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ARTIFICIAL INTELLIGENCE FOR SUPPLY CHAIN MANAGEMENT (SCM): A THEMATIC LITERATURE REVIEW

Leong Chan[1], Pei Zhang[2], Rao Kowtha[3], Chung-Shing Lee[4]

[1]*School of Business, Pacific Lutheran University, Washington, USA*

[2]*Department of Engineering and Technology Management, Portland State University, Oregon, USA*

[3]*School of Business, Science & Humanities, SUNY Maritime College, New York, USA*

[4]*School of Business, Saint Martin's University, Washington, USA*

Abstract

Artificial intelligence (AI) is rapidly diffusing and becoming increasingly popular in the business world, as the most vital driving force to transform the business process in recent years. The applications of AI now are impacting all aspects of business operations, which also include Supply Chain Management (SCM). This research examines and discusses the current AI technologies used in logistics and SCM, including AI methods like Machine Learning (ML) and Advanced Data Analytics. We have conducted comprehensive research from literature research on available AI-based industrial applications today and explored some significant AI challenges for the SCM in business and related careers. The discussions cover AI's primary functions, including supply chain configuration, agility, demand forecasting, inventory control, scheduling, and solving SCM logistics issues. To sum up the discussions, we provided managerial implication suggestions for SCM professionals and researchers.

Keywords

Artificial Intelligence, AI, Logistics, Supply Chain Management, SCM, Big Data, Machine Learning

I. Introduction

Artificial Intelligence (AI) is changing how all businesses conduct their operations and fulfill their strategic goals (Chan et al., 2022). Among some of the latest uses of AI in Supply Chain Management (SCM) operations, AI helps employees conduct a variety of essential tasks, including inventory control, scheduling, demand forecasting, and supply chain configuration (Ageron et al., 2020; Dubey, Gunasekaran, & Childe, 2019; Dubey, Gunasekaran, Childe, et al., 2019; Kamble et al., 2019; Kamble & Gunasekaran, 2020; R. Sharma et al., 2018). Recently, AI has been used to predict a business or agriculture organization's probability of blockchain adoption in the supply chain (Balci & Surucu-Balci, 2021; Kamble et al., 2021); (Kamble et al., 2020). Also, researchers developed a model that describes the role of adopting Big Data Analytics powered by Artificial Intelligence (BDA-AI) and Operational Performance (OP) of Entrepreneurial Orientation (EO) (Dubey et al., 2020). AI has been extensively integrated into the supply chain via autonomous vehicles and ships, route planning, port operations and industry practices of sustainability among others (Song & Cao, 2024; Vu et al, 2024; Wong, Yeung, Lau & So, 2021). These recent developments of AI applications to various SCM operations aim to improve business performance and achieve long-term strategic goals.

From small businesses to large corporations, continuous growth is always one of the biggest operational concerns. There are some ways to help with business organizations' growth, such as driving demand for the products, predicting future demand trends to win the customers and competitors, and developing new target markets (Green et al., 2018). One of the meaningful ways to support these operations is to increase production efficiency, which is highly related to every stage of the organizations' supply chain operation. Firstly, it begins with the SCM in the production planning stage. Organizations need to consider critical factors of improving production speed, minimizing errors, and not overproducing the product beyond market demand, trying to achieve lean manufacturing. In the production stage, raw material delivery planning, production line designs, and product quality control are critical to the supply chain operation. The second stage would deal with transportation and storage efficiency while still handling errors in the process. This stage's overall objective would be to minimize the operational costs while still achieving the maximum amount of product sales within various markets. The final stage of the supply chain management process deals with the product handling with advanced data analytics of historical sales data, current sales trends, and future market demand predictions. The analysis of customer and marketing data can sense the product-handling stage's future supply chain planning.

With the introduction of AI technologies, much of the past work was tedious and challenging for human laborers to sort through and obtain accurate models can now be significantly optimized in time efficiency and give businesses more accurate results. Utilizing AI techniques can configure more optimal supply chain operational paths between suppliers, producers, and customers to minimize production costs by distributing the demand efficiently. Also, AI techniques can automate order and monitor inventory tracking processes and effective prediction of product restoration and storage spaces. After the product's handling to customers, a crucial aspect of AI is predicting future market trends with the businesses' current operation methods to let them know what to expect of their future performances and send signals of potential changes for the improvements (Li et al., 2017).

