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A Review of Artificial Intelligence and its Role in the Ports and Maritime Supply Chain

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Abstract

The procurement system, operations management, logistics, and marketing channel become the main engine of trade in the world in recent years, so the results obtained by recent authors have a paramount role in the supply chain. This paper aims to present a review of the artificial intelligence process in supply chain management. Two stages of literature studies are proposed. The first focuses on the presentation of theories and methods related to artificial intelligence and supply chain management. Where the Method is A review of artificial intelligence and its role in the ports and maritime supply chain supported as a review of recently published papers. The findings suggest that the previous literature is largely focused on supply chain management, thus leaving the research screening at a very limited level. The second stage presents the literature on the application of artificial intelligence in the Ports and Maritime Industry. The most remarkable finding is that most studies ignored the theories related to the issue of artificial intelligence and supply chain management. Additionally, the previous works show a lack of adoption of certain types of artificial intelligence in the port and maritime industry. Consequently, the studies of the impact of artificial intelligence on the port and maritime sector remain unexploited as it is based on a bibliometric review. In this case, it is recommended that researchers study other types of artificial intelligence on supply chain management, develop a systematic review of the impact of artificial intelligence on the port and maritime sector, and link theory and practice.

Keywords: Artificial intelligence (AI); maritime supply chain; Industry 4.0; PMI Method.

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1. Introduction

Nowadays, the importance of artificial intelligence has increased dramatically in the management of logistics and supply chains and has become a vital part of it, and it is expected to reshape this industry in the future. This transformation is not easy, as reliance on artificial intelligence requires huge investments in technology, as well as the use of the services of professionals and specialists in the fields of artificial intelligence and information technology. Specialists in the field of artificial intelligence emphasized that the current interest in relying on artificial intelligence is mainly due to several key factors such as recent technological advances, large investments in data by major investors in artificial intelligence, and the increasing demand for it by shippers. Long before the use of artificial intelligence, major logistics service providers relied on analytics and research personnel to analyze the huge amounts of data generated from the day-to-day operations of the logistics business. After that, the gradual reliance on artificial intelligence began, and then its benefit appeared in its ability to simplify many supply chain and logistics operations, thus giving a competitive advantage to those who initiated reliance on artificial intelligence by reducing shipping time and reducing costs (Allen, 1986).

Generally, the role of artificial intelligence in managing logistics and supply chains is a much-discussed topic, and this makes a lot of sense because the combination of intelligence Artificial intelligence and logistics are the foundation for companies seeking to enjoy a competitive advantage and hoping to prosper and progress strongly in the future. We at Gulf Pinnacle Logistics believe that artificial intelligence can provide great benefit to supply chain managers, provided that it is based on solid foundations that take into account the diverse nature and changing modern supply chains that exist today (Holland, 1975).

In a study conducted by the leading McKinsey Company (Lawrynowicz, 2007); (Luger, 2002) on several industries relying on artificial intelligence, the study showed that the first adopters of artificial intelligence had a proactive strategy in the transport and logistics sector and benefited from profit margins of more than 5%. Of the transportation and logistics companies surveyed, only 21% have passed the initial testing phase and have adopted AI-based solutions on a large scale or in key parts of their business. The challenges of relying on artificial intelligence in the field of supply chains and logistics are varied and require large capital investments and organizational changes into able to overcome these challenges (Nilsson, 1980).

In a statement, ***Rodney Viegas***, General Manager of AMO Shipping Corporation, said: “In my view, large organizations are the first to use artificial intelligence, due to the large investments required to install new AI systems and analyze large databases of data, in addition to the use of Services of IT experts to improve operations. ***Rodney Viegas*** adds that the significant decrease in the number of workers soon after resorting to artificial intelligence, and this is due to the need for companies to develop frameworks that show how the roles of workers change as a result of the trend of artificial intelligence and automation (Rohde, 2004).

