Rethinking Supply Chain Management: A Machine Learning Perspective

Arpit Singh
Assistant Professor
Jindal Global Business School
O.P. Jindal Global University, Sonipat, India
asingh6@jgu.edu.in

Ashish Dwivedi
Full Professor
Jindal Global Business School
O.P. Jindal Global University, Sonipat, India
adwivedi@jgu.edu.in

Suchi Dubey
Associate Professor
School of Business
Manipal Academy of Higher Education, Dubai
suchi.dubey@manipaldubai.com

Abstract

The large volume of data generated across different stages of supply chain has necessitated the adoption of new technologies to decipher patterns and yield meaningful results useful to managers and practitioners. Various machine learning (ML) tools have revolutionized data analysis across all industrial sectors. ML tools hold immense potential in supply chain management (SCM) by providing a comprehensive understanding and analysis of the data generated in the supply chain ecosystem. Limitations of existing data analysis tools such as statistical techniques have led researchers to dive deep into the ML paradigm to lend a better understanding of the large volume of data generated in supply chain processes. The main objective of this article is to understand the concept of ML in decision making and classification problems and to assess the utility of ML techniques in various supply chain areas including Demand Forecasting, Revenue Management, Transportation Planning, Inventory Management, and Circular Economy.

Keywords
Machine Learning, Supply Chain Management, Data Analytics, Artificial Intelligence

Introduction
The fourth Industrial revolution and economic globalization fueled by customer's expectations has led to significant changes in the companies' supply chain management (SCM), underscoring the competition between supply chains rather than companies (Koh et al. 2019). SCM is defined as the management of flow of goods and services and include all processes that transform raw material into final products. It includes active streamlining various supply side activities to maximize customer value and achieve competitive edge in the market (Richey et al. 2022). A copious amount of data are generated on a daily basis due to the integration of business activities with automation and smart technology. The data are routinely created, collected, and archived in different processes which is an important foundation for process control, design, and control (Naeem et al. 2022). The big data generated from the business processes contain meaningful information that has to be intelligently interpreted thereby enabling businesses to attain the competitive edge. SCM has seen an explosive growth in big data emanating from various supply chain divisions. This has forced companies to develop and implement new technologies that are capable in handling and interpreting big data. Since traditional decision support systems are incapable of dealing with big data satisfactorily, it is important

to deploy modern and sophisticated tools that can efficiently understand and decipher patterns in big data leading to effective policy decisions to improve and make profits (Lutfi et al. 2022).

Artificial Intelligence (AI) provide the best mechanism for tackling the challenge posed by big data. Machine learning (ML) is the subset of AI that is instrumental in detecting patterns hidden in big data and generate meaningful insights that directs the stakeholders toward desired objectives (Gandomi et al. 2022). ML techniques find applications in diverse disciplines including manufacturing, operation, housing, etc. (Shi 2022). The field of ML based operating frameworks has gained traction among researchers in the SCM. Big data handling incapability of traditional decision making systems has made ML systems gain unprecedented popularity in recent times (van Elten et al. 2022). Some of them major bottlenecks in traditional systems such as nonlinear datasets, unstructured information, and multiple simplifying assumptions are handled effectively by ML algorithms (Guerra et al. 2022). Since ML techniques rely solely on the structural properties of data, it does not need any external assumptions for the decision making process. ML based techniques have demonstrated stronger performance in predicting effective factors in supply chain performance (Yang et al. 2022). In a competitive market where businesses are constantly struggling to enhance profit margins, reduce costs, and provide unrivalled customer experience, emerging technologies like ML and AI offer some extraordinary opportunities (Alanne and Sierla 2022).

Big data analytics coupled with new information can provide a platform for making informed decisions and predict future trends in various parts of SCM. Emerging technologies such as Internet of things (IoT), Blockchain Technology (BT), cloud computing, and several other algorithms can induce a paradigm shift in the way data is handled and operated (Pandey et al. 2022). In the current scenario, SCM needs self-adaptive systems that can handle fluctuations in customer demand effectively (Raja Santhi and Muthuswamy 2022). Increasing the transparency and visibility of supply chains using technologies such as BT and IoT can help in managing changing customers' demand with ease (Wamba and Queiroz 2022). Integrating supply chain processes with new technologies enables real time data and information sharing across various parts of supply chains anywhere in the world (Balamurugan et al. 2022).

