Artificial Intelligence for Supply Chain Success in the Era of Data Analytics

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Artificial Intelligence for Supply Chain Success in the Era of data Analytics

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Abstract

Nowadays, artificial intelligent (AI) is becoming a more effective digital domain promised to facilitate immediate access to information and effective decision making in ever-increasing business environments. The researchers understand the extensive use of artificial intelligence among firms as an essential and necessary tool for shaping the future of supply chain 4.0 industry. This chapter discusses the role of AI applications for the success of a supply chain in the big data era. From a holistic perspective, today, manufacturers, particularly those with global operations and presence, are under enormous pressure to keep up with the continuous growth of disruptive innovative procurement models. This has open doors for the firms to aggressively seek out big data management capabilities to improve operational efficiencies and to innovate the process. This chapter provides a better understanding related to the application of data analytics in the supply chain context. The research issues are classified into different categories, including big data management and machine learning, a business case for the supply chain and innovation in supply using data. This study also present machine learning data analysis steps.

Keywords: Data Analytics, Artificial Intelligence, Machine Learning, Database management capabilities

The Logic of Artificial Intelligence -- and data volume in Supply Chain Management

The rapid increase of human-computer interaction in recent years has called for further exploration of how human and machine co-exist in an existing artificial intelligence environment. Artificial intelligence, machine learning and internet of things are a major source of generating information among others in a variety of ways, such as the volume of information, diversity of information and divergence of information are a few data flashpoint for big data that can be used for decision making. For the supply chain problems which are predominant by uncertainty, in that case, Artificial intelligence is more effective than other tools of information technology. The extensive use of artificial intelligence is understood by researchers as important and necessary for shaping the future of the supply chain of industry 4.0. The term ” artificial intelligence” (AI) is used to describe the process involved in machines learning to recollect patterns and features directly from the data to take actions using algorithms (Miller and Brown 2018). The origins of AI as an area of scientific research is not a new concept; its conception goes back to 1965 from “Dartmouth conference” then the term typically referred to as “intelligent machine”. However, looking back, the term intelligent machine did not convey the scope of human and machine interface. Therefore, later on, the term artificial intelligence emerged. Figure 1 illustrates the history and developments in AI. Figure 1 is adapted from (SAS, n.d.)

More recently, it has been argued that principles of artificial intelligence are suitable to any industrial organisation, from software developments to industrial production and supply chain services. There are many layers of supply chain system; every layer provides enormous data, linking data from every layer and creating connection into useful results which require smart artificial intelligent applications. The role of the AI is a trade-off between the different actors that make up what is commonly called networks for the supply chain. This metaphor is linked with the distribution, logistics management, procurement, monitoring and traceability of material, production inspection and control, fault detection and predictive maintenance, ideally in a way to optimise the processes, reduce cost and decision making. As (Duan et al. 2019) states the importance of AI is to replace or support decision-making issues with limited involvement of human interfere. Because of the shift in the use of internet of things (IoT) in different spheres of the supply chain, such as production and distribution, it is noteworthy that now supply chain networks recognise the value of artificial intelligence with the internet of things. IoT is defined as, a group of infrastructures, interconnecting connected objects and allowing their management, data mining and the access to data they generate" where related objects are "sensor(s) and/or actuator(s) carrying out a specific function that are able to communicate with other equipment" (Dorsemaine et al. 2015). Thus artificial intelligent supply chain management (AISC) begins with the application of internet of things concerning the seek optimization and decision making to develop a direct relationship with the individual customers. In AISC, the production process can be tailored automate to develop customized products for particular customers or in specific situations.
Many tools, methodologies and terminologies have been developed over the years, including fully digitalized mechanisms and hybrid machine learning techniques (Sarhani and El Afia 2014). AI is an advanced step in technology digitalization to use computer systems for interpretation, developing and recognizing patterns, conducting or understanding an organization's behaviours from an occurrence. As sentiment analysis, attaining and maintaining acquaintance, and generating enormous sorts of inference to solve the problems in decision-making circumstances where most favourable or accurate solutions are either too luxurious or complicated to construct (Luger 2002). In literature, different forms of artificial intelligence have already been discussed for example Roughly, Set theory (Pawlak 1982), Machine learning (Samuel 2000), Expert systems (Jackson 1999), Genetic algorithms (Michalewicz 2013) and Fuzzy logic (Tanaka 1997).

