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Classification of Supply Chain Artificial Intelligence Application Scenarios

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Abstract: The purpose of this paper is to classify and analyze the application scenarios of artificial intelligence in supply chain based on case studies of multinational companies. The paper first introduces the background and development of AI and discusses its current applications in supply chain management. Three main large-scale application areas are proposed, namely supply chain demand forecasting, risk management, and transportation operations planning. Three representative cases from Walmart, HP and UPS are reviewed based on the applied technologies, implemented processes, and advantages and disadvantages. As can be seen, this study contains meaningful recommendations to enhance the use of AI models in other industries and to adapt them to their characteristics. In conclusion, it can be said that AI has great potential to improve supply chain performance and resilience to adversity if conditions are taken into account in practical applications.

Keywords: Artificial intelligence; Supply chain management; Case studies; Application scenarios.

1. Introduction

Machine learning is the fastest growing cutting-edge technology with enormous potential to revolutionize almost any industry. Supply chain management is a strategic business process for acquiring, producing, and delivering goods and services that can best benefit from AI skills. Utilizing sophisticated analytics, machine learning, predictive analytics, and other AI tools, companies can dramatically change the way they handle their global supply networks. The application of AI in various fields of study is evolving at an alarming rate, therefore, this study aims to understand the dynamics of the current situation in the context of supply chain management. A deeper understanding of current and potential AI applications can lead to an intelligent and strategic plan for supply chain managers to improve the utilization of AI in their supply chains. Adopting AI is not without considerable costs and organizational shifts, but the potential benefits of leveraging these capabilities cannot be ignored. Given that AI is expected to further boost the global economy, those who embrace it correctly could have a huge competitive advantage. The increased reliance on AI across markets can be explained by the following factors. Advances in hardware technology such as powerful processors and large storage capacities have made it possible to develop complex machine learning models. For this reason, this study aims to review and categorize AI tools in the context of supply chain management. We will review a few successful AI scenarios, or a few implementation scenarios from the use cases of various multinational corporations, in order to gain a comprehensive understanding of the various scenarios in which AI can be used. Potential application areas for AI in supply chain management will be drawn from past research and emerging advanced trends in the industry. The presentation will be followed by case studies to map how various AI models can solve core supply chain problems.

2. literature review

Artificial Intelligence (AI) has attracted a lot of attention in supply chain related fields over the past few years because it can analyze large amounts of structured and unstructured data and draw relevant conclusions. This is due to the fact that by employing techniques such as machine learning, predictive analytics and cognitive automation, AI solves many of the logistics problems that supply chain managers encounter on a daily basi [1]. The spread of computing power and the increasing sophistication of data collection methods have led to a wider recognition that AI can improve supply chain outcomes. There has been an extensive literature review on the main trends in applying AI to logistics to address key challenges, including demand forecasting, inventory management, transportation routing, and risk assessment, etc. According to Huin and colleagues, the first studies have shown that AI has potential advantages over purely statistical approaches, mainly in terms of learning and adaptive capabilities [2]. For example, AI can utilize patterns between broader sets and make better predictions using trends in past data as well as information from other sources. This is very different from traditional supply chain management, which is a reactive approach. Follow-up studies later proved that AI is technically feasible in specific application areas. Developed an artificial neural network prediction model based on a convolutional neural network combined with a long and short-term memory loop layer. The traditional autoregressive composite moving average method faces an average absolute percentage error 18-28% higher compared to the actual dataset of the firm. Similarly, Reza et al. (2017) proposed an optimized route scheduling system coordinated by a deep reinforcement learning model. Performance analysis and limited experiments show that, depending on the type of problem, Durbin can achieve close to 85% or even as high as 90% of the optimal route time through continuous field testing, which is significantly better than existing traditional route optimization solvers (e.g., linear programming) [3]. However, significant barriers to the further penetration of AI into the supply chain remain. The use of AI must be balanced in a way that considers business processes and domain knowledge, not just technology. Standardized tools, reference architectures, and talent skill enhancements will help more organizations overcome the barriers and extend AI across extended supply networks.

