service excellence. Distributors and retailers face the challenge of maintaining competitive pricing while keeping inventory levels low. An adequate supply chain and accurate product data are crucial for product availability and reducing stock issues. This ultimately increases profits and customer satisfaction.

Keywords: Inventory Management, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM)

1. Introduction

The global automotive industry spends billions on robotics for automation. However, current methods for inventory management need to optimize cost efficiency. The industry needs help finding the right skill level of labor for manual management. The solution proposed is the introduction of AI and ML for predictive analysis in inventory management. This breakthrough could bring about cost efficiency and increased productivity (As shown in Figure 1).

Figure 1. Introduction to AI and ML.

1.1. Background

Inventory control systems in the automotive industry are often driven by personal ambitions, which lead to overstocking and stockouts [1]. This approach, intended to improve fill rates, actually decreases them and results in obsolete inventory. With rising demand, this problem will worsen. Many automotive executives acknowledge the importance of reducing inventory, but calculating costs and benefits is complex. This highlights the need for a cost-effective solution to the significant inventory management problem (As shown in Figure 2 and Figure 3).

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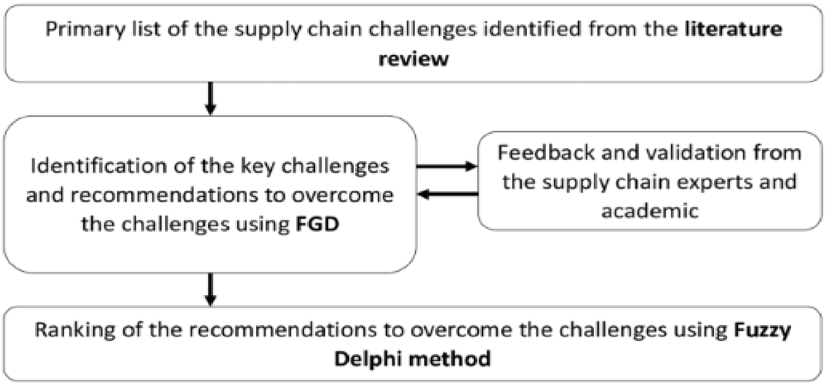

Figure 2. Inventory Management - Main Issues.

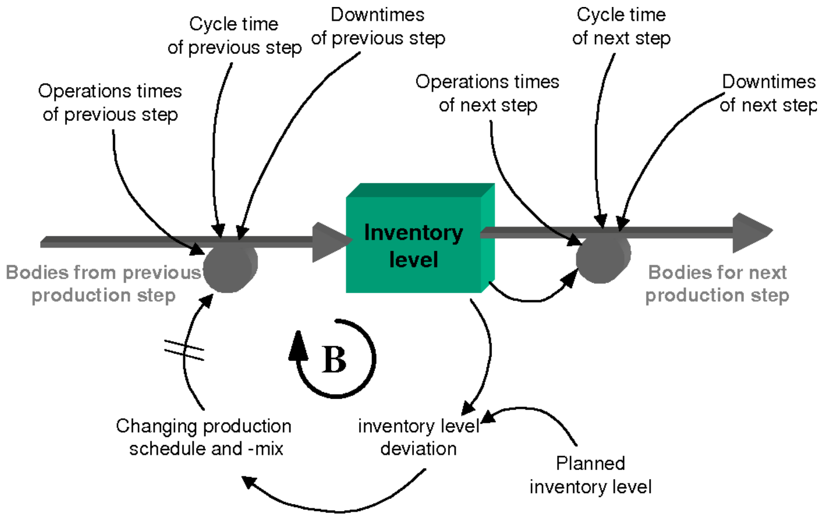

Figure 3. Inventory Management in the Automotive Industry.

1.2. Problem Statement

AI techniques for optimization can be divided into two types. The first method is based on heuristics and domain knowledge, while the second method applies constraint and optimization problem-solving AI [1, 3]. Although advancements have been made in using AI for inventory management policies, the latter approach still needs to be explored.

Inventory optimization is crucial, and extensive research has been done in this area. Static policies have been replaced by dynamic models in order to manage inventory effectively. These models define when and how much to order over a specific period [2]. The decision is then adjusted based on updated forecasts. These methods have proven to save costs in the long term. However, accurate demand forecasts are still necessary, and heuristics are used to find optimal inventory policies. Dynamic models balance overstock and under stock costs [3, 5].

Complex global supply chains for automotive spare parts face challenges in minimizing inventory costs and streamlining operational efficiency. Over 25% of the inventory cost is attributed to hundreds of thousands of low-demand items. These items have erratic demand patterns, making accurate demand forecasting challenging. Additionally, different partners manage various supply chain stages, leading to a need for synchronization in planning processes.