The shift from big data to pattern data has undoubtedly been most apparent. The effects of AI and pattern data in manufacturing have produced a striking impact on the development of customized products. AI is a way of representing data and transforming business for further development (Daugherty and Wilson 2018). An additional advantage of AI is the ability to decoupled data, and to rationally explore using algorithms to improve the organisation's ability to reduce the cost of making sustainable decisions (Agrawal et al. 2018). The AI offers an ontological perspective of describing or representation of data as patterns rather a than standard form. As noted by (Duan et al. 2019), traditional data modelling approaches are abstract, does not encourage specific data patterns. In contrast, data analytics offers a more flexible way out to engage and visualise the influence of different sources of information for decision making and could advance the practical success of artificial intelligence applications in different domain. It's beyond human capacity to analyze huge bulks of data; machine learning can assess huge bulks of data and come up with recommendation. This data includes market trends, trade obligation, advertisement trends, and consumer's sentiment expressions over social media, competitive scenarios and the presence of websites to launch the information about product quality. It does not just supply chain system which needs tracking to reduce the cost and increase the efficiency, but machine learning also supports the norm of labour performance evaluation.

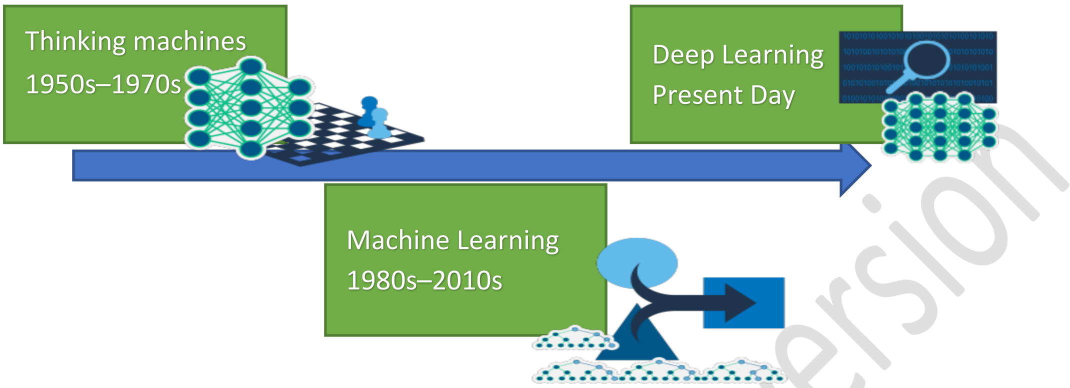


Figure 1. AI devleopment adapted from (SAS)

Application of Data Analytics and Machine Learning -- in Supply Chain Industry

Big data modelling is an emergent field. Big data refers to as "the information asset characterized by high Volume, Velocity and Variety to require specific technology and analytical methods for its transformation into Value" (De Mauro et al. 2016). This implies that big data is a plausible set of unstructured large data sets that provide an opportunity for organizations to apply scalable algorithms to capture, store, and analyze the information to gain business intelligence. Big data focuses on the extraction of data form micro and macro level of the system and to offer a transparent process to make the process easier. Thus, big data provides a viable picture with details of relevant characteristics to spot trends between different data nodes to find new correlations. Big data and machine learning induce more value-added infrastructure towards a new era of technology. Particularly, when it comes to supply chain performance. The large amounts of collected data sets irrespective of qualifying to be Big data is now an integral part for improvement, competency, and superiority in the supply chain for companies to avail smart benefits (Sanders et al. 2015; Hazen et al. 2018). The benefits are manifold as big data deals with massive amorphous data which is required for high-velocity detaining information for business, government agencies and private entities (Chen et al. 2014). This information supports the fundamental models of logistic companies for including estimation of the real-time supply chain, supply chain sanctuary hazards, evaluation and forecasting of demand-supply determinants, appraising supplier performance, process and cost-effective optimization, resourceful interaction between business to business (B2B) and business to consumer (B2C), and competent strategic decision making. According to (Addo-Tenkorang and Helo 2016) large amounts of data sets provide opportunities to manufacturing industries for efficient realization of output by improving process quality in terms of minimising the risk of out of stock. Various companies, software developers and analytics are offering sophisticated and advance tools and platforms to enhance the supply chain performance in stock and operation planning. Like routes and location distance trailing, tracking unforeseen disasters, delivery time cycle, parts assembling operations, storage capacity and approaches, limitation of goods distribution to retailers, customer behavioural patterns, and competitor standing point. For example, ‘Blue Yonder’ are developers of data-intensive forecasting methods, ‘IBM’ links production planning and weather forecasts, ‘Google trend’ provides information on supply disruptions. Similarly, ‘Caterpillar’ is a massive information provider on an industrial quotation, ‘ForkLift 3’ is trying to achieve a big data hub for warehouses, ‘Logivations’ is a developer of cloud-based 3D warehouse layout planning and optimization tool, ‘UPS’ is a developer of Optimization and Navigation system (Orion), Amazon’s Dash service is for consumer’s Internet-connected for reordering (Alicke et al. 2016).