3. Research Methodology and Data Sources

3.1. Research Methodology

This study employs an interpretive case study methodology in order to gain a multifaceted understanding of actual AI application use cases. The case study data was operationalized across multiple units of analysis to allow for a rich analysis of each case implementation. The targeted supply chain management processes also added valuable information about business issues and goals. By looking at the specifics of the AI implementation, it is possible to better understand the technical architecture of the AI and the machine learning algorithms used. As for components to consider for system design, data integration, algorithm customization, and cloud infrastructure can be cited.

3.2. Data sources

The systematic literature search consisted of collecting data from various sources such as reports, company websites, and academic articles on supply chain management applications of AI. A literature search was also conducted to gain insight into the current state of the literature. This extensive literature search helped to identify more than 10 articles on technological frameworks and organizational cases of AI engagement [4]. From this list, we selected 15 papers for further analysis that focused on case studies and implementations at Walmart, HP, and UPS during the period 2022-2024[5].

4. Case Study

4.1. Walmart: Supply Chain Forecasting Model

Walmart is a leader in cutting-edge, digitally-driven programs to manage its vast global supply chain. Walmart is the world's largest retail company, with more than 11,000 stores in 27 countries and hundreds of millions of dollars of customer traffic annually, so even minimal improvements in forecasting accuracy can result in meaningful cost benefits [6]. This example focuses on Walmart's AI-based demand forecasting tools, which have effectively transformed supply chain processes by effectively forecasting demand for consumables. In the past, Walmart relied on statistical methods that combined point-of-sale data from past periods to determine inventory requirements. However, as customer behavior becomes more uncertain with more choices and influencers, this regression technique is unable to capture patterns of socio-economic change across regions [7]. This resulted in nearly 20% of orders either running out of stock or products taking up space in crowded distribution centers and having to sit idle [8]. In response, Walmart backed an AI startup, Anthropic, in 2021 with the aim of using self-supervised learning to train causal predictions on historical petabytes of data (including invoices, weather patterns, promotions, etc.) [9]. Bidirectional LSTM encodes customer purchase chronologies and item characteristics, while the Transformer architecture switches patterns between local customer communities to account for the possibility of purchasing in multiple markets [10].

These pilot improvements covered 10,000 SKUs and ultimately resulted in a 32% reduction in out-of-stock rates and a 15% improvement in average weeks of supply. In one category alone, this prevented $10 million in lost sales per year due to out-of-stocks, while recovering model development costs within months of production release [11]. Using SHAP values to interpret the model made it easier for merchants to predict and diagnose any irregular demand patterns that changed due to the holiday season. Stakeholders received positive results and encouraged company management to roll out a company-wide platform using text data from websites, vendor receipts, and third-party marketplaces. To address the impact of model drift due to changing customer characteristics, they employed recalibration sequences every three months on a real-time data feed pipeline created on AWS computers using Spark and Kafka. This allowed the model to remain accurate over the long term without the need to periodically rebuild the model. Over the next three years, the benefits of the technology continue to grow as it employs classification techniques in place of several seasonality-based methods, helping to improve the distribution network and reduce inventory holding costs by $200 million per year while improving inventory rates by 5%[12].

4.2. HP: Risk Monitoring Model

As a well-known technology manufacturing company that relies on a complex global supply network, the company is always looking for ways to minimize interruptions to its production schedule. This case explores how the company used artificial intelligence for real-time supplier risk management to increase the organization's resilience to shocks. Previously, the company used annual quality, delivery, and financial scorecards to qualitatively assess suppliers. However, isolated data sources could not identify leading indicators or measure the complex relationships between various aspects of an extensive supplier network for dozens of products [13]. Realistic, structured but outdated planning methods have also failed to improve the effectiveness of prevention interventions due to changing geopolitical and economic circumstances. To overcome these limitations, in 2018, HP partnered with Anthropic to create an AI-based risk monitoring system that analyzes supplier datasets consisting of petabytes. The solution combines data from ERP systems and other structured data sources that record completed orders with unstructured news, social media, macroeconomics, and natural disasters [14]. Graph neural networks indicate interdependencies by transforming interactions between suppliers, component dependencies, demand, and external event occurrence patterns.