1.3. Objectives

The objectives of this research are to (As shown in Figure 4):

- Examine the global automotive industry and its role in the supply chain,
- Assess trading relations between OEMs and suppliers,
- Investigate a real-world business situation in an outsourced supply chain network and develop an inventory management solution,
- Produce industry-specific guidelines for inventory management,
- Develop a mathematical model for evaluating inventory levels and
- Generate interest in inventory management from academics and automotive professionals.

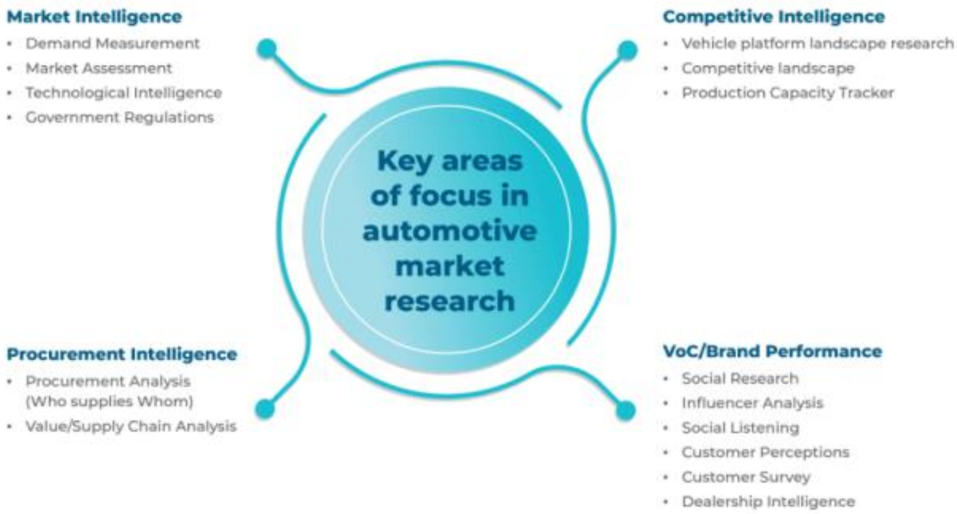

Figure 4. Key areas of focus in automotive market research

2. Literature Review

The 1970s saw centralized inventory management, which aimed to benefit from economies of scale. The newsvendor model improved inventory planning by optimizing the probability of meeting demand with available stock. This led to later supply chain inventory coordination models in the 1990s, reducing redundant inventory [4, 6]. The shift was from owning inventory in anticipation to pulling inventory in time based on immediate need. (305 symbols)

Inventory management research is rooted in economics and operations research (OR). Early work focused on lot size and reorder point. The EPQ model minimizes production and inventory costs.

To reduce inventory in the automotive industry, efforts have been focused on improving forecasting methods to minimize supply chain uncertainties. The bullwhip effect, which amplifies demand oscillations up the supply chain, has been studied and shown to be prevalent in the industry [13]. Improving forecast accuracy at the OEM level will lead to less volatile orders and production schedules at lower levels, resulting in reduced inventory throughout the supply chain. According to a recent study by the AIAG, a single week of forecast error can lead to a minimum of two weeks of excess inventory.

2.1. Inventory Management in the Automotive Industry

Manufacturers and suppliers face challenges managing complex, expensive equipment in the automotive industry. One issue is maintaining equipment long after it is out of production. Replacement parts are needed to keep equipment operating but are no longer sold. This leads to stockpiling spare parts for future demand, stored for easy accessibility. Stocking many parts ensures customer service but can result in unused overstock [7]. Managing spare parts in the automotive industry is crucial for a smooth supply chain. An effective inventory system minimizes costs and maximizes availability. Spare parts management is essential for after-sales maintenance and repairs (As shown in Figure 5).

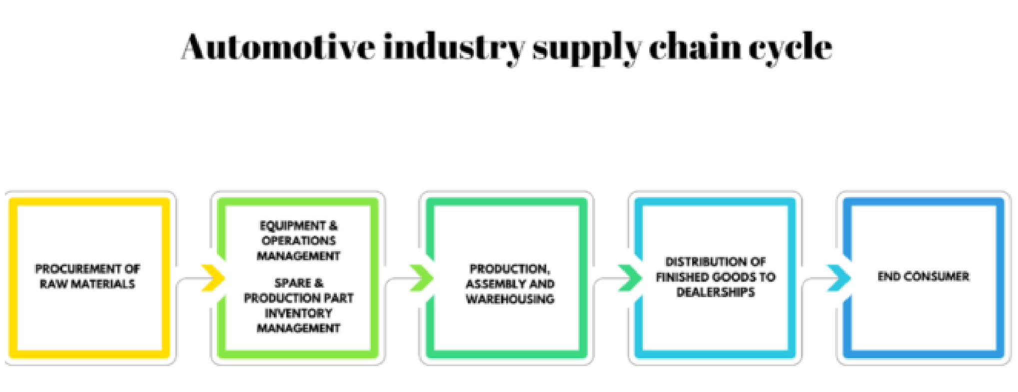

Figure 5. Automotive industry supply chain cycle

2.2. Traditional Approaches to Inventory Management

Outsourcing inventory management to third-party logistics providers is a cost-saving trend that transfers decision-making power. It is a different approach, allowing providers to use their systems and avoid upgrades for potential long-term savings.