The supply chain is one area of business operations that have implemented modern-day technology into their day-to-day work. Specifically, the supply chain has worked feverishly to include AI technologies. This research has arranged the following discussions: evolution of AI in SCM, related AI-SCM methods and functions that apply in supply chain management, and significant challenges in the current AI-SCM field. Lastly, managerial implication suggestions are summarized and provided for business and research.

II. Evolution of AI in SCM

The research on artificial intelligence (AI) started in the 1950s. While it was still not consistent, more SCM and logistics research started during the 1970s since AI evolved its capabilities to recognize business patterns, phenomena and to analyze data intelligently. Many organizations were skeptical of integrating AI to benefit SCM potentially, so there was very little research done for decades on the topic of AI in SCM, even though we are now stepping into the AI era.

It was not until the last decade that AI research for SCM and logistics started to increase rapidly, including research works on predictive analytics, information or data procurement, and warehouse management. Predictive analytics is used primarily for demand forecasting of companies' logistics to support the decisions on materials and products' arrangements and the manufacturing and inventories. A typical application of AI techniques on information and data procurement is Chatbots. The first chatbot was introduced in the 1960s. Chatbots are generally computing programs with conversations with humans, much like Amazon's Alexa and Echo Dot use machine learning (ML) to mimic human conversation. Thirdly, warehouse management is one of the most involved aspects of AI. Warehouse management includes automated inventory tracking, monitored shipments, logistics updates, and more. From this point of view, AI has certainly come a long way since being first introduced. To thinking about the AI technology in SCM, there are many research papers about SCM published in well-known journals (Afshar et al., 2017; Martinho et al., 2019; Qrunfleh & Tarafdar, 2015; Sari et al., 2021; Selvaraj & Reeves Wesley, 2020a, 2020b; S. Sharma & Shah, 2015), but there are not too many publications that introducing AI techniques to SCM. It is still an early stage for AI technologies in supply chain management (Kamble et al., 2021; Priore et al., 2019).

During the summer of 1998, the first study on AI in supply chain management was conducted. The term "artificial intelligence" was still not widely used at that time, which is an example of the amount of research progress we have made within twenty years (Swaminathan et al., 1998). Therefore, our research focused on literature from the 2000s to 2020s in SCM, inventory management, logistics, and machine learning as our main topics. This period of literature allows us to cover a wide range of modern technologies and AI systems. Especially for AI researchers in the SCM field, we started picking up the research works from the 2010s until today.

The research done on the application of AI within the supply chain is ever-changing. Current research shows that AI has been implemented in e-commerce, international business affairs, inventory accuracy, retail product demand forecasting, and warehouse management regarding inventory accountability within the supply chain (Bharadwaj, 2018).

III. AI Methods in SCM

In this section, we looked at different AI methods applied in the SCM. These methods are data mining and predictive data modeling, various machine learning algorithms such as artificial neural networks, reinforcement learning, Swarm intelligence, decision trees, and other relevant methods. (Cao et al., 2017; Chan et al., 2019; Kosylo et al., 2018; Staples et al., 2019; Stephenson et al., 2019).

Most AI issues in SCM are related to data, data science and related methods play an essential role in this field. SCM field introduces and applies Big Data and Data Mining techniques to create sophisticated AI algorithms, considering the essential input data issues. Big data and predictive data modeling are traditional workflows for AI-based SCM analysis. Data mining is the most widely adopted AI technique. Data mining includes essential tools for extracting and handling data and establishing patterns to produce useful decision-making information (Jha, 2015). Data mining explores data deeply in various logistics and SCM areas, including bar-code scanning, sensors, inventory information, and traffic analytics. The data mining technique pulls data from various data sources in logistics to build predictive models for logistic transportation, traffic analytics, and automation transport vehicles. Big Data and data mining technology currently help shape machine learning models and build intelligent AI (da Silva et al., 2015).

Machine learning (ML) is a significant trend in SCM that is beginning to pick up speed. We can see new algorithms integrated with computer programs used every day in various branches of businesses. Machine learning covers numerous techniques and algorithms for AI. These methods include both traditional statistical methods and newly developed algorithms. Here we briefly discuss some techniques that have been applied to the fields of SCM.
Naive Bayes and the K-nearest neighbor model can be used in demand prediction. Naive Bayes deals with dynamic decisions with uncertainty attached, while K-nearest-neighbor is a supervised learning algorithm to determine trends. Research shows that the Naive Bayes method may surpass Nearest Neighbors in detecting relations in datasets for prediction demand in the supply chain [2]. Support vector machines reduce error on a test example and seek to minimize error margins rather than seek a specific output. Therefore, Naïve Bayes can handle fuzzy margins (a solution can be found even if there are contradicting examples in the training set) and overcome demand forecasting concerns, including full labeling of index data and a solved model are difficult to interpret and slow to train.