Extant literature on ML based frameworks in various supply chain processes indicates that most of the research in this field is limited to one, two, or limited areas of SCM. For instance, hybrid demand forecasting grounded on ML using Autoregressive Integrated Moving Average with Explanatory Variable (ARIMAX) and Neural network was developed by (Feizabadi 2022). Supply chain collaboration was studied from the perspective of fusion based ML framework; where the ML performance was found to be better than traditional probability based framework (Ali et al. 2022). A combination of ML and AI based techniques was used to observe the effects on waste reducing designs, tracking production in real-time, and enabling shorter process cycle times (Pnamala et al. 2022). Sharma et al. (2022) identified 5 major research clusters in the domain of ML and AI in SCM namely supply chain network design (SCND), supplier selection, inventory planning, demand planning, and green supply chain management (GSCM). Inventory control using ML tools was studied by (Lumban et al. 2022). The research on comprehensive ML applications in various aspects of supply chain is relatively scarce thus limiting the ability to understand the application of ML in SCM holistically.

Objectives

This article highlights the applications of ML algorithms in some key aspects of SCM including Demand Forecasting, Revenue Management, Transportation Planning, Inventory Management, and Circular Economy. The main contributions of the article is as follows:

- The review and analysis of major ML techniques in the domain of SCM
- Providing a detailed framework to explain the outputs of the application of ML techniques in various aspects of supply chain

The article is organized as follows: Section 2 discusses basic preliminaries of ML techniques. The applications of ML in various aspects of SCM are presented in section 3. Section 4 outlines the discussions and managerial implications of the study followed by conclusions ad scope for future work in section 5.

Preliminaries of Machine Learning

Arthur Samuel, a pioneer in the field of artificial intelligence defined ML as "Field of study that gives computers the capability to learn without being explicitly programmed" (El Naqa and Murphy 2022). ML can be explained as the process by which computers imbibe human-like behaviour to learn from experience. More technically, this implies leveraging good quality data to train computers and build effective models for unseen data using different algorithms

(Dambhare et al. 2022). The kind of algorithms depend on what kind of data are we dealing with and what kind of tasks are we trying to automate. The main steps in the data analysis using ML can outlined as follows (Egger 2022):

- Gathering past relevant data in any form suitable for processing. It is important to collect good quality data for better modelling. ML works on the principle of Garbage in garbage out (GIGO).
- Data processing: This step is required when raw data is collected from various sources. In situations where there are missing values, it is replaced by the average value of that attribute or in the case of categorical variable it is replaced by the mode. Data processing is needed to transform the data into a format suitable to be fed as input to ML classifiers.
- The input data is divided into training, cross-validation, and testing sets. The ratio between the sets should be 6:2:2.
- The model is built using suitable algorithms and techniques on the training set.
- Final model is used for predicting objects from the test data which was not exposed to the learning algorithm. The classification and prediction performance is tested using various metrics such as f1 score, precision, and recall.

AI and ML have become buzzwords across various verticals including SCM. Disruptive technologies based on ML algorithms automates processes thereby enabling management to focus on more strategic and important business activities (Patriarca et al. 2022). Using intelligent machine learning software enterprises can optimize inventory and find most suitable suppliers to run businesses efficiently. In the recent times, organizations are increasingly focusing on ML based techniques to use the huge amounts of data generated from warehousing, transportation systems, and industrial logistics (Geng and Du 2022). Some of the prominent ML techniques are collected in Table 1.

This study attempts to chronicle the major applications of ML algorithms in some of the basic supply chain activities that provides directions and insights to practitioners and management to create machine-intelligence powered supply chain model thereby mitigating risks and enhance performance which is extremely crucial to build a globally competitive supply chain model.

Table 1. Brief Description of Major Machine Learning Techniques

Types of learning	**Algorithm**	**Description**
Supervised learning	Linear Regression	Linear regression is used to find the relationship between variables and forecasting. Different regression models differ based on the kind of relationship between variables and the number of independent variables considered (Montgomery et al. 2021).
	Nearest Neighbour	An item is placed in an n-dimensional plane that corresponds to the n-features (characteristics). A new item is placed with the set of items closest to it based on distances such as Euclidean or Hamming distance (Nurdiawan et al. 2021).
	Naïve Bayes	Naïve Bayes classifiers are the collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a collection of algorithms that share a common principle. It is best suited for document classification and spam filtering (Wickramasinghe and Kalutarage 2021).
	Decision Trees	Decision trees are powerful tools for classification and prediction. It is a flowchart tree-type structure where each internal node represents a test on an attribute, each branch denotes the outcome of the test and each terminal node represents the class label (Kumar et al. 2021).
	Support Vector Machines (SVM)	SVM is a discriminative classifier that outputs an optimal hyperplane separating labelled examples into distinct classes. SVM can efficiently perform non-linear classification by mapping the input examples (items) into high-dimensional feature spaces (Guo et al. 2021).
	Random Forest	Random forest is an ensemble technique capable of performing classification and regression effectively. It collects multiple decision trees and with techniques such as bootstrapping and bagging determines the final output using multiple decision trees (Singh and Misra 2022).
Unsupervised learning	K-means clustering	It is a clustering algorithm which collects items in an n-dimensional space (corresponding to number of features) in k-groups of closest means. The closeness is measured using Euclidean distance (Gupta and Chandra 2021).