Machine learning is a scientific algorithm developed in order to recognize the patterns to forecast the estimates of activity (Shahrabi et al. 2009). Machine learning and supply chain management collaborate on the mandatory information to generate high pitch analysis of the system for cost eliminations and for a better forecast of operations (Priore et al. 2019). It seems big data, machine learning and supply chain operations complement each other in a multipath flow where data entry is supplied by humans which in turn generates large volumes of data so that machine learning can be implemented to define the accurate estimations for forecasting in the supply chain management. The relationship between Artificial intelligence, Machine learning, deep learning and analytics is shown in figure 2. Figure 2 is adapted from (Intel). The adoption of big data application means that the organizations are able to scrutinize their forecasting, delivery schedule, sourcing and execution, and reverse logistic management.

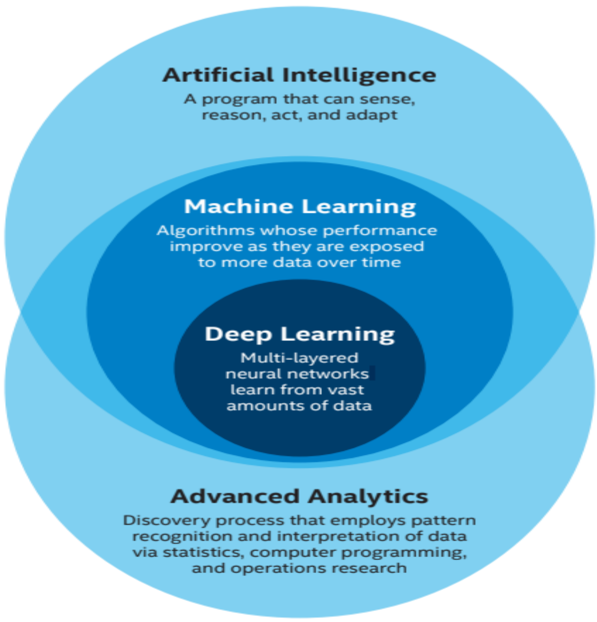


Figure 2. Advanced analytics relation to artificial intelligence , machine learning and deep learning. Adapted from (Intel)

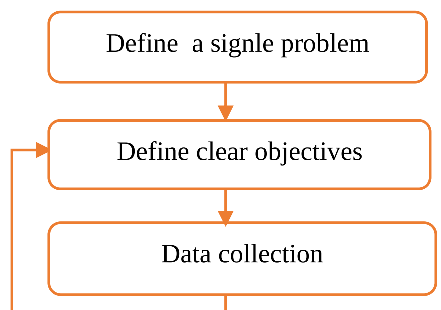
Business intelligence intends to automate data that can help to support decision making based on various data sources. Business intelligence is defined as a system whose "the major objective is to enable interactive access to data, to enable manipulation of data, and to give business managers and analysts the ability to conduct appropriate analyses"(Sharda et al. 2016)(p.16). Business intelligence consists of different tools, such as business analytics, data warehouse, business process management and user interface. The purpose of the BI is to transform large volumes of information into data. Large amounts of data collection and management have brought about a big change in the decision-making process. For example, in the supply chain domain, the use of machine learning is where most of the data pattern is focused while some previous studies have shown that data analytics has significantly contributed to business performance (Gunasekaran et al. 2017; Wamba et al. 2017).
Large volumes of data are the primary motivation for a supply chain organizations to refine its customer services, customization of products with the aim of increasing the customer relationship value (Anshari et al. 2018). The success of data analytics largely depends on the ability of an organization to manage the supply chain industry's 4.0 tools. Data analytics aim to improve understanding related to business process to support better decision making in the organization(Wang et al. 2016). The data analytics in the supply chain relationship foster improved trust and predict what supply and demand-side partner expect from firms to build and sustain the growth (Perera et al. 2018). Data analytics solutions can be used to minimize logistic delays to analyze task using environment data (geographical position system, weather and traffic) to generate value and insights (Xu et al. 2016).