Traditionally, inventory policies have been determined using intuition and basic cost/service level formulas. However, these methods must be revised for complex inventory systems and may result in suboptimal solutions. Iterative simulation has been proposed to model the decision-making process and obtain optimal policies for complex inventory systems [8]. Although simulation offers flexibility, achieving an optimal policy through simulation optimization can be time-consuming and challenging (Simulation methodology), as shown in Figure 6 and Figure 7.

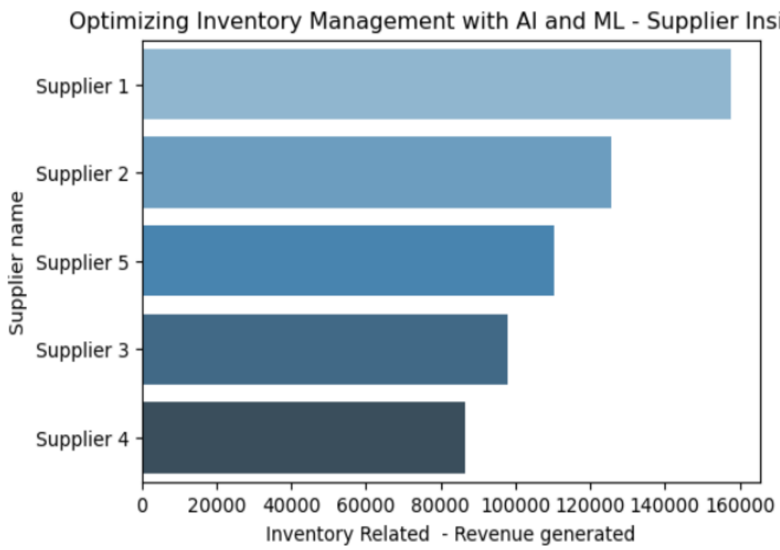

Figure 6. Supply Chain -Revenue

Traditional Managerial Approaches	Supply-Chain Managerial Approaches
Project-based management	Supply-based management for multiple projects
Separation of design, fabrication, construction and operation functions	Total life-cycle management
Uniquely engineered facilities and components	Assembly of unique facilities from standardized modules and components
Liquidated damages	Target costing and problem solving through strategic alliances for key products/components
Competitive bidding	Emphasis on long-term working relationships

Figure 7. Differences Traditional & Managerial Approaches

One way to reduce inventory costs and risk is using cycle stock instead of safety stock. Cycle stock is the inventory between replenishments, while safety stock is extra inventory held for unexpected demand. By solving the vehicle inventory routing problem, you can determine the optimal amount of cycle stock to hold, minimize costs, and respect production concerns (The vehicle inventory routing problem), as shown in Figure 8.

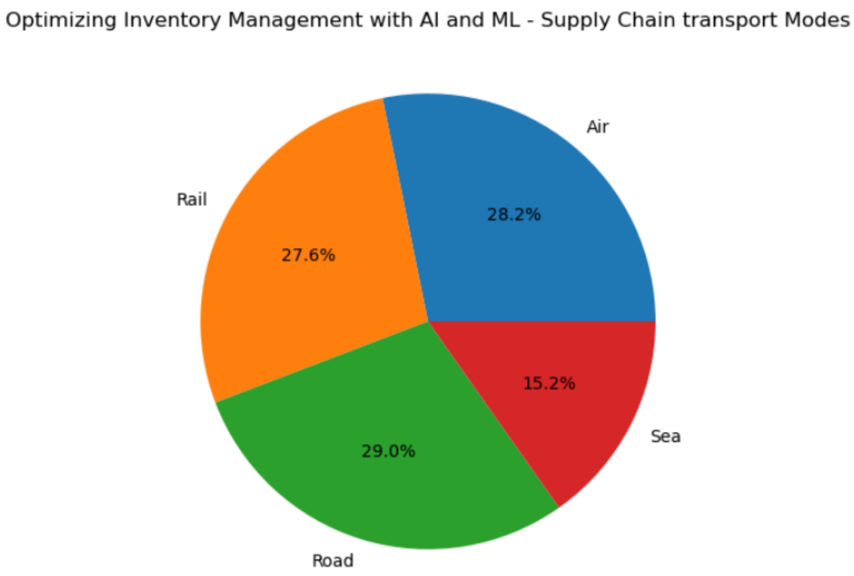

Figure 8. Supply Chain Transportation Modes

Reduction in lead time, uncertainty of demand, and variance stock are primary sources of inventory savings. Various ways to alter stock include flexible production schedules and varying production between products [8]. High-demand products can be produced more, while others can be deferred. Hiring and laying off laborers can also impact production. These strategies involve risk, so frequent re-evaluation is essential.