	Density-Based Spatial Clustering of Applications with Noise (DBSCAN)	DBSCAN is based on the intuitive notion of clusters and noise. It is used in situations where clusters are irregular in shape and contain noise. The fundamental principle is that given a point in a cluster, the neighborhood of a given radius should contain at least a minimum number of points (Gholizadeh et al. 2021).
	Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH)	BIRCH deals with large datasets by first generating a compact summary that retains as much distribution information as possible and then clustering the data summary instead of the original dataset (Li 2017)
	Hierarchical Clustering	Hierarchical clustering is a method of clustering where clusters are created step by step from an initial set of singleton clusters (agglomerative clustering) or a set of singleton clusters created from an initial cluster containing all the items (divisive clustering) (Grabowski and Smoliński 2021).
Semi supervised learning	Self-training	In this semi supervised learning algorithm the classifier is trained on a test data which are some labelled instances from the original data. The trained classifier predicts the label of the remaining unlabelled data called pseudo labels. The labelled and pseudo labelled data are concatenated and fed to the classifier once again to retrain it (Chen et al. 2022).
	Transductive Support Vector Machines	This algorithm is similar to SVM but with an additional constraint of assigning labels to the unlabelled data. This adds complexity to the optimization problem where the margin between the positive and negative instances is maximized subject to the conditions that the instances are separated by the hyperplane (Wang et al. 2021).
Reinforcement learning	Positive Reinforcement	Positive reinforcement is the reinforcement learning where an event increases the strength oand frequency of the behaviour. In other words, it positively affects the behaviour. Positive reinforcement maximizes performance and sustain changes for a long period of time (Degrave et al. 2022).
	Negative Reinforcement	Negative reinforcement implies strengthening of behaviour because a negative event was averted. Negative reinforcement can be used to learn about the negative events and gain control on it to increase the behaviour (Prowacki et al. 2022).

2. Machine Learning in Supply Chain Management

The capability of ML algorithms to automate processes can be used to improve the supply chains across industries (Feizabadi 2022). Despite the fact that ML techniques hold immense potential in revamping the supply chains, research on the applications of ML tools in a variety of supply chain processes remain inadequate (Tripathy et al. 2022). This can be attributed to the lack of proper knowledge about the technical aspects of ML tools and its area of applications (Tseng et al. 2022). This article puts forth the utility of ML tools in the SCM that will enterprises identify areas of supply chain where ML techniques can be effectively applied to mitigate risks, improve insights, and enhance performance thereby leading to a globally competitive supply chain model.

Demand/Sales Forecasting

In SCM, planning relies largely on the estimation of demand or sales. Generally, the estimation of demand is inaccurate when the relationship between the response variables and causal variables are assumed to be linear (Mohammad et al. 2022). ML enables the hypothesis of a non-linear relationship between variables thereby increasing accuracy of the demand and sales forecast. In addition, this also helps in predicting the inventory levels thus optimizing the supply chain performance holistically. A forecasting system that works automatically and intelligently is a prime candidate for optimizing performance, reduce costs, and increase sales and profits. To achieve better accuracy in the predictive models it is paramount to have scope of assuming non-linear relationship between the explanatory and dependent variables. In the real life scenario it is very unlikely to have a strictly linear relationship between variables of interest. Heavy dependence on historical data limits the ability of traditional methods such as ARIMA (Autoregressive Integrated Moving Average), exponential smoothing, Box-Jenkins method, and moving averages in making reliable predictions for demand and sales forecasting thereby hampering the planning process. ML, on the other hand, works with the current data to yield forecasts which has been found to be more accurate and reliable than the other traditional methods.

Several ML techniques such as Support Vector Regression (SVR), Random Forest Regression (RFR) and Decision Tree Regressor (DTR), deep learning techniques were used for the demand forecasting based on marketing expenses. Of all the methods, LSTM proved to be the best performer in predicting demand with marketing expenditures with the minimum forecast error (Babai et al. 2022).