Companies are making remarkable progress in the use of artificial intelligence and the integration between human work and machine work and cooperation in logistics services, and technological advances in the work of artificial intelligence, robotics, and automation will contribute significantly to improving the logistics services sector. Manufacturers have also shown interest in the services of industrial robots for a long time, but the complex processes in logistics services and the high costs of robots have constituted a major obstacle to relying on robots. Today, costs are lower and the process of programming robots is easier, more comprehensive, and more flexible, making robots cost-effective in repetitive and physically demanding logistics work (Russell & Norvig, 1995)**.**

In a world dominated by the apparition of Industry 4.0 technologies, some industries have entered a fifth stage of evolution conjugated by a huge digital mutation. One of the industries, which has been engaged in Industry 4.0 practices since 2010, is the Port and Maritime Industry (PMI (Kumar, Ramachandran,, & Kumar, 2021). Thanks to the adoption of different technologies (artificial intelligence (AI), blockchain, big data, Internet of Things, cloud computing...etc.), the Port and Maritime Industry (PMI) has undergone a dramatic evolution starting with local port integration (port and terminal integration), and ending with global scale integration while passing through integration on a regional scale (port and urban integration). This evolution later led to the full integration of ports and terminals (P&T) into the Global Supply Chain (GSC).

According to (Zarzuelo, Freire Soeane, & López Bermúdez, 2020), through the application of artificial intelligence (AI) in Supply Chain Management (SCM) practices, some industries have undergone a real evolution in recent years. (Dirican, 2015); (Jarrahi, 2018); (Simon, 1965) give a new definition for AI as "the Machines will be capable of doing any work a man can do". AI consists then in imitating human capacities (or real intelligence) to exploit a large volume of data with the help of machines (Munim, Dushenko, Jimenez, Shaki, & Imset, 2020). It is adapted in various fields (marketing and advertising, finance, retail and customer services, healthcare, and legal applications) (Cross, 2022). In the Port and Maritime Industry (PMI), AI plays a fundamental role in improving port and maritime operations.

Certainly, the application of AI in the maritime and port supply chain has attracted the attention of researchers and scholars (see, among others, (Cariou, Parola, & Notteboom, 2019) However, research in this area remains less exploited. Therefore, there is a need to explore the contribution of AI in the maritime and ports supply chain domain. To fill this gap, we will conduct a literature review in this study, while providing an answer to the following research question: (Main RQ): How could the application of AI improve maritime and port supply chain practices.

Specifically, (Stock & Boyer, 2009) shows that SCM is based on four main areas, namely marketing, logistics, production, and supply chain management (including purchasing and material suppliers). These four areas allow for the effective management of a network of relationships within a firm and between interdependent organizations and business units to increase performance and ensure customer satisfaction. Certainly, this definition leads to the existence of four keywords for this research. However, our research is not limited to understanding the contribution of AI in SCM practices (especially in the four areas mentioned above). It requires understanding how this new technology is applied in the Port and Maritime Industry (PMI). The answer to this question led us to resort to the literature to find a simpler definition that unites AI with maritime and ports supply chain and to identify the keywords in this field. According to (Chu, et al., 2018), maximizing value and performance in the terminal and its ecosystem requires strengthening the connection between all actors (terminal operator, trucking companies, railroads, shippers, logistics companies, and freight forwarders).

The rest of this paper is structured as follows. The second section presents the literature review. The third section will be devoted to the review results. Then, the fourth section discusses the research results. This paper will end with a conclusion.

2. Literature review

2.1.Theories related to AI and SCM

Nowadays, the implementation of strategies by managers based on Industry 4.0 technologies has brought about a major transformation in various fields. In this context, AI plays a crucial role in generating innovation and novelty in industries. Its application in the Supply Chain (SC), solicits the consideration of certain techniques while relying on different methods whose most widespread are optimization, expert systems, and methods related to planning and scheduling and simulations and modelling. The choice of such a method at the expense of the other depends on the types of IA opted for the (Pournader, Ghaderi, Hassanzadegan, & Fahimnia, 2021). As an example, the Expert System method is used for Machine learning (ML).

Regarding optimization methods, they have evolved from the 1960s (solving optimization problems) to the 2000s (solving dynamic problems). This in turn has led to the emergence of numerous methods and theories in this area (Allam & Dhunny, 2019); (Pournader, Ghaderi, Hassanzadegan, & Fahimnia, 2021); (Jiang, Yang, Wang, & Zhou, 2017); (Dey, 2018); (Abbasi, Madramootoo, Zhang, & Tan, 2020); (Melo, Nickel, & Saldanha-da-Gama, 2009) ; (Saghaei, Ghaderi, & Soleimani, 2020). Theoretically, the application of AI in SC has its origins in numerous theories. Each theory is related to an optimization method specific to it. According to the existing literature, the classification of optimization methods refers to nature-inspired methods (e.g., genetic algorithm), knowledge-based methods, decision theory (e.g., Bayesian approaches), game theory (e.g., cooperative models), market theory (e.g., trading and auction algorithms). In practice.