2.3. Role of Artificial Intelligence (AI) and Machine Learning (ML) in Inventory Management

Inventory management is vital for cost containment in the supply chain. Modern business pressures are causing companies to reconsider inventory management, particularly in the automotive industry [3, 8]. AI and ML can significantly improve inventory management in this industry. AI allows machines to imitate human behavior, while ML enables computers to learn and improve from experience. These technologies have the potential to learn from data, make recommendations, and forecast future outcomes. For example, ML can predict part failures in automobiles and recommend optimal orders for immediate and future failures [9]. This is particularly useful for complex systems with numerous low-cost parts. Managing spare parts inventory in the automotive industry is a significant challenge, but AI and ML can help overcome it (As shown in Figure 9).

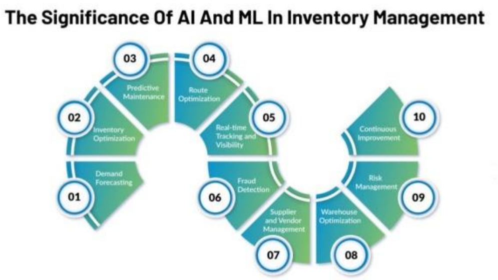

Figure 9. Significance of AI & ML in Inventory Management

3. Methodology

A database of automotive components and products was created to develop an AI/ML system for inventory management. The system uses static data instead of real-time data. It includes information on assemblies, parts, raw materials, Bills of Material, inventory, production cycle lead times, and supplier info. Only one warehouse is considered, without multiple locations or distribution network complexity [4, 10]. The primary function is to minimize inventory costs without affecting customer service. Inventory optimization aims to balance stockouts, overproduction, and carrying costs, which is challenging in the automotive industry due to complex production processes and global supply chains. Simulation is used to assess different inventory policies and compare systems. This research focuses on an AI/ML-enhanced system, with a simple example of stationary demand and deterministic lead time (As shown in Figure 10).

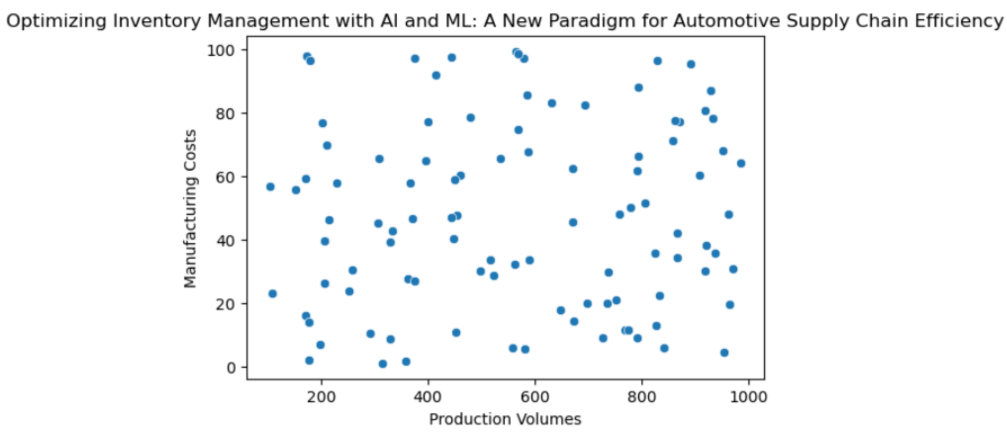

Figure 10. Implementation steps

3.1. Data Collection

Data collection is the first step in using AI and ML to improve inventory management. It includes three generations of data. The first generation is internal data companies collect, such as demand, order, and inventory information. Many companies have collected much of this valuable data but have yet to utilize it [7, 10]. AI and ML techniques can help leverage this data for decision-making. The second generation is publicly available data, like economic indicators, which can impact industries with broader supply chains. Companies may make decisions based on current conditions when adjusting inventory decisions based on predictions of future changes is more effective. AI and ML techniques can identify relationships between data and provide methods for adjusting decisions based on predictions of future changes.

3.2. AI and ML Techniques for Inventory Optimization

This section introduces an AI and machine learning technique for inventory optimization. Placing safety stock on each inventory increases inventory costs. An example is given: a specific automotive part has a 10% chance of demanding 100 units and a 90% chance of demanding 1000 units in the next two weeks. Optimization theory is used to determine the order quantity to minimize total cost [11].

The discrete Event High-Level Architecture (DEHLA) is used to simulate the effect of inventory levels to simulate the effect of inventory levels. A reinforcement learning algorithm is applied to make decisions based on long-term rewards for excess and shortage order quantities [5]. The Markov Decision Process is used to handle sequential decision-making and its impact on future conditions. The simulation shows significant changes in inventory levels and costs between scenarios (As shown in Figure 11 and Figure 12).