In the past years, many researchers had emphasized the application of machine learning techniques for demand forecasting in the supply chain procedure. The evaluation and accuracy of demand which business requires to control the capacity enlarge the process system of supply chain structure. The validation demand through signals allow to generate accurate forecasting for a supply chain to accommodate enough inventory in stock at real-time, and such collaboration has certain advantages for business and organizations (Gunasekaran and Ngai 2004). Large data has enabled many industries to apply the right data mining approaches to enhance the operational process (Addo-Tenkorang and Helo 2016). Many supply chain oriented organization not only try to avail accurate tendency of demand but also require avoidance from demand tendency in data to avoid wrong forecasting (Heikkilä 2002). For example (Carbonneau et al. 2008) discussed that collaborative and networking techniques are worth trying, they further presented many machine learning-based techniques for demand forecasting in supply chain management including naive forecast, average, moving average, trend, multiple linear regression, neural networks, recurrent neural networks, support vector machines.

Moreover, (Kochak and Sharma 2015) described in their work that artificial neural network techniques for demand forecasting in the supply chain are more effective. This technique utilizes multiple layers of data for assessment and networking than traditional methods (e.g. naive forecast, average, moving average, trend, multiple linear regression). Many scholars are expecting the need for more advanced level artificial machine learning techniques for better demand forecasting in supply chain management (Kochak and Sharma 2015). There are many techniques which have been developed and tested by research scholars over time, a few of them are Decision Trees (DT) and Random Forests (RF) (Cheng et al. 2010), HyperBox Classifier (Kone and Karwan 2011) Gamma Classifier (Uriarte-Arcia et al. 2015). Further,(Bousqaoui et al. 2017) proposed long-short-term memory prediction model based on machine learning, they argued that data which has been processed with the long lapse of time could generate mistakes on long term dependencies of data in forecasting results. They also referred to the fact that long-short-term memory prediction model could be a useful tool which will be helpful for further validation as this model emphasizes on the short and long lapse of information overtime periods.

Many manufacturing industries in supply chain 4.0 see data as another source of competitive advantage to proactively comprehend customer requirements and understand market trends and to predict upstream as well as downstream issues regarding scheduling, recovery, Fuel Costs offering Customized Services and compliance with regulations. An improved understanding of data analytics is primarily based on a healthy organization's ‘ healthy data culture’. Healthy data culture is referred to as, in which organizations are specialized in data deployment for better decision making (Diaz et al. 2018). Analytics culture is of great concern for the organizations aiming to create competitive advantage but also transform data to generate significant insights into decision making (Kiron et al. 2014). The essential characteristics of data analytics are to provide instant information and creating knowledge in the various domain to take market advantage (Xu et al. 2016). The application of data analytics is just starting to get attention, and much of the current research focuses on how to deploy and re-organize data within the organization. Data analytics can visualize hidden patterns of data structures with correct visualization techniques. A schematic flow diagram for machine learning and data analysis steps in a Data-driven decisionmaking methodology is depicted in Figure 3.

Analytics refers to extracting hidden insights from data (Gandomi and Haider 2015). While some researchers advocate the need for healthy data culture or analytics culture (Germann et al. 2013). Recent research effort has been directed to predict sales forecast using analytics in multi-industry data sets (Hallikainen et al. 2019). The applications of machine learning in scientific research is used to improve forecasting techniques since early 2000 to understand forecasting issues better. The implementation of different algorithms used in machine learning proved cumbersome and ineffective in representing accurate forecasting issues. When data become large or too complicated, it is challenging to make forecasts using existing data analytics techniques. Machine learning approaches are becoming more effective in this era as they provide different types of machine learning techniques, supervised learning, unsupervised learning, deep learning, and reinforce learning. The major types of machine learning are summarized in Figure 4. Decision making via using machine learning is becoming a key performance indicator. Figure 4(a), 4(b), 4(c) shows different machine learning algorithms applications.