Expert Systems, also called the knowledge-based systems are another application of AI. According to (Giarratano & Riley, 2005), the Expert Systems method includes several domains and methods of problem-solving, thus supporting systems to perform tasks that would be performed by human experts. In this framework, (Zarbakhshnia, Soleimani, & Ghaderi, 2018) indicates that Expert Systems methods can integrate rule-based, fuzzy, frame-based, and hybrid methods. Therefore, this will allow for the combination of more than one intelligent system. In addition, some researchers show that the proper functioning of Expert

Systems requires the formalization and structuring of human intelligence in different domains. However, when human intelligence (or real intelligence) is not well structured, this is likely to lead to failure and downfall of Experts Systems. This problem is amply considered when solving cognitive problems.

Recently, the application of AI in the modeling and simulation of complex systems has become widely used in the literature. This method plays a fundamental role in performing in-depth scenario-based analysis. This is likely to help in making the right decisions due to better design of the system behavior. One of the main methods, which allows modeling the interaction of the system components and examining the performance in real-world scenarios, corresponds to that of basis computing.

In addition, the methods that facilitate the decision-making of intelligent systems, given a set of constraints (i.e., resources in a production facility), correspond to AI planning and scheduling. (Jakupović, Pavlić, & Han, 2014) defines the planning as a set of decisions, having as a goal the optimization of the order of the desired activities. It therefore examines the temporal allocation of tasks to resources.

In summary, the application of AI offers certain advantages to managers. In fact, this technological progress constitutes a relevant tool, supporting them in the detection and prediction of disturbances capable of affecting the usual operations of the system (system failures, fraud detection and predictive maintenance). It allows them to recover the proper functioning of the system (Haenlein & Kaplan, 2019).

After having a general idea of the theories and methods related to IA, it is important to present in what follows the empirical studies related to this area.

2.2.Empirical studies

In this section, it is important to first discuss the Empirical studies related to AI and SCM. The next step is to present the Empirical studies related to AI and Ports & Maritime Industry (PMI). This classification will provide a better understanding of the scope of AI application in various sectors and domains. It further helps to explore the benefits of AI in Ports & Maritime Industry (PMI), as well as the challenges faced. Certainly, the gaps and shortcomings in the field, will help to identify some recommendations for Ports & Maritime Industry (PMI).

2.2.1. Empirical studies related to the AI techniques in SCM

In the literature, it can be observed that researchers focus first on the choice of sectors that massively apply AI. (Stock & Boyer, 2009) shows that the application of AI in SCM is closely related to four main areas namely Marketing, logistics, production, and supply chain. Similarly, proves the existence of five main areas of AI. These sectors include Marketing and advertising, finance, retail and customer services, healthcare, and legal applications.

In this context, it appears that the application of IA on SCM has been important in the recent literature. This literature has advanced several IA techniques. As such, what follows is a discussion of these different techniques in different fields of SCM namely marketing, logistics, production, and supply chain.

2.2.1.1 Artificial neural network and SCM

According to (Peterson & Flanagan, 2009) , Mathematical regression is considered the main tool of ANNs. It allows to correlate the input and output flows of the processing units. The ANN techniques have been used in different areas of the SCM. In Marketing field (Lee, Ho, Ho, & Lau, 2011) employs an ANN to develop a pricing model with lower errors and higher accuracy. The result shows that ANNs generate significantly lower dollar price errors.

In logistic field, ANN technique is less exploited in the literature (Li et al, 2013). Investigate the role of ANN as an AI technique can enhance the responsiveness of the logistics workflow. However, in the field of production, the ANN has been used in several studies. For example, (Gligor & Dumitru, 2018) employs ANN for oil production prediction. Compared to the NDT approach, the result shows that the ANN model has a higher classification rate. The main finding shows that this technique can be used to predict the energy produced. It is also conditioned by an appropriate structure of the neural network.

Finally, in the supply chain field, several studies have used this technique. For instance, to handle fuzzy demand with incomplete information, (K., 2012) propose an AI forecasting mechanism modelled using ANN technique.