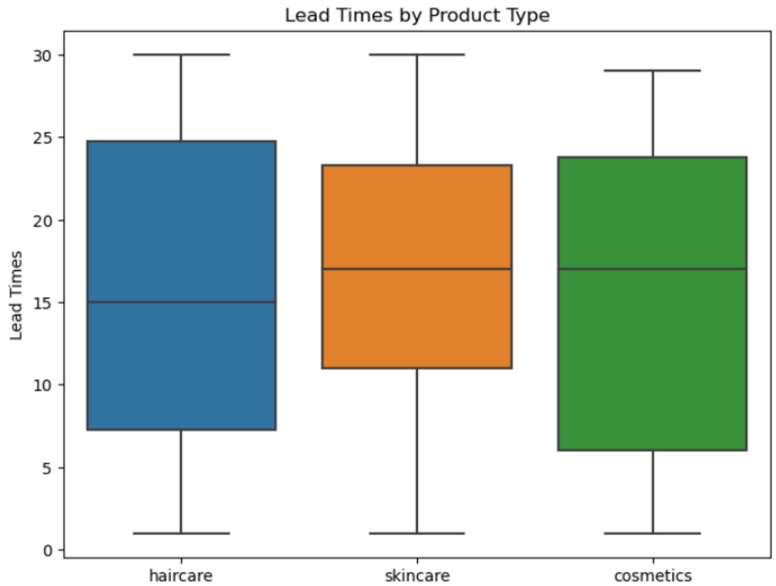

Figure 11. Data Collection Product Types

Figure 12. AI and ML Techniques for Inventory Optimization

In addition to inventory decisions, a forecasting application can help determine order quantities and inventory levels based on known demand [12]. This application can also compare demand levels and offer discounts to increase demand. However, due to the complexity and ambiguity of the data, machine learning methods are needed to implement this forecasting application effectively (As shown in Figure 13 and Figure 14).

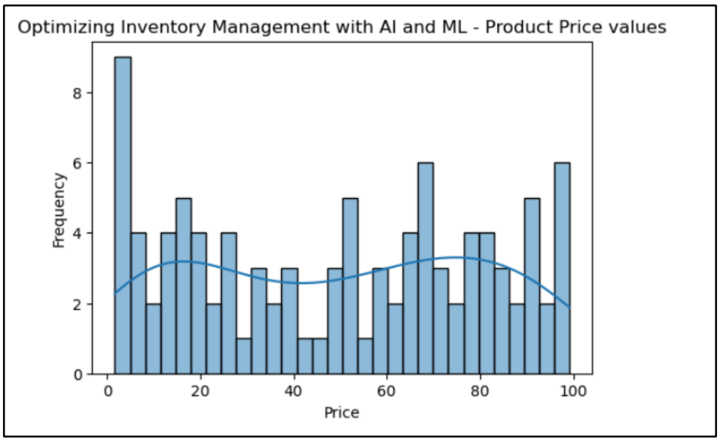

Figure 13. AI and ML Techniques for Inventory Optimization – Price insights

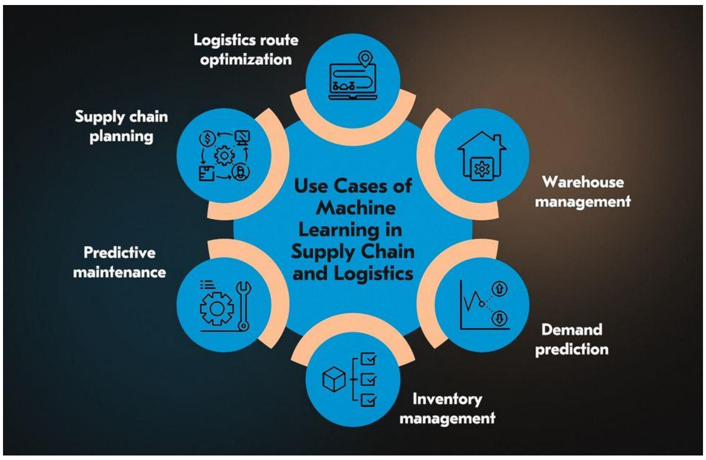

Figure 14. Use cases of machine learning in supply chain and Logistics

3.3. Implementation Framework

Industry players often need help with correct forecasts and fear to act on the information available. The idea is not to provide a solution that changes or adds process to the user but to optimize the output given current constraints. We aim to provide the user with a list of ranked suggestions considering the entire supply chain, from the manufacturer to the OEM customer [6, 9]. This enables the customer to take action on a suggestion that may only affect a localized part of the chain. This is done through the use of intelligent agents. These can be implemented as simple if-then statements; for example: If a component is needed for an urgent order, then increase the inventory of that component. However, we foresee these agents being machine learning routines that will adapt and improve over time. The use of these agents provides a systematic way to evaluate the multitude of inventory policies, both existing and new and their effect on the chain without the need for simulation (As shown in Figure 15).