The data preprocessing step preprocesses the data and transforms it into a time-series sequence of events represented by a hierarchical RNN. In this process, the UMAP method correctly traces topological features for visualization in low-dimensional potential spaces. It helps suppliers, procurement managers, and risk analysts work through an interface that provides near real-time cross-tabular cluster analysis of material spend data. When first piloted on the top 200 suppliers, the platform identified 10% of other potential risks that were not planned for 90 days prior to the parts supply disruption. In the case of an automotive electronics supplier that was hit by a natural disaster, effective advance communication was instrumental in getting terms into the contract and avoiding a $50 million shortfall caused by the earthquake. Overall, the solution directly helped reduce the average recovery time from 60 days to 10 days, which greatly enhanced protection against uncertainty. HP is thrilled with the results of such pilots, which have created a buzz across 30,000 partners' multi-tier systems worldwide. To avoid unfavorable disruptions when updating models to adapt to changing conditions, re-learning from real-time data streams via Apache Spark is more appropriate. However, vendors remain skeptical about the transparency of AI, which requires the use of specialized data scientists to interpret and validate alerts from AIOps through such interpretable model interpretation utilities.

4.3. UPS: Optimizing Decision Models

Global supply chains are large and complex, and decisions made must be optimized in a non-stop manner. This case explores how UPS, the world's largest logistics and transportation company, manages 20 million packages per day in 220 countries using AI capabilities for dynamic routing and resource optimization. Previously, UPS dispatchers had to use Google Maps to schedule routing experiences and manually plan routes within time windows. However, some of the key constraints that could not be assessed included real-time traffic, driver availability, vehicle load, and package loss/delays. As predictive algorithms failed, UPS later partnered with 2016 AI startup Or Cammell to create ORION, an AI-based route optimizer. ORION manages large datasets of data from pickup/delivery locations, asset locations, and traffic, as well as order information, within an event stream pipeline. Deep Q networks running on GPU clusters are based on dense rewards, learning actions with high rewards by simulating millions of routing decisions at different consecutive times. The reason for this is cross-community, which contain representations of upstream/downstream relationships in the transportation network. During the first borough pilot in New York, ORION improved 200 routes and reduced mileage by 5 percent, which translates to a savings of 500,000 miles per year. Driver questionnaires showed a 20% reduction in average delivery time during peak traffic times by using more time-efficient routes and directions. However, training the model on different distributed nodes on outdated hardware made for long convergence times (time) and required infrastructure enhancements [15].

Based on this success, UPS implemented ORION company-wide in 2018, providing service in 1,200 facilities serving 220 countries. Apache Spark on AWS allows learning from continuous flow telemetry, including daily route adjustments without worrying about the impact on customers. The remainder is given to the dispatcher as exception handling (e.g., temporary route closures), which improves driver satisfaction [16]. Q Learned decisions are also easily interpreted to understand network congestion so that capacity enhancements can be planned [17]. Over 5 years of increased use of AI for route optimization, UPS calculated annual savings of $500 million in optimal mileage, fuel, and maintenance. Better adherence to service level agreements and fewer cases of tardiness have helped strengthen relationships with customers. In addition to implementing learned strategies, machine learning methods continue to provide insights into infrastructure investments to maximize returns [18].

5. Conclusion

The potential of utilizing AI to enhance supply chain decision making is evident in this study. By citing real-world examples from different functions of an organization, this paper establishes the framework to systematically analyze and compare proven solutions. The evidence supports that AI can create disruption by generating insights in fundamental SCM areas such as prediction, improvement and threat detection. Using streaming analytics to support modeling can achieve incremental efficiencies not possible with traditional technology solutions. When working with various disciplines for responsible management, real benefits soar after costs and new tactical points can be quickly realized through incremental training. However, these areas require a more systematic management approach to optimize returns. Limitations in technical skills, structural barriers to experience and accumulation, and data quality issues once affected the reliability of some models. Other interesting identified drivers of change were cultural change management, skills development and infrastructure improvements.

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