A Business Case for the success of Supply Chain

Supply Chain Artificial intelligence (SCAI) is automatic decision-making by making sense of data analytics function for taking action. SCAI enables organizations to develop capacities and process and to integrate those input data coherently. The input data is used to ensure that the functions and behaviour of a complex system are in alignment. In August 2018, JDA acquired Blue yonder (Dignan 2020). This acquisition helps to automate supply cyber-physical systems to external data to optimised business decisions. AI helps organizations to manage data analytics and the process of gathering data from different sources using different protocols. AI enables organizations to understand the patterns of data distribution, especially those that can get in the way of doing thing correctly. AI helps a firm to collect, analyse and understand the optimal use of resources that is useful to respond quickly in different spheres of operations

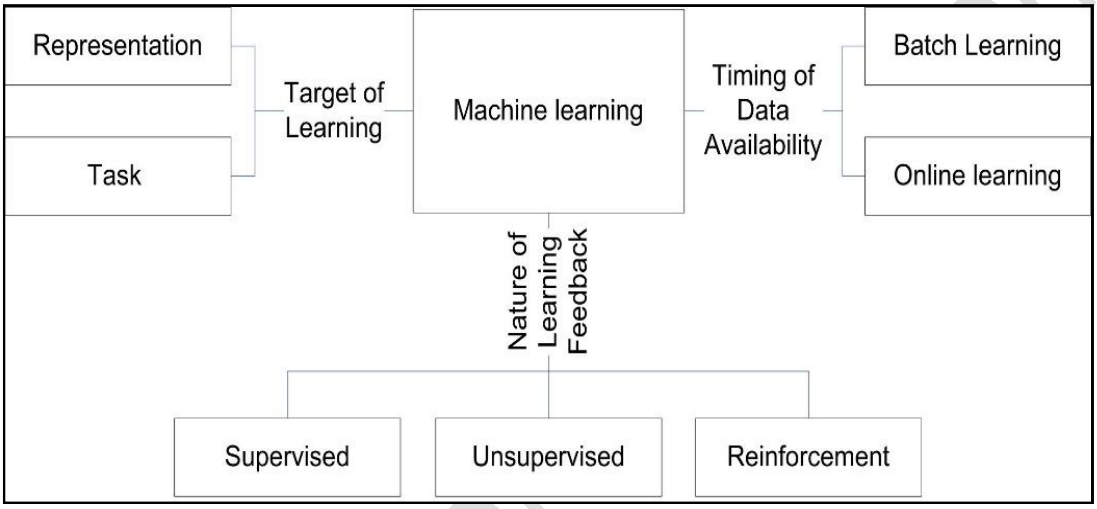
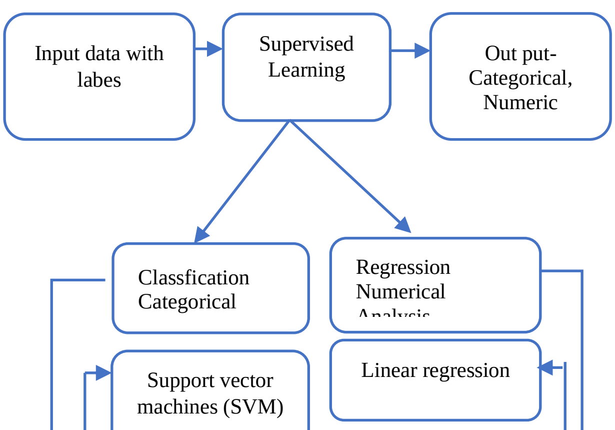
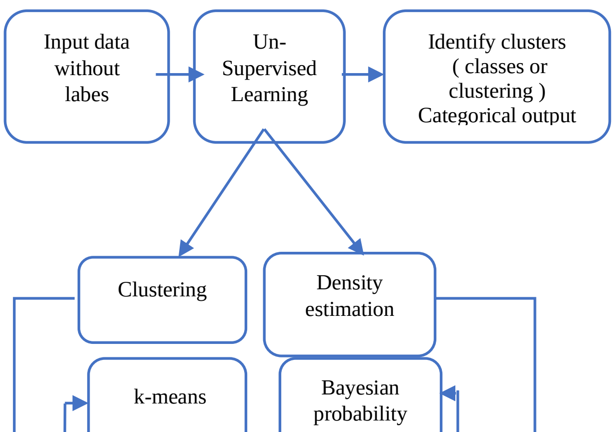