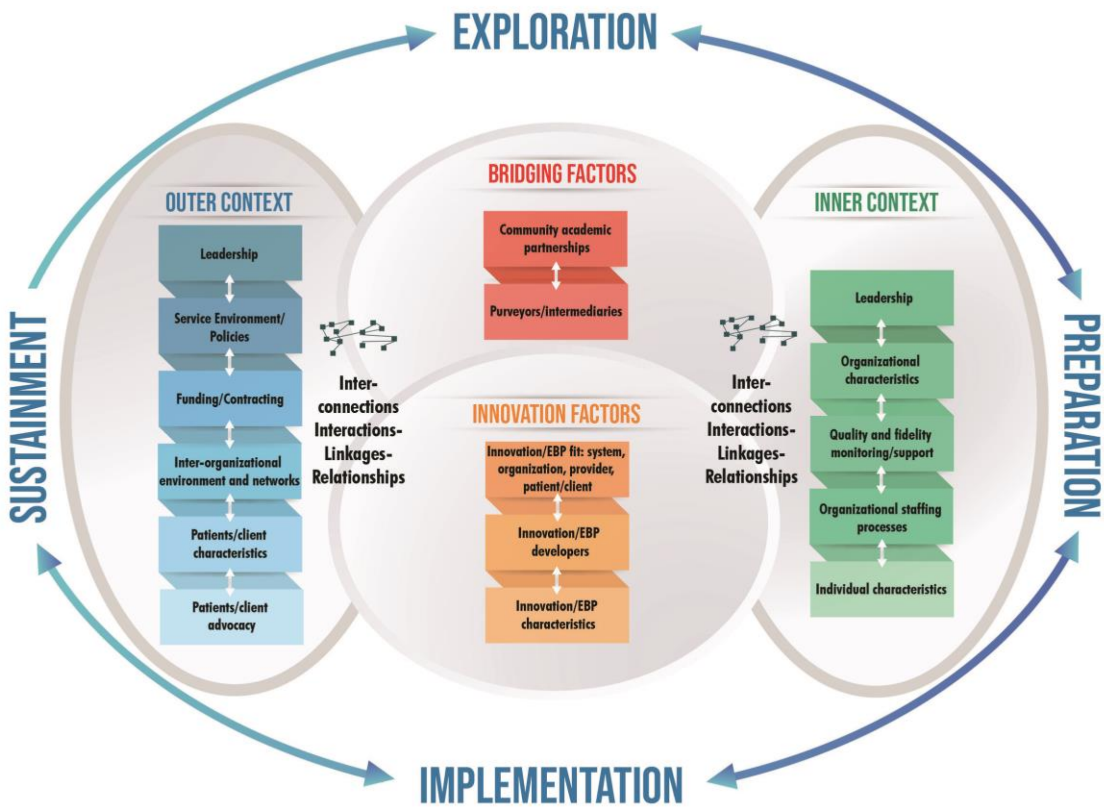

Figure 15. Implementation Frameworks.

4. Results and Discussion

This section documents case studies on the benefits of AI/ML for inventory optimization. It provides an overview of current inventory management, details on the AI/ML technology, and proof of its potential [7]. One case study implemented an AI/ML-based system for a major automotive manufacturer's North American service parts operations. The previous rule-based system led to inventory imbalances [1, 12]. The AI/ML approach created a holistic inventory optimization model that considered supply chain processes and dynamic inventory targets. Simulation tests showed the potential to free up capital tied up in inventory.

4.1. Case Studies on AI and ML-driven Inventory Optimization

Case studies of AI and ML-driven, inventory management implementations, are necessary for credibility and showcasing real-life possibilities. These methods have been applied in aerospace organizations for inventory management [6, 8, 14]. The MRO organization tested the implementation of machine learning on high-cost, erratic-demand parts. One challenge in the MRO industry is maintaining high service levels without incurring high holding costs. Overstocking is a common strategy, but more is needed to improve fill rates [15]. Pricing and lead time optimization are basic strategies, but determining the impact of various service levels on different parts remains challenging. An experiment was conducted to identify parts where a slight increase in service is too costly. The inventory policy was modified to prioritize those parts. This method improves service for high-cost parts with varying criticality. Other analyses, such as regression analysis and simulation, were also performed (As shown in Figure 16).

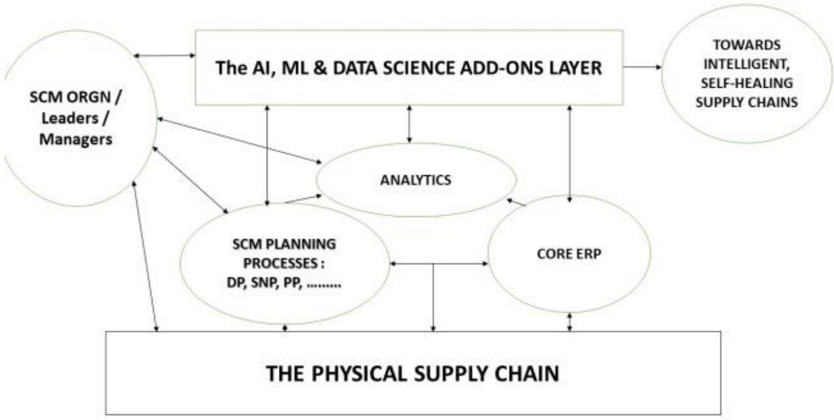

Figure 16. Case Studies on AI and ML-driven Inventory Optimization.