Other than Naïve Byes and the K-nearest neighbor model, Artificial Neural Networks (ANNs) prove to be a good integration into the supply chain. ANNs are a highly interconnected system of neurons that receive and transmit information along with a structured network. Through this inter-connective transmission of information, neurons can process signals and decide whether the inbound information is valid or not and determine if they pass along that information to the network structure (Partovi & Anandarajan, 2002). ANNs were created to mimic or clone the mind process as human-beings, allowing them to pick up on and trace patterns found within data. ANNs support complex, non-linear relationships without prior assumptions for the data. They are data-driven and useful for time series modeling and forecasting without restraining numbers' assumptions and rules. Given specific inputs, the model will train itself with weights for a given attribute and final output. This technique is intelligent and very precise but has the caveat of being difficult to train and make adjustments. When creating an artificial neural network, there are many elements, such as the number of layers, the number of units in each layer, connections between units, design of training algorithm, initial weights, and specifying the stopping rules.

The most common model for ANNs is the Multilayer Perceptron Model (MLP). This model usually comprises three layers, which are the input, output, and the hidden layer. The hidden layer is where the magic happens, which is put into place to transform the input layer into something useful for the output layer to deliver. Three factors can affect the accuracy of the ANNs' predictions – the total number of neurons, the number of neurons on each layer, and the number of layers (Dormehl, 2019).

On the other hand, reinforcement learning is based on constant interaction between the learning agent and environment. The agent selects an action to the environment, and the environment responds and feeds a new situation back to the agent. The reinforcement learning ordering mechanism consists of two stages – exploration and exploitation (Chaharsooghi et al., 2008). The reinforcement learning model is weak at the beginning because of the lack of knowledge about the environment. The exploration stage takes place by exploring the given information in order to build a more robust model. However, with the lack of understanding of the environment, the learning agent's input information is not good enough for the model construction. The poor environment data inputs lead to a minimal exploitation stage. Later on, in the process where the model is considered strong enough, exploration decreases while the exploitation increases. In the exploitation stage, the system exploits the model by testing each stage in every single action. Each test generates an action-value reward and contributes to the action-value function called the Q-functions. These results from the exploitation stage will be then injected back to the model as an input for the exploration stage to improve the model. After the learning process is done, action with the highest Q-function is selected for each arriving state in the supply chain as the best optimal policy (Chaharsooghi et al., 2008).

Swarm intelligence is an optimization technique that is applied to the supply chain. This method can determine the nearly lowest cost that the supply chain can produce with the given suppliers, producers, distribution centers, and customer zones. The model used a multiple integer non-linear model to create the solutions, using 0's and 1's to represent whether a specific component was in use or not. It can then determine solutions by testing the solutions with particular product distribution to each customer zone. The final solution is the optimized result. This method is comparable with genetic algorithms and traditional global search algorithms, which also have good potential to be applied in SCM.

The decision tree method is another critical tool for SCM when considering multiple processes or factors. Decision trees come with various branches and possibilities of each branch sequentially. Every decision needs to be analyzed quantitatively or qualitatively depending on the different data types, impacting the tree-shaped structure's next decision. However, from the view of the decision tree's overall structure, one decision may affect the entire manufacturing line from beginning to end (Liu et al., 2013). If a decision is made to improve only one part, it could negatively impact the rest of the process. There can be multiple-layer models for lean SCM's knowledge system, which provided managers and engineers with suggestions and solutions regarding supply-chain efficiency (Liu et al., 2013). Decision trees provide a method and a guide within SCM to help the processes improve in any industry.

Random Forest Regressor (RFR) is an extension of the decision tree algorithm, and it is also a supervised machine-learning method. RFR yields high accurate predictions, and can be reliably used for both linear and non-linear problems (Mansoursamaei et al, 2023; Vu et al, 2024). The algorithm analyzes several randomly selected individual DTs of varying depths and nodes individually and provides the final prediction by averaging the predictions of each tree. RFR is useful for dealing with large and unbalanced data sets. Because of the algorithm's capability to deal with large and unbalanced data sets combined with random selection of DTs for training and prediction, it yields more accurate risk predictions along the supply chain (Brintrup et al, 2019; Wang et al, 2022).