Figure 4. ML types adapted by (Zhou et al. 2017)

- **Machine learning improve supply chain performance**

Machine learning as digital and automatic technology in the future will run algorithms to read the data patterns and operate the functionality on its own to perform supply chain tasks. In future supply chain system will work through machine learning techniques. For example, DHL and Amazon is the giant bidder to facilitate their system with high speed and efficient machine learning system. (Russell, 2019) discussed in the article that machine learning is the future source for unsupervised operational systems for the supply chain, providing high logistic solution and discoveries for resource and cost-efficiency. Machine learning can support complex supply chain systems with huge data inflow to achieve low error predictability of operations required in future, demand and supply equilibrium of productivity, cost management and avoidance from risks in the last-mile delivery system.





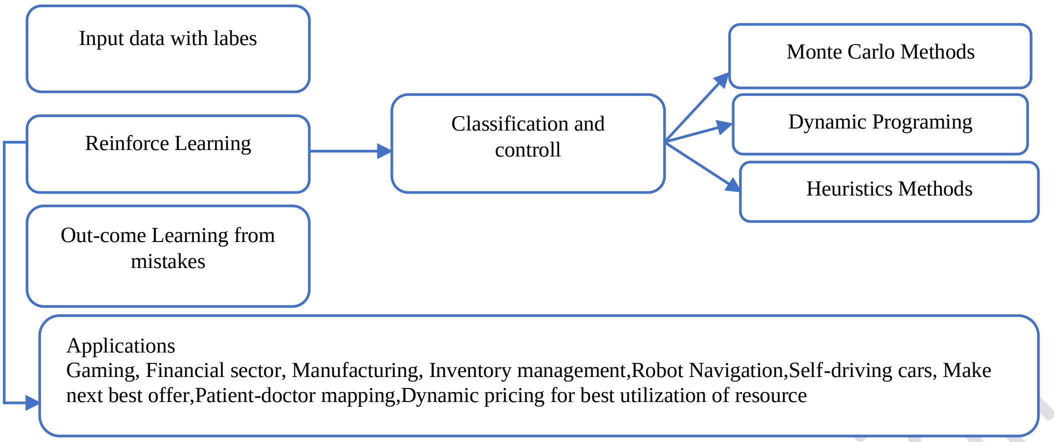


Figure 4(c) Reinforce learning algorithms

For companies, it is a much better and easy task to evaluate their labour performance as they have been rated by customers and information are recorded to run machine algorithms. (De Treville et al. 2004) addressed that delivery leading time management is a chief factor for supply chain management systems if intermediary parties are traceable, then it can reduce risks and possible errors in delivery time. (Zhu et al. 2017) state that finances in supply chain management for small and medium business is a real point of deep consideration; machine learning is one of the methods which proficiently manages and supervise the credit visibility for the small and medium business in effective way. (Chang et al. 2013) states that for supply chain system integration information sharing between stakeholders is a vital source for improvement in supervision, it's imperative to have a clear set of rules between partners, e-procurement can provide this transparency when parties are dealing with intensive contracts. In short, machine learning can be involved in every step of supply chain management system and improve the facts and figures of the business toward more efficency.

Linkages between Data Analytics and Artificial Intelligence

The application of data analytics can be categorized depending upon how it is analyzed. For example, in customization product development, in the production department, products are developed according to the demands of the customer, often associated with a complex set of process. A customer data could be used for assisting in customization of designs in future. The use of customer data could reduce the risk for procurement managers. In supply chain literature form 2000, there is an ever-greater focus on the use of the large volumes of data to exploit an organization's knowledge, to enhance its analytics capability. Data has become one of the primary assets for the organizations to foster strategic alignment of goals (Sivarajah et al. 2017; Albergaria and Jabbour 2019). Generation of large volumes of data has been the focuses of supply chain research (Frank et al. 2019; Ivanov et al. 2019) for some time with great importance. The application of data analytics has become valuable only when an organization realize a promising value of processing and management of the data. The processing and management of large amounts of data could bring exceptional value and enable organizations to respond to profound opportunities and challenges (Sivarajah et al. 2017). There are various characteristics of large data collections well known as big data, and it is widely accepted that big data to have six characteristics: (i) volume; (ii) variety; (iii) velocity; (iv) veracity; (v) variability; and (vi) value (Gandomi and Haider 2015).