4.2. Analysis of Supply Chain Efficiency Improvements

Inventory data analysis evaluated the improvement in supply chain efficiency by implementing machine learning algorithms. The milestones were as follows: simulating the effects of machine learning reorder quantity recommendation using historical data, developing KPIs to measure algorithm effectiveness, visualizing inventory levels over time, and using case study insights to develop the algorithms for different plants further [2, 16]. (As shown in Figure 17).

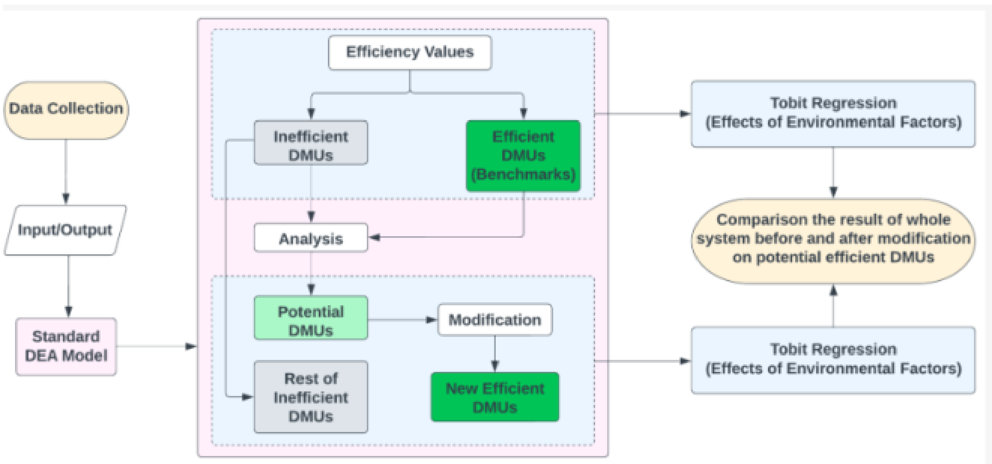

Figure 17. Analysis of Supply Chain Efficiency Improvements.

4.3. Challenges and Limitations

The new paradigm presents challenges and limitations in its practical application and measurement. The research used a case study approach and simulated the impact of AI on decision-making. Validation is achieved only when the decision maker and AI use the same process. Developing new decision-making methods without fully implementing the system is complex and costly [3, 7, 9]. High-consequence systems require extensive validation and testing.

Implementing the AI-driven method is a barrier, but it can lead to cultural change in the industry. Deciding when to use the AI method over traditional methods is challenging, especially when human and system decision-making is involved. Implementing the new system may face opposition and result in suboptimal results. Determining the exact values of parameters is complex and essential for optimization (As shown in Figure 18).

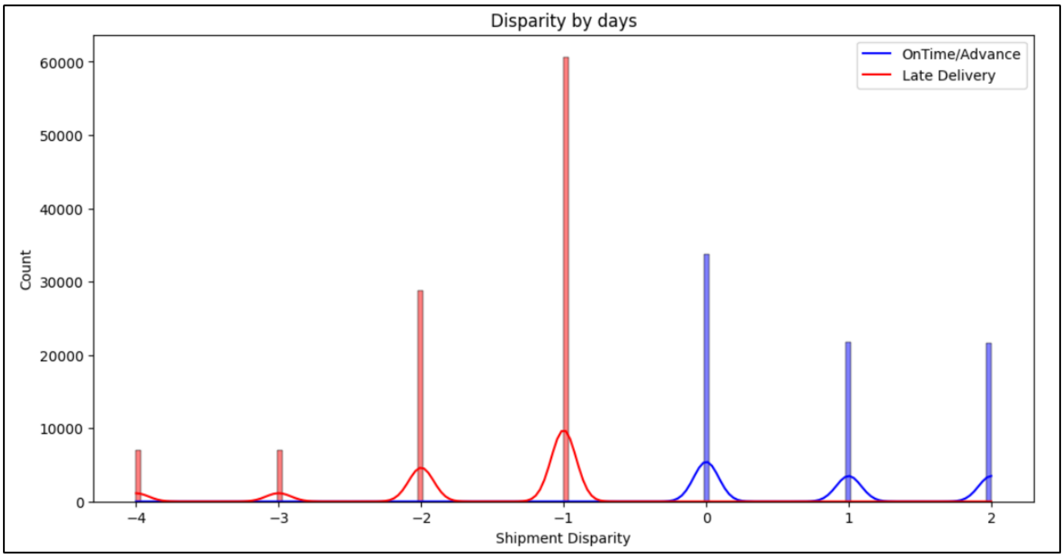

Figure 18. Analysis of Supply Chain Efficiency Improvements – Late Delivery Issues.