AI techniques in supply chain and logistics have recently exploded in popularity and application. AI-based algorithms can be applied to solve various problems in industries. Supply chain and logistics is a sector of many companies that require constant data-entry, prediction, and efficient organization of many assets. This section explored primary techniques for SCM problems that can be encountered. The goal of machine learning and AI methods in supply chain and logistics is to increase efficiency, detect errors, automate processes, and improve other relevant factors' performances.

With a study on the existing research works, we want to show the following article thematic table that researched on the AI techniques discussed in this section with their implications of various sector areas regarding SCM (Table 1), to show the trend and research works that worth notice in the AI-SCM research field. Also, there may be more research opportunities to explore if there are no existing research works in the related crossing-areas.

	SCM Sector Areas			
AI Methods	Inventory	Transportation/Distribution	Warehousing	General Operations
Big Data/Data Mining	Sanders, 2016	Richey et al., 2016	Ma et al., 2015	Awwad et al., 2018; Raman et al., 2018; Tiwari et al., 2018; Nguyen et al., 2018
Naïve Byes and K-nearest Neighbor Model	Tangtisanon, 2018; Beardslee & Trafalis, 2005	Paul et al., 2020	Kamble et al., 2015	Jiang, et al., 2019; Gaur et al., 2015;
Artificial Neural Networks (ANNs)	Partovi & Anandarajan, 2002; Sustrova, 2016	Kuo et al., 2010	Smith & Gupta, 2003; Pandian, 2019	Mohiuddin et al., 1996; Kochak & Sharma, 2015
Reinforcement Learning	Giannoccaro & Pontrandolfo, 2002; Oroojlooyjadid et al., 2021	Chaharsooghi et al., 2008	Barat et al., 2019; Peng et al., 2019	Pontrandolfo, et al., 2002; Stockheim et al., 2003; Valluri et al., 2009
Swarm Intelligence	Moncayo-Martinez et al., 2016; Krumar et al., 2013	Zhang et al., 2016	N/A	Soni et al., 2019; Zhang et al., 2015
Decision Trees	Moon, 2001; Stefanovic, 2007	Berger, 2004	Baker & Canessa, 2009	Trzpiot, et al., 2009; Ponnambalam et al., 2013
Genetic Algorithms	Rahakrishnan et al., 2009; Celebi, 2015	Jeong et al., 2002; Naso et al., 2007; Costa et al., 2010	Whitley, 1994	Carbonneau et al., 2008; Jauhar & Pant, 2016
Case-based Reasoning	Roßmann et al., 2018	Kwon et al., 2007; Pal, 2017	Chow et al., 2006; Poon et al., 2009	Watson et al., 1994
Support Vector Machines	Sarac et al., 2010	Gaus et al., (n.d.)	Sarhani & Afia, 2014	Min, 2010

IV.AI for SCM Functions

AI in SCM is essential in various aspects, including logistics as an integral part. Without proper SCM, everything along the production line would be at risk of failure. Implementing AI into SCM can help companies ensure their materials and products are reliable and plentiful enough to continue their business operations. In this section, we identified several critical aspects of SCM with AI applications from recent literature.

A. Supply Chain Configuration

The configuration of a supply chain is a general topic discussed in literature which involves picking up proper material suppliers, choosing production methods, monitoring production schedule and amount, and the cost control. Various factors within each component, such as material quality, production capacity, and business relationships, may be less integrated into the SCM process itself. There are some ways that AI has been used to try to take in all those factors and produce a complete supply chain out of it (Ülkü & Schmidt, 2011).

One of the most critical aspects of the supply chain is from the very beginning, which begins with the supplier. Suppliers provide raw materials as the baseline foundation of the product. Suppliers must provide quality materials that last throughout the supply chain operation stages even until they experience the products. Suppliers also must be highly dependable on the number of materials to fulfill the market demands (Akanle & Zhang, 2008). There are many criteria to define the suppliers' performance, including the criteria that are hard to quantify to scale, which can be attempted through the combination of fuzzy logic in tandem with an analytic hierarchy process (Kar, 2015). Quantifying the results into an ANN can help determine the quality level of the suppliers' performances. A case study was used on a high-profile steel manufacturer whose top executives were asked what criteria had the most significant impact on the decision-making process. These responses were converted to fuzzy sets depending on each weighted factor. A consensus was achieved amongst the group to achieve a priority vector using the analytic hierarchy process, explicitly using the geometric mean method. These results were passed in as the first layer to the ANN. The priory criteria determine the nodes' weights, which can help sort the quality of each supplier's attributes. This was tested on 45 different suppliers, and when compared to the executive's consensus on each supplier, only one misclassified. This shows a promising potential method to objectively classify suppliers while still taking some of those subjective opinions into account to better classify the relative belonging of a value to a set with fuzzy logic (Che et al., 2014).