Another source of framing encouraging scenarios for business success is through the idea of 4.0 centred on artificial intelligence and big data. Organizations with better data management and analytics capabilities are able to utilize organization-specific resources, such as database management capabilities. The use of such tangible and intangible organization-specific resources can provide the path to handle performance edge than those who are not focusing on data analytics. The previous research had recognized that manufacturing industry invests in the data analytics are better able to exploit their resources (Dubey et al. 2019a). Data analytics has been identified as a source of reaching favourable innovation outcomes to predict the future demands of customers (Perera et al. 2018).

Big data analytics examines large amounts of data to uncover hidden patterns, correlations and other insights (SAS, n.d). Big data analytics can be defined as a "… a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage …"(Akter and Wamba 2019) (p. 86)). Big data analytics has become a major theme in academic research, for example, business process management(Dezi et al. 2018), Performance of coordination in the supply chain (Dubey et al. 2018), impacts on social and environmental sustainability (Dubey et al. 2017), operational performance (Dubey et al. 2019b), the effect on firm performance (Müller et al. 2018), service innovation (Lehrer et al. 2018). The purpose of big data analytics is to re-design the process to deliver and creating avenues for innovation. Previous research shows that the motive behind the use of big data is to reveal the hidden knowledge at the firm level (Davenport 2014). The literature on bigdata emphasizes how firms explore and reconfigure internally existing understanding in new ways to gain insights from data, which can not be translated through perspective analytics. Big data analytics enable firms to discover related and unrelated patterns of data among different variables to strengthen their supply chain management operations and customer relationship management. Data analytics wants to analyse raw data in order to discover hidden patterns and relationships among different variables. In a word, the main aim of data analysis is to extract useful information from rough data and transfer it to effective knowledge to improve product and process understanding and to support decisions (Gunasekaran et al. 2017; Nam et al. 2019).

The benefits that data analytics may bring to firms encompasses to strengthen their supply chain operations (Gunasekaran et al. 2017) and support customization of customer services (Anshari et al. 2018). The ability to work with agility gives firms an advantage that could have a profound impact on overall business performance. The type of data has a profound effect on business performance. Management must determine what mix of data (textual, multimedia, machine to machine, cyber-physical system) makes sense for each decision making. Different combination of textual, audio and video data give rise to significant data management capabilities. A mix of data plan can both motivate data analyst to direct their activities that are consistent with the organizational objective and plan for building long-term data-storage functions. In fact, more and more firms are moving towards big data management capabilities that may drive data analytics to make long term business decisions. Bigdata management capabilities are always in the domain and paying the firm to realize their full potential.

Research has demonstrated the potential to use bigdata analysing technologies, WibiData and Skytree, BigQuery, MapReduce, NoSQL Databases and Hadoop is a means of understanding and improving business strategies(Yi et al. 2014). According to (Chen et al. 2013), data management and processing can facilitate in responding to challenges and opportunities and help bridge structural holes between them. (Jukić et al. 2015) have demonstrated how the appropriateness of management to analyze the bigdata could be employed to identify new knowledge, proposing insights to deal with uncertain environmental events. Table 1 helps understand the main steps in data analysis and data management, adapted from (Troisi et al. 2019).