5. Conclusion

With AI and ML, our methods for automotive inventory management are more efficient than traditional ones. Our findings show how our methods define an optimal inventory balance point while traditional systems struggle due to complexity. Our developed methods automate the process for precise results.

Our methods are more flexible than current industry practices as they allow for the analysis of multiple variables. The AI can accurately predict the impact of inventory balance changes by analyzing historical data and supplier performance statistics [17]. In contrast, current practices make determining the cause of unexpected results difficult, often leading to reversals and retries. Our research shows that this strategy is cost-effective and efficient in managing inventory and reducing holding costs and stockouts. The simplified methods also require less labor and personnel.

5.1. Summary of Findings

In conclusion, the current study's findings enhance understanding of the complex relationship between inventory performance drivers and financial measures. By doing so, they provide some helpful general guidelines for managers attempting to optimize inventory investment to enhance competitiveness [15]. In the specific context of the automotive industry, we have demonstrated the potential benefits of using more advanced analytic technologies for inventory management (As shown in Figure 19).

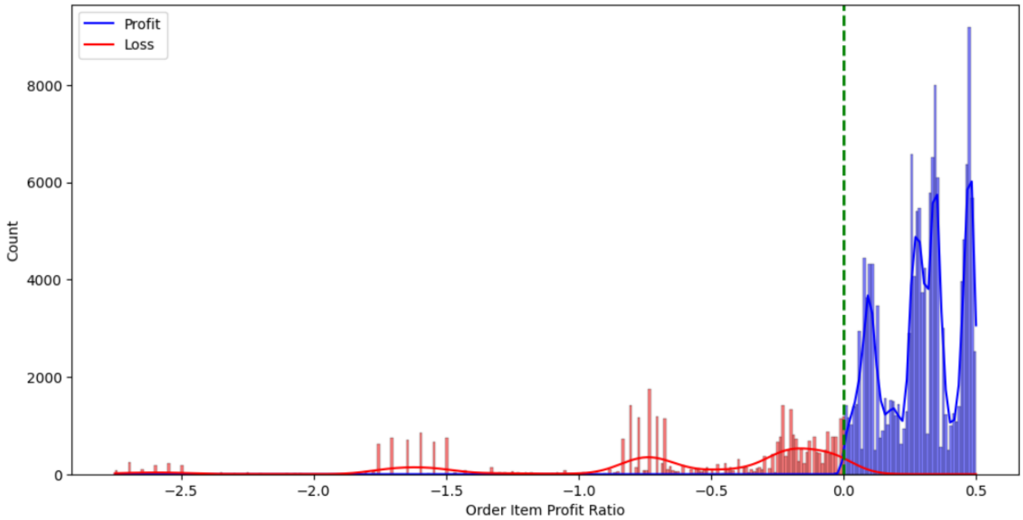

Figure 19. Analysis of Supply Chain Efficiency Improvements – Profit /Loss Insights.

As a customer service differentiator, inventory deployment improves sales and margins without increasing inventory investment. Service part availability enhances sales and production. Aligning inventory with demand reduces costs and achieves conflicting objectives through AI/ML optimization.

5.2. Implications for the Automotive Industry

The successful application of AI and ML to forecasting demand for low-volume, slow-moving service parts in the automotive industry provides a new paradigm for optimizing inventory management [2,17]. The conventional approach has been to categorize parts based on demand and manage them with simple ordering to advanced planning methods. However, rule-based methods often need to fit better to actual demand patterns, some parts may be interdependent with sporadic demand, and advanced methods require extensive labor. In contrast, machine learning models can accurately predict future demand based on part characteristics and history, and AI can optimize inventory policies in new ways.

The case study shows performance improvement against conventional approaches. New methods, such as high part interdependence, low volume parts, and evolving demand, may significantly impact industries where current methods could be more effective. If AI and ML can achieve effective inventory management with minimal inputs and labor, it may disrupt inventory management practices.

5.3. Future Research Directions

A future area of research is the study of automotive SCM initiatives across various IT systems, including traditional and new technologies. For example, we compare expert systems and data mining in the automotive supply chain to aid decision-making.

The search for benefits in inventory management, specifically in the automotive industry, is in its early stages. This study is a starting point for future research. One potential area for future investigation is cost savings in the automotive industry through increased integration and information sharing. Additional research can focus on specific sub-industries and the changes needed for closer relationships between suppliers and OEM/vehicle assemblers. Another area of research is how inventory and information integration strategies can be applied to smaller suppliers who believe e-business benefits are inaccessible.

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