In reality, there are many other complex factors, such as the shifting market or the quality of a supplier relative to cost. An adaptive or dynamic configuration of the supply chain takes advantage of the available information in each stage of the supply chain to generate an optimized ordering policy with better performance, both the number of orders fulfilled and the overall monetary profit. Considering the supply chain with multiple stages and each stage consists of multiple agents, the number of stages involved essentially multiplies the number of combinations of these stages to get any given product through the supply chain from beginning to the end (Türk et al., 2017). Ideally, the supply chain should be dynamically configured as per the dictates of the environment (e.g., vendor choice, customer preferences, product choice) at any given point in time. The research framework can utilize the decision tree technique or hierarchical decision model (Chan & Daim, 2018). First, the framework gathers and filters the data from each player of that stage. It extracts necessary entities of each stage, such as the cost, lead-time, and quantity ready as an input for the learning module. The learning module will then generate a learning rule that decides the best optimal decision considering each stage's entity. The framework assumes that there is always a dominant node in the next stage upstream, and there is no long-term historical relation that could bias the decision between stages (Sang, 2016).

B. Demand Forecasting

One of the most critical factors of a supply chain is predicting a company's demand shortly. Reasonable demand forecasting can lead to a minimization of shipping costs, as the complete number of products could be shipped at the same time, rather than underestimating demand and having to pay extra shipping costs (Syntetos et al., 2016). Overestimating the demand costs extra money for the companies because of the additional products that are not sold. Applying AI can improve the accuracy of the demand predictions for the company to expect.

With a promising benefit with the usage of neural networks in demand forecasting, several new techniques can optimize the existing neural network with the combination of other machine learning methods(Carbonneau et al., 2008). One of them is the extreme learning machine (ELM), a single hidden layer feedforward neural network. Firstly, the method normalizes the data by filtering the raw data that includes all the factors affecting the sale amount. The most critical data is then used for the ELM. The input weights (the connection between the input and the hidden layer) and the hidden biases are randomly chosen. The output weight is being denormalized by using the Moore-Penrose inverse. The output from this method is to predict the demand amount (Sun et al., 2008).

Another form of method is the hybrid intelligent model (HI model) that combines the harmony search (HS) algorithm with ELM to produce optimal input weights. The integration of HS on top of ELM generates multiple forecasting outputs by repeatedly running the network with different numbers of hidden neurons. Then the model uses a heuristic fine-tuning process to analyze the outputs and generate a prediction of the amount of sale (Wong & Guo, 2010). Since the HI model is primarily based on the ELM model, there is no surprise that the HI model performs much better because it adds an HS algorithm that selects an optimal weight instead of the randomized weight used in ELM.

In summary, available literature uses traditional methods and artificial neural networks to test the training data set. Results were often compared using various machine learning techniques (Mousavi et al., 2009). Overall, demand forecasting is one of the most significant components of the supply chain and maximizing a company's profits. Many existing research papers focused on the improvements of demand forecasting, which proposed various methods. ANNs are generally on the top of the lists, with various training mechanisms for handling various shifts from the market.

C. Inventory Control

Inventory is the resource and asset for a company to supply market demand. However, it does generate high costs for an organization to maintain and manage accurate inventory amounts. Therefore, the ability to plan and control inventory at a minimum cost while still making sure the number of available products is enough to please customer satisfaction is essential to any business's success (Inegbedion et al., 2019).

Currently, many companies use machine learning algorithms to train their inventory control systems. The goal is to collect data from the supply chain and then use various sensors to detect and alert when an item reaches a low storage count. Next, using the past sensor data feed in to develop the predictive models, which anticipate the exact number of products needed to be restocked (at a specific retail store or distribution center). AI continuously helps to evaluate the sensor data, known as "root-cause analysis" activity, and is used to find what causes warehouse inventory levels to drop faster than usual (Mahamuni, 2018).