Table 1. The main steps of data management	
Main data analysis steps	Main management steps
Data collection	Establishment and sharing of a cohesive data-oriented culture
Data organization	Selection of an integrated set of analytics in line with strategic goals
Data extraction	Adequate technological infrastructure
Data integration	Computing skills
Data analysis	Analysis and research skills Management's ability to interpret results in line with strategic goals and to catch opportunities
Data sharing	Data report and diffusion
Data storage	Feedback collection
Data reuse	Renewal of the knowledge acquired for continuous improvement
Source adapted from (Troisi et al. 2019)	

Business analytics is a source of progression in supply chain management and performance efficiency. But what dynamic capabilities should be the sponsorship of business analytics, to avail more cost-efficient and proficient supply chain structure, is still under the focus of many scholars and researchers. As (Chae and Olson 2013) described in their study that data management capability is the former tool to have competitive advantages over other businesses (e.g. Wal Mart). Furthermore, they discussed that data IT infrastructure and data storage effectiveness is the leading player as data management capability. Supply chain management is crucial when the output of the supply chain procedure is manufactured goods, failure in the production can be a complex scenario for business to deal with, and it can cost the high prices, compromised quality and delay in delivery of output. Therefore, in the manufacturing industry, industries wanted to make sure that end to end, supply chain management is conscious and properly supervised. Many researchers proposed business and data analytics methodologies to reduce the risk of production, wastage of material, and overlapping in the operational system.

On the other hand,(Mikalef et al. 2020) extended the definition of BDAC and emphasized on the inclusion of the organizational resources. They defined it as the ability of a firm to effectively deploy technology and talent to capture, store, and analyze data toward the generation of insight (p.2). Previous literature has emphasized that when assessing the business performance, it is essential to take a broader view of different capability performance, and particularly to highlight the notion of knowledge management. In the global information age, the business performance hinges on combining data management and analytics capabilities to achieve a long term performance. Research suggests that bigdata analyst capabilities (BDAC) impact upon the understanding operations management and service information (Albergaria and Jabbour 2019), (Lozada et al. 2019) and competitive performance (Mikalef et al. 2020). A study by (Troisi et al. 2019) showing the importance of big data and cognitive computing, is particularly relevant for unlocking and accelerating innovation. According to (Gupta and George 2016) BDA capability encompasses a set of tangible, intangible and human skills which are useful for the organization to incorporate data-driven culture and organizational learning. In the last decade, big data has emerged as a source of analyzing large volume of data and has paved the way for exploration of the complex nature of organizational knowledge management practices. Big data, perhaps the most successful application of artificial intelligence, has been employed effectively within the sphere of supply chain management. Many manufacturing industries do seem to be geared efforts within the supply chain to improve efficiency, maintenance and reduce the risk of theft and accidents. There has been the various deployment of data analytics applications in an organization all over the world. Along with its practical sens, machine learning concept has found to have profound implications for automatic acquisition of knowledge for decision making. Artificial intelligence fills the gap for the supply chain management system by processing the data in quick results for companies, so advance forecasting of operation can be acquired.

Conclusions

This chapter reviews the advance of some artificial intelligence methods in the supply chain. Considering the features of big data and artificial intelligence, this chapter provides a schematic flow of diagram for machine learning data analysis step by step in data analysis. The step by step data methodological filtering approach could provide data analyst with a sense of superiority in handling data. Especially, when carrying out the data analysis in the machine learning environment, the data analyst must understand, why there are inconsistencies in the output. This chapter has provided some remedial measures in case of, if there are data inconsistencies reveals during the data analysis. We also suggest applying in the proposed schematic method in some machine learning applications to improve the data validation and to test its usefulness and applicability. This chapter indicated that the schematic flow diagram could be used to correct the inconsistencies in the model. The chapter highlights that supervised, unsupervised and reinforce learning algorithms can effectively be used to perform different statistical analysis. Researchers understand the extensive use of artificial intelligence among firms as essential and necessary for shaping the future of the supply chain of industry 4.0. AI strategies should be at the forefront of the management of supply chain practices and must build up through years of data generation and contain a wide variety of machine learning approaches. IA creates a new analytics intelligence to justify the choice of strategic decision making rather to heavily focused on intuition intelligence. AI can also provide an in-depth assessment of the future, at capturing big picture of information and learning within the bounds of paradigm. There is a need for research the results of which could in selecting only the most appropriate machine learning approach for supply chain management, especially for the forecasting in logistics and production. Academicians and universities should work together and create affordable and reliable artificial intelligence solutions for the supply chain management that have the potential to contribute towards sustainable development goals. To be able to grasp new market development opportunities, firms must be able to think beyond the current trends. One of the biggest challenges in the emerging field of a supply chain in industrial revolution 4.0 is to improve firm decision making for a move towards a big data system

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