Feizabadi (2022) postulates that firms situated at the upstream supply chain suffer from variance amplification due to distorted demand information emanating from multi-stage supply chains. To mitigate this effect and improve the performance, advanced ML algorithms are employed for better demand forecasting. Hybrid demand forecasting method integrated with ARIMAX and neural networks was developed where both time series and explanatory factors were fed in the method. The predictive performance shown by ML method was statistically significant as compared to traditional method.

Real time product demand forecasting can be efficiently achieved by considering the highly non-linear nature existing between the demand and historical sales data. In a forecasting model, where product demand was forecasted for an e-commerce company, an extreme learning machine (ELM) model coupled with Harris Hawks optimization (HHO) algorithm was used. The prediction performance was much higher than other algorithms depicted by different performance metrics such as Root mean squared error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Percentage Error (MPE). The fast computational speed of ELMs was combined with accuracy gained by tuning hyperparameters using HHO (Chaudhuri and Alkan 2022).
A typical demand forecasting model is shown in figure 1.

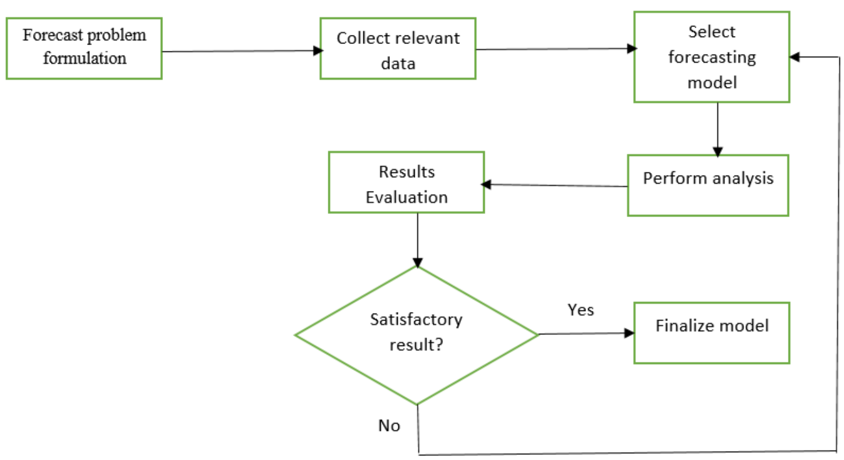

Figure 1. Basic flowchart for demand forecasting

As can be seen in the figure 1, the basic layout for the demand forecasting remains the same as for the traditional systems. The stage where traditional and ML based framework differs is the selection of forecasting model. Traditionally, techniques such as ARIMA, Delphi method, moving averages are used in this stage. With ML, methods such as neural networks, multilayer perceptron, Long-short term memory (LSTM) networks and other ensemble techniques are used.

Supplier Segmentation

One of the major strategic activities of an organization through which suppliers with similar features are grouped together is called supplier segmentation. Supplier segmentation is often the most ignored part in research as opposed to customer segmentation (Lajimi 2021). The management and contracts of suppliers are similar in a group and different in unrelated groups (Ahmed and Shafiq 2022). Supplier segmentation enables organizations to streamline processes and pay individual and focused attention to each department thereby promoting efficiency and healthy professional relationships with the suppliers (Lajimi 2021). Sustainable and effective relationship with suppliers is an integral aspect of a successful and functional supply chain. Past literature suggests that most researchers and scholars have paid relatively more attention to the customer segmentation which is a market demand side attribute as opposed to supplier segmentation which is in the area of market supply side (Kaur and Singh 2021). The limited research available on the topic of supplier segmentation is confined to the usage of multi-criteria decision making (MCDM) based methods in segmenting and grouping suppliers based on similar characteristics.

It was found in a study that supplier segmentation problem can be solved using MCDM methods but this poses issues in modelling supplier behavior uncertainty in real time (Shiralkar et al. 2021). A Chinese research on deciding the most suited supplier for the new energy vehicle (NEV) postulated that every supplier cannot equally contribute to the buyer's innovation. A hybrid fuzzy-symmetrical MCDM model was proposed to rank suppliers that integrated fuzzy linguistic sets, best-worst method (BWM), prospect theory (PT), and VIKOR (Liu et al. 2021). A dynamic generalized multi-criteria group decision making (MCGDM) was proposed to address the issue of supplier selection and segmentation in the context of supplier's environmental concern. The suppliers were ranked using the centroid-index ranking approach (Duc et al. 2021). To guide chemical manufacturers with supplier relationship management an Integrated Sustainable Supplier Evaluation & Development Framework (ISSED-F) was developed. The model leveraged analytical mechanisms from Materiality analysis, Analytic Network Process (ANP), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and cluster analysis. The successful implementation of ISSED-F paved the way for chemical supply chains to become sustainable and ensure continuous development (Coşkun et al. 2022).