In reality, when a product demand suddenly increases on a particular occasion, it causes the warehouse inventory to drop. An AI method can show the various times throughout the day or week where the highest sales volume occurs, allowing managers to anticipate the future inventory demands (Sustrova, 2016). While some businesses still control inventory flow manually, gathering information without sensor technology, AI innovations allow a more efficient and streamlined approach to track retail inventory. Another critical component to ensuring that inventory counts stay accurate is guaranteeing an accurate inventory. For many companies is a sad but true reality; whether it is internal or external theft, the cost of losing inventory can have a devastating effect on business success. AI can once again integrate these practices and functioning as a form of loss prevention.

AI provides new ways to optimize the process in the supply chain in order to minimize the cost of inventory by having a low inventory stock while at the same time consistently and continuously meeting the demand. The research described a reinforcement learning ordering system that uses machine learning techniques to deal with complex ordering tasks caused by the uncertainty and changing environment. In the research, environmental uncertainties include customer demand and lead-times as two typical uncertainties in genuine world supply chains. The article applies reinforcement learning and agent-based simulation techniques to model a four-echelon supply chain that faces non-stationary customer demands. This increases the coordination of ordering processes, especially in dynamic situations with many variables to account for (Mortazavi et al., 2015).

AI helps to save time and improve accuracy in managing inventory. With the help of asset-tracking technologies such as Radio Frequency Identification (RFID) tag, many firms nowadays can effectively manage their inventories by knowing what is in hand, where and when it is, and when to reorder accurately. AI can deploy predictive analytics - proprietary algorithms to reduce stock depletions, maximize stock levels, and improve efficiency.

D. Scheduling

The current research on SCM scheduling using AI focuses on collecting and using various data sources and showing what is continuously being changed and done. One of the main goals with AI and scheduling is to replicate human-like behavior and even go beyond to assist humans (Foresti et al., 2020). The typical approach is to apply machine learning in scheduling. It would use parameters like the number of employees and the number of deliveries in a specific period. Using the AI method helps improve efficiency and erase the human-bias (Atabakhsh, 1991). The goal is also to help improve human skills because machines are better at detecting and solving problems simultaneously in a time-consuming fashion.

There are a variety of different types of AI technologies currently being used in scheduling. One of the most widely used AI scheduling techniques in the supply chain is using the integrated model (Potts & Strusevich, 2009) essentially grouping all production and distribution operations as grouping the shipping customer orders. Another example would be for multiple parts of the supply chain, like delivery to the supplier, the manufacturer, and the customer, which saves the cost and time. Researchers introduced a method called permutation scheduling, which is slightly different from permutation within mathematics. It explained schedules as "in which the order of processing the jobs is the same on all machines" (Terekhov et al., 2012). Constraint-based scheduling is widely used within the supply chain currently. The variables used within the scheduling process are stated as constraints to help to solve the problem at hand. The last concept found used advanced planning and scheduling APS. Similar to most AI technology which applies most of the algorithms with the scheduling process. It is applied to help solve constraint satisfaction problems within supply chain production planning in business (Juan & Peng, 2014).

E. Logistics

Logistics planning is a vital activity in many businesses because of the large volume of data that companies process daily. Since any company's logistic activities aim to plan and coordinate all processes, AI techniques can play an important role and make such complicated tasks more accessible and effective (Klumpp, 2018).

Route optimization represents an important logistics area that companies focus on when looking to maximize customer satisfaction and reduce waste. While optimal route planning is highly desirable for many companies, currently available GPS technologies alone cannot mimic human decision-making abilities (Orgaz et al., 2015). AI-driven solutions utilize data mining, case-based reasoning, and genetic algorithms in conjunction to identify optimal shipping routes using historical data and working zones generated using case-based reasoning. This hybridization of multiple technologies creates an artificial intelligence approach to a traditionally relied-on human expertise. Moreover, understanding that in supply chain deliveries, every minute and mile matters, many logistic companies take advantage of AI algorithms to manage weather disruptions and create the most optimal route to avoid traffic and reduce downtime. It helps drivers make their deliveries on time safely and save companies money spent on logistics (Pandian, 2019).

Some companies are starting to use virtual enterprises to solve logistics problems because AI programs can simulate material flows and transportation using fuzzy logic to determine the best routes in any step of the process. Different programming variables such as weather, speed limit, and pavement conditions into a fuzzy logic program can calculate the best route with the lowest time and lowest cost for the process (Pavlenko et al., 2017). Companies need such algorithms to examine these variables in any setting to make sure their products can quickly and efficiently reach the destination.