The major disadvantage of using MCDM based methods for supplier segmentation and selection is the inability to deal with big data. Since the MCDM based techniques rely on experts' opinions and pairwise comparisons, the reach of these methods is confined to a limited area in terms of domain and information density (Singh and Pant 2021). MCDM coupled with ML techniques can alleviate the limitations stated above. The basic flowchart of using a ML algorithm based on clustering analysis is shown in figure 2. A typical application of ML techniques in supplier segmentation can be found in (Islam et al. 2021). In this interesting study a two stage solution approach was adopted to address the issues of supplier selection and order allocation by integrating forecasting method with optimization model. In the first stage, demand is forecasted using a novel relational regressor chain method which was found to perform better than Holt's linear trend and ARIMA models. The output was then fed to a multi-objective programming model to identify suppliers and order quantity from each one of them. The algorithm employed for this purpose Weighted-sum and Є-constraint method for obtaining efficient results.

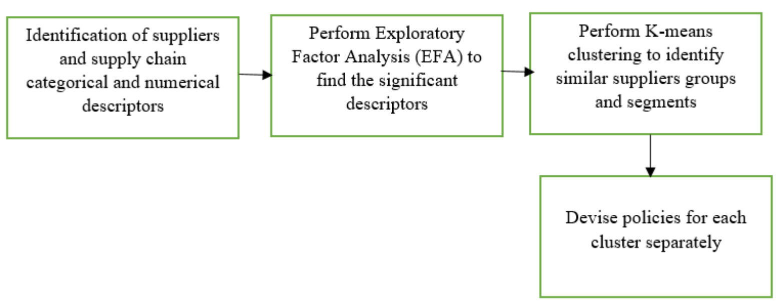

Figure 2. Basic flowchart for supplier segmentation

Revenue management: Price optimization

Revenue generation is the backbone of any business. It is obvious that a business needs to cover the expenses and achieve a specific level of revenue to find a sustainable place to survive. The glaring question here is how to price goods and services? Is it going to be a fixed pricing mechanism or a dynamic pricing system that also incorporates competitive scenarios? This demands a pricing strategy for today's competitive scenario as well as flexible enough to make necessary changes if required (Gao et al. 2022). Price optimization is one of the key drivers for revenue growth, yet it is considered a tough nut to crack by many organizations (Arslan et al. 2022). This is primarily due to the complexity associated with the implementation of price optimization models and the inability of traditional methods to include all the factors that determine pricing levels (van de Geer and den Boer 2022). ML provides a viable alternative to traditional methods of pricing optimization process by enabling organizations to handle more complex features and generalize the result to optimize other areas of the supply chains (Navidi et al. 2022).

Generally for the ML techniques to offer services in the price optimization, there should be ample historical data to learn the price elasticity. In real-time availability of historical data is a monumental issue which can be effectively solved with the usage of trained ML models on prior occasions of price optimization (Hütsch 2022). A typical price optimization process using ML is carried out by firstly estimating the price elasticity from the available dataset. In this stage, the changes in demands are documented for a unit change in prices. To effectively gauge the impact of price increase on revenues, efficient forecasts of future demands are required. Demand forecasts made using the traditional methods suffer from the inability to account for the inter-relationships between wide variety of factors influencing demands and limited generalizability. ML based tools are the best option to combat the limitations inherent with the traditional analytical tools majorly attributed to its ability to process a wide range of data and provide a more generalized outcome for unanticipated events (Bal et al. 2022).

A general flowchart demonstrating the process of ML model selection for the purpose of optimizing prices facilitated by Amazon's Sage Maker (Amazon Sage Maker 2022) is shown in figure 3.