Nowhere is the route planning more critical to supply chain than in the maritime industry as witnessed in the current geo-political uncertainty around the Red Sea or the 2020 Ever Given incident in the Suez Canal. The maritime environment is highly dynamic and uncertain with many constantly-shifting parameters. Heuristic search algorithms such as A* and sampling-based algorithms such as Rapidly-exploring Random Trees (RRT) are being increasingly deployed in conjunction with AIS (Automatic Identification System) and weather chart data to assess and reduce risk while optimizing the route (Liu et al, 2024; Song & Cao, 2023).

Anticipatory logistics can maximize the use of resources to achieve a higher degree of efficiency, which the human being's brain alone cannot. It incorporates computers to analyze and search data, view purchase history and cookies to predict what and when a customer wants something, then automatically shipping the product even before an order has been placed (Winkelhaus & Grosse, 2020). For instance, a busy customer may forget to pick up their favorite laundry detergent that they used the last of, but with AI incorporation, they will not have to worry about running out, which brings extra convenience and incentive to online shoppers. Moreover, it provides the company with data to predict the market demand accurately and shorten delivery times by relocating inventory closer to customer locations and quickly distributing resources to permit unanticipated demand (Borgi et al., 2017).

V. Challenges of AI for SCM

Introducing AI into the supply chain has been an industrial breakthrough. Now more than ever, companies are grasping at straws in an attempt to take advantage of this new technology that has completely disrupted the industry. However, AI does have overall challenges, drawbacks, and both positive and negative impacts on this business line (Makdridakis, 2018). As with any significant integration, the addition of AI in the supply chain will inevitably accompany several challenges along the way. While the automation of specific processes can streamline workflow, reliance on algorithms or other technologies to perform meaningfully, recurring tasks may pose problems in hardware or software failure. Besides, technological turbulence creates obstacles for companies attempting to keep up with constant changes in the technological landscape, ultimately increasing the difficulty or cost of constant improvement and advancement (Tsai & Hung, 2016).

Much of a business' supply chain data can be quantified numerically, making it a prime field for AI to be incorporated. Again, some of the exceptions to this would be business relations and public relations. However, another problem may lie in incorporating it effectively. Large corporations have a much easier time utilizing it, both with the more significant resources to apply it in their company and the simply more significant amount of data to utilize to provide the AI techniques to develop better and more accurate models. A smaller business, when incorporating AI, may have more significant trouble in the accuracy, as they may not have as large of, for instance, sales numbers to be able to achieve an accurate prediction of future demand or trends amongst their products. Secondly, small and medium businesses may have sunk significant investments in legacy systems that may not be compatible with the demands of AI, and these businesses may balk at the size of new investment needed, putting them at a disadvantage.

Even for larger corporations that rely on or operate in remote environments, the quality and timeliness of data transmission impact the outputs and predictions. Ensuring data transmission in real-time and data integrity continues to be challenging in the maritime environment (Balci & Surucu-Balci, 2021; Wong et al., 2021). Ships transport about 90% of all goods including raw materials in global commerce, and the impact of inaccurate models and predictions can be severe. An extension of this would be that an inaccurate model could have a much more significant negative impact on their business, as they do not have the resources to compensate for such errors.

AI presents several technological issues, including security issues and the problems that may arise during certain AI technologies' learning time. Since machine learning requires time to train through repeated processes, programs that use AI can make mistakes during this learning period. Cybersecurity issues are prevalent in the technology field due to risks associated with handling mass amounts of sensitive information. With the possibility of driverless shipments with autonomous vehicles shortly, cybersecurity poses a significant issue to companies and the public.

One of the immense foreseeable challenges for AI in the future will be on the human side of AI. AI's fast growth means there will be more people laid off or without their jobs or compensation reduced for the machine, AI to take over. It may become an obstacle to utilize AI in every corner of every industry, especially in logistics and the old-minded transportation working system (Zgrzebnicki, 2017). One of the key demands and concerns of the striking workers in 36 ports of the US Northeast in 2024 is the projected growth of AI and Robotics. Based on current literature, we can expect to see a shift from menial, labor-focused jobs into technology-based work, which could be a problem, as is the fact that not everyone is suitable for technology work. As stated by Albert Einstein, "Everyone is a genius. However, if judging a fish by its ability to climb a tree, it will live its whole life believing that it is stupid." The concerns about job security and cultural resistance to automation might impede the speed of adoption of AI in many industries and supply chains.