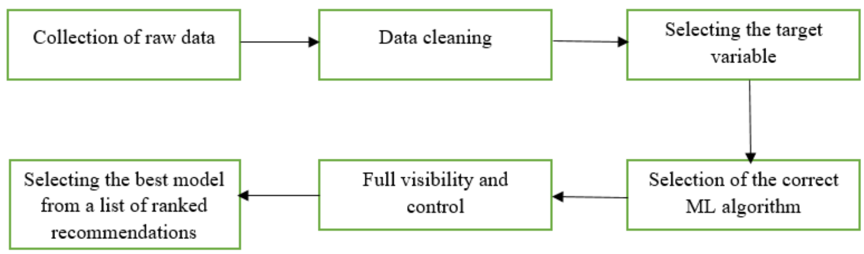

Figure 3. Building an ML workload around the raw dataset

The first stage in figure 3 is the data collection stage. Raw data collected is organized and cleaned/modified for any missing data. Proper classification of variables into specific feature sets and assignment of a decision variable is accomplished in the first stage. If operating on auto-pilot mode then in the next stage the software automatically tests different algorithms and selects the best model. If the selection of model has to be done manually then the decision maker has to apply all the possible permutations to finally reach to the best model. The results obtained from the model has to be cross checked and validated using different algorithms such as k-fold cross validation method and confusion matrix. Finally, with the help of metrics such as Precision, Recall, Sensitivity, Specificity, and f-measure the performance of the algorithm is tested.

Literature is rife with studies pertinent to the application of ML techniques in pricing optimization. One such study considered Deep Q learning approach to model optimal pricing strategies and supply demand problems. The theoretical underpinning of the technique was based on the fact that the sequence of actions can be optimized by maximizing the reward function (Pavlyshenko 2022). A two echelon supply chain model was employed to model a supply chain with the objective of optimizing the total profit generated during sales and distribution of the product. For the purpose of this study the two-echelon supply chain model consisted of one supplier, one retailer, and one product at a pharmaceutical supply chain. The problem was optimized using two different models: traditional supply chain model and two-echelon supply chain model (Yıldırım and Denizhan 2022).

Transport planning

ML shows immense potential in improving supply chains' profitability by empowering enterprises to bank on prescriptive analytics that enables mitigation of risks and expediting resolutions of delays to prevent vehicle breakdowns (Tsolaki et al. 2022). ML is crucial in predicting unforeseen situations and provide effective and applicable solutions. Particularly in the transportation industry, there are several factors influencing the expected time of arrivals (ETAs) which are beyond human control such as natural calamities (Nipa et al. 2022). With the use of prescriptive analytics coupled with ML algorithms the occurrences of such disasters can be readily predicted and logistics activities can be planned accordingly. ML enabled transportation platforms browse through historical data of previously travelled routes to generate insights about optimal paths thus boosting productivity and reducing costs (Najafi Moghaddam Gilani et al. 2022). In a typical scenario of optimizing travel route consider a situation where the travelling path are from points A to B and then C to finally reach the customer's location. ML based techniques will follow historical data of the time consumed in traveling through points A, B, and C. ML will feed the timings in the database and use it to track the time taken for future journeys. It will send alerts to the transportation stakeholders in case the threshold is exceeded thereby reducing delays (Accorsi et al. 2022). ML can be extremely helpful in charting out the secured routes for the transportation of cargoes. In industries such as manufacturing where freight is carried to different locations spread hundreds of kilometers apart, the problems related to theft and pilferage are pronounced (Jin et al. 2022). ML can learn from historical data about the routes on which there has been repeated stoppages which could be a potential reason for theft and breaking in. It can send alerts to management about a possible red flagged route through its learning and predicting mechanism (Elfahim et al. 2021). To gain the competitive edge a business needs to be agile in making deliveries not only in full but also on time. Timely delivery of goods involve numerous constraints that need to be tended to. ML helps enterprises deliver shipments on time by predicting ETAs based on a number of constraints and key performance indicators (KPIs). This is an on-going learning process which gets better with experiential learning. Thus, ML posits to be the best candidate to develop a prediction based framework hinged on historical data such as pick up window, delivery window, unavoidable delays, and tonnage (Pugliese et al. 2022). ML tools can also be leveraged to predict the working conditions of vehicle by pointing out how disparately parts are performing at a given time and situation (Wang et al. 2021). The applications of AI and ML in logistics is captured in figure 4.

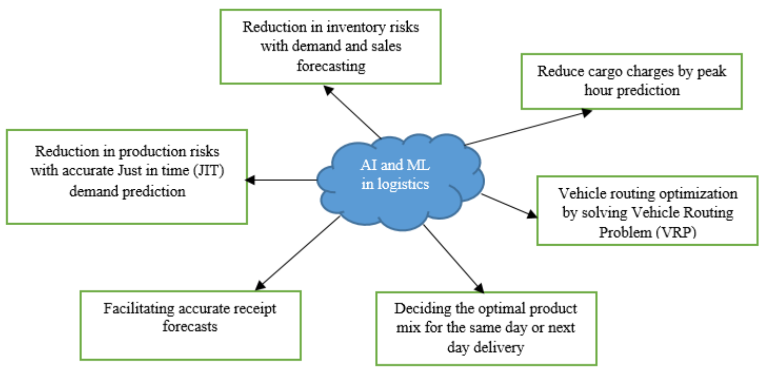

Figure 4. Major areas of AI and ML applications in logistics

2.1 Circular Economy

With the world's population increasing at an exponential rate it is inevitable for the finite resources to be fully used up at some point in time in the near future (Sakhlecha et al. 2022). It is, therefore, paramount to ensure the sustainability of the planets' resources. The wasteful and toxic consuming behavior is exploiting the ecosystem in ways beyond comprehension. Solid waste production is on the rise which is expected to reach to a staggering 2.2 billion tones by 2,025. 53 million tones of the total solid waste is expected to be accounted for by the electronic wastes by 2,025 (Ma et al. 2022). It is evident that linear economy, which is based on the tenets of make, use, and dispose, cannot sustain in the long run. Massive energy use and overuse of natural resources are eroding the ecosystem and huge amount of waste generation cannot continue (Kashiwar et al. 2022).

However, the operating models of major organizations across industries still rely largely on the excessive usage of natural resources and they are not willing to switch to other methods of operations unless it offers them the opportunity to grow efficiently (Sabharwal et al. 2022). Combining AI with circular economy can accelerate a paradigm shift towards a regenerative system (Ghoreishi and Happonen 2020). Circular economy is based on the principles of designing out waste and pollution, keep products and materials in use, and regenerate natural systems (Wilson et al. 2021). The advantages offered by circular economy are manifold. It is anticipated that circular economy is to grow by EUR 1.8 trillion by 2030 while addressing insurmountable challenges of unemployment, spurring innovations, and generating environmental benefits (Ramadoss et al. 2018).

The three major areas where AI can restructure circular economy are Design, Data Analysis, and Recycling strategies. Using different learning algorithms ML can design products, materials, and components using circular economy principles. Leveraging historical and real-time data collected by interrogating products and users, ML can predict and highlight competitive circular economy models that helps in better asset utilization and product circulation by forecasting demand and inventory management (Jose et al. 2020). AI can be useful in sorting, disassembling, re-manufacturing, and recycling products and materials (Poschmann et al. 2020).
The range of services offered by AI enabled technologies in the domain of circular economy is summarized in figure 5.

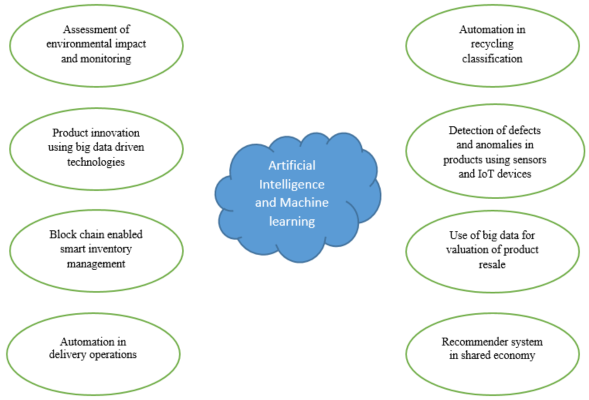

Figure 5. Potential areas of AI applications in Circular Economy

Discussions and Managerial Implications

The application of ML in various facets of SCM was studied in this article. Some limitations associated with the traditional data analysis can be effectively overcome with ML and AI based tools. ML classifiers and predictors such as SVM can extract seminal features for making efficient decision of supplier selection and segmentation. Moreover, the techniques based on ML can significantly reduce the amount of analytical work required for the most suited features selection in supplier selection problem. Inclusion of ML based framework in SCM can foster an efficient and resilient supply chain thereby ensuring profitability and continuity of organizations. An important application of ML in demand forecasting enables prime accuracy in predicting demand and sales which leads to reduction in inventory costs by estimating the actual level of inventory required in an organization. Automated methods of inspections ensure mitigation of damages inside logistics hubs and in-house delivery. Another area of SCM where AI and ML have proved its caliber in refurbishing the operational model is the transportation and distribution. Through models such as Vehicle Routing Problem (VRP) and shortest route possible calculations products are delivered timely and with high quality. Use of AI and ML in restoring ecological balance by minimizing over usage of finite resources is extensively studied. The mettle of intelligent and smart technologies in measuring the impact of industrial activities on the environment is sufficiently visible.