Given the challenges mentioned above, AI can have a substantial positive impact on the supply chain. Companies can expect that the business runs more efficiently by adding AI to the supply chain management process. AI allows businesses to track the location, shipment quantities, potential disruptive weather scenarios, and more. This technology makes the supply chain run more efficiently, but workers and clients will be more satisfied due to this rise in the level of efficiency, which will make the companies that utilize AI within their supply chain

more desirable and create a more stable relationship between workers and clients, leading to a potential of boosts in profits.

VI. Managerial Implications

After observing both the positive and challenges AI has on both businesses and careers of the supply chain, businesses can have many managerial implications. First, AI is an ever-changing field. If businesses focus on predicting technology's future trends, they are more likely to have an edge in the marketplace. Second, identify what aspect of the supply chain would experience the most benefit from implementing AI. Many businesses may not have the funds to supplement themselves with AI. However, if it is feasible, current investment is likely to see a greater return in the future. Third, businesses must remember their workers. Without these people, businesses would not be where they are today, and while implementing technology can certainly benefit a company, it is not ethical to abandon loyal workers. Instead of laying people off, it might serve well to introduce the possibility of shifting from their labor-based job to one based around technology.

A significant managerial implication of businesses is how people trained and acted. Just because people will not be doing as much, especially in factories, does not mean that they will be obsolete. People and workers will be highly trained in more specific areas of their business and learn more strategic values to use. Employees will still have a place in certain occupations that require human intuition and the application of experience. While many machines are highly independent, not all are, and they still need to be guided by humans. Especially regarding machine learning - programmers need to make sure that their robots are learning the right things and that they are good to go, rather than just letting them continue on their own without checking in on them.

Because AI is such a disruptive field to the supply chain and businesses in general, the government will likely end up interceding and implementing its policies at a higher level. Government policy should regulate the security measures that companies employ when storing mass amounts of information in business. As with many fields outside of supply chain and management, many of the AI applications used within this area store sensitive information regarding customers. Government policy should mandate several security measures that make it difficult for outside parties to obtain this information. A mandatory number of security checks such as frequent security audits, multi-step authentication, and ways to dispose of hardware would be bolstering some AI companies' security measures.

VII. Conclusion

According to the above comprehensive literature review, AI brings many incredible benefits to SCM and logistics. Streamlining and optimizing logistics and SCM can be extremely advantageous in the competitive marketplace. Companies that quickly and efficiently identify and capitalize on market opportunities gain a competitive edge over other enterprises. Anticipatory logistics, technology-driven inventory control, and efficient demand forecasting can increase customer satisfaction while reducing waste and cost. Automating tasks traditionally completed by humans may reduce the required workforce, thereby reducing the amount of money used on labor.

Future trends of AI technologies for SCM are essential for stakeholders to understand to prepare for them. Many researchers are at dispute deciding where the future of AI is in the supply chain. However, at this moment, the future of this field is uncertain. The current research works are consistent regarding the rise of AI usage within the supply chain. It is because every branch of the supply chain has its unique use of AI - robotics within manufacturing, software that can identify if a transportation driver is distressed, cloud-based services designed to schedule tasks, and data mining that makes time-consuming decisions on a company's inventory. Because of the rise of efficiency levels within the supply chain of AI, it is safe to assume that this new technology is not going anywhere and is on track to continue advancing.

We recommend that companies invest in incorporating more AI technologies into their supply chain operations, including areas such as demand forecasting, inventory control, and logistics. Using AI in SCM can increase a company's efficiency and reduce waste, leading to profit maximization. In particular, we recommend investing in technologies such as machine learning algorithms so that companies can utilize real-time data to improve operations. Although AI that implements machine learning requires a learning period with human checks and guidance, we believe that the prevalence of this type of technology in the supply chain and logistics fields is indicative of its lucrative nature. Investing in applications that utilize machine learning now may prove profitable in the future.

Overall, the effects of AI present many un-noticed significant potential growth opportunities in a long period for the significant improvements on a company's efficiency and ability to predict future planning. However, the extreme promise and potential for growth that AI withholds in supply-chain and logistics may outweigh that risk and force businesses into the future. When a business can create the best forecast thanks to AI's help, that business can easily outperform its competitors and gain more market shares. It is recommended to invest significantly in AI technology to maintain an edge in the marketplace.

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