Despite the numerous advantages offered by AL and ML in SCM there are some limitations of the tools based on ML protocols. The ML methods decipher patterns in the dataset and provide insights based on the historical data. The basic premise of ML is to learn from a given data and subsequently devise strategies to improve the situation. However, in the event of unanticipated circumstances where the validity of historical data is challenged ML will not be able to yield logical results. This is due to the fact that the history has changed and so are the learning models. For instance, ML models that worked perfectly fine in the pre-COVID era might have to rewire everything from scratch to attain optimal results. In several occasions it is found that ML tools are just replicating the problems that are supposed to be solved owing to the dependence on the historical data. Therefore, human intervention is required in SCM to monitor, assess, and evaluate the outcomes of ML based algorithms to categorically gauge the logical desirability and cultural feasibility of the results.

The study proposes several implications for the management and stakeholders in the domain of SCM. It is suggested to the management to exercise caution when deciding to choose ML algorithms for solving supply chain problems. There are certain pre-requisites for a typical ML algorithm to be applicable. Informed judgment about the data and its interpretability for the industry is pivotal when making the decision of selecting ML algorithms. Organizations must hire skilled personnel to impart technical training to the employees and also equip them with the necessary background to understand the applicability of ML in SCM. Frequent presentations and seminars should be conducted in organizations to sensitize workers about the new technologies and the bright prospects they bring with them. Senior management should be properly informed about the specifics of the technologies and its exact application in SCM through use cases. Use cases of ML in supply chains are versatile. If the organizations have to manage a wide network of suppliers, warehouses, logistics services providers, etc. ML can prove immensely useful in automating manual processes and reduction in paperwork thereby leading to increased end-to-end visibility into supply chains.

Conclusions and future directions

The present article aimed to study various aspects of ML applications in SCM. A wide range of supervised and unsupervised techniques were reviewed and their applications in different areas of SCM viz-a-viz demand forecasting, supplier segmentation, transportation and distribution, revenue management, and circular economy. The application areas of the ML algorithms in the aforementioned areas of SCM were presented with the help of flowcharts and graphics to familiarize readers and concerned authorities with the process of implementing and utilizing powerful ML tools across all stages in a typical supply chain. It was gathered from the detailed review of the literature and general understanding of the discipline of ML and AI that the tools based on ML tends to make systems and processes in a supply chain intelligent and smart which in turn enables organizations to work more efficiently resulting in a better productivity. The choice of ML algorithms depends a great deal on the kind of industry one is studying. A more focused and streamlined research is planned for a supply chain specific to an industry. Integrating mathematical optimization modelling with ML techniques paves the way of a better optimized supply chain ecosystem. Future studies aim to combine mathematical optimization with ML to explore new operational frameworks. A proper hypothetical framework can be structured to explore the relationship of various factors influencing the ability to use ML algorithms in industries.

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Biographies

Dr. Arpit Singh is currently employed at Jindal Global Business School (JGBS) at O. P. Jindal Global University (Institute of Eminence), India. He holds a doctorate (Ph.D.) from Department of Industrial and Management Engineering (IME), Indian Institute of Technology Kanpur. He holds an M. Tech degree in Operations Research (Gold Medalist) from National Institute of Technology Durgapur, West Bengal. He is an engineering graduate in Electrical and Electronics Engineering from Dr. K.N.Modi Foundation, Modinagar, Ghaziabad. He has rich industrial experience in the Investment banking and Private Equity Research sectors. His research interest is in the areas of Decision making under uncertainty, Big data Analytics, Statistical applications in business problems, and adoption of new technologies in the business domain.

Dr. Ashish Dwivedi works as a Full Professor in the area of Operations Management and Decision Sciences at Jindal Global Business School, O.P. Jindal Global (Institution of Eminence Deemed to be University), Sonipat. He holds a doctorate (Ph.D.) from Department of Management Studies, Indian Institute of Technology Delhi. He holds a M. Tech degree in Mechanical Engineering with specialization in Computer Aided Design and Manufacturing from Motilal Nehru National Institute of Technology Allahabad, Prayagraj. He is an engineering graduate in Mechanical Engineering. In his doctoral research, he developed information and decision synergy models for performance improvement in product recovery systems. His research has been published in various journals of international repute including International Journal of Production Research, Annals of Operations Research, Journal of Cleaner Production, Business Strategy and Environment, Technology Forecasting and Social Changes and so forth. He has also presented his research works in various international conferences held in US and Dubai.

Dr. Suchi Dubey is the Associate Professor at School of Business, MAHE Dubai. Her area of research is in valuation, risk assessment, decision sciences, block chain and analytics. She has published research paper in the international journal of repute and has a patent in Method for Investigating the Manipulated Financial Statements from South Africa Companies and Intellectual Property Commission. She holds a Ph.D. Degree in Finance from Motilal Nehru Institute of Research and Business Administration (MONIRBA), University of Allahabad, India.