2.2.1.2 Agent-based/multi-agent systems and SCM

According to (Grimm & Railsback, 2013), An agent-based model is one of the main computational models. Their main role is to simulate the actions and interactions of autonomous agents. Among the fields that are based on this technique, there are mainly elements of complex systems, game theory and evolutionary programming etc... The Agent-based/multi-agent systems technique has also been employed in different areas of the SCM. In Marketing field, from the existing literature, it appears that only two papers have used this technique. Using agent-based systems (ABS), (Taratukhin & Yadgarova, 2018) offers a real-time model for sales management. Specifically, they attempted to explain the use of regime models for informing short-term pricing decisions and long-term resource allocation decisions. The results show that this method outperforms the more traditional short- and long-term predictive modelling approaches. (Ferreira & Borenstein, 2011) Proposes an approach to product lifecycle management with multi-agent systems. To manipulate concurrent engineering knowledge, this approach allows for an understanding of the interrelationships of the different life cycle steps.

In supply chain field, Agent-based/multi-agent systems technique is employed by only one study. To ensure supply chain planning, (Bundy, 1997)offers a simulation framework using ABS and MAS techniques. Similarly, in the production field, it appears that few studies have employed this technique.

2.2.1.3 Fuzzy logic (FL)/modelling and SCM

According to (Heger, Branke, Hildebrandt, & Scholz-Reiter, 2016) FL/modelling is the boundary between AI and non-AI techniques. FL technique has also been employed in different areas of the SCM. In production field, using fuzzy logic, (Ferreira, L.; Borenstein, D., 2012) approaches manufacturing systems. The finding shows that the introduction of intelligent vehicles in complex manufacturing systems depends mainly on current technology. Furthermore, to analyze the cosmetics industry, (Vahdani, Iranmanesh, Mousavi, & Abdollahzade, 2012) develops a fuzzy-bayesian supplier selection model. In addition, (Hand, 2013) recommends a neuro-fuzzy supplier selection model to also examine the cosmetics industry.

2.2.1.4 Data mining and SCM

Data mining refers to the process of analyzing massive volumes of data and Big Data from different angles to identify relationships between data and transform them into usable information. According to (Wang & Yue, 2017), this new technique has stimulated primarily by the growth of gigantic databases. In the field of supply chain management, this technique has generally been employed to monitor several areas, namely food supply chains, supply chain sustainability etc... (Shaw, Subramaniam, Tan, & Welge, 2001). In this case (Tan, Zhan, Ji, Ye, & Chang, 2015) suggest that it enables improving knowledge management and marketing.

2.2.2. Empirical studies related to Maritime and ports Supply Chain

In this subsection, we will present studies related to AI and maritime and ports supply chain. It is mainly to use the literature related to Industry 4.0 in the port and maritime industry. In fact, due to the appearance of new technologies (robots and autonomous systems, Internet of Things (IoT), cybersecurity, Horizontal and Vertical Systems Integration (HVSI), Cloud Computing (CC), 3D Printing (3DP) and Additive Manufacturing (AM), Big Data (BD) and Business Analytics, Augmented Reality (AR), Simulation and Modeling (S&M) ...etc.), Industry 4.0 has appeared, and ports are increasingly evolved. This evolution started with information technology (IT) and ended with the development of digital ports and smart ports, while passing through the rise of informational ports.

Given this background, research in this area is beginning to develop and the notions of “Port 4.0” and “*Port intelligent*” are beginning to be felt in the Ports and Maritime Industry (PMI). (Zeng, Chan, & Pawar, 2020). Conduct a bibliometric review to address the impact of Industry 4.0 on PMI. The authors select the most relevant databases to further strengthen their search (Scopus, Mendeley, Science Direct, Google Scholar...etc.). The work by (Abebe, Shin, Noh, Lee, & Lee, 2020) opt the nine pillars of Industry 4.0, while classifying them into three main categories (advanced methods and tools in Ports 4.0, horizontal and vertical in Ports 4.0, and open challenges). The results of their studies suggest that some technologies are sufficiently mature in the port and maritime industry (Internet of Things and sensing solutions, cybersecurity, horizontal and vertical systems integration, cloud computing, 3D printing...etc.). However, others are still in their infancy in this business (e.g., Artificial intelligence).

[6] develops a bibliometric review of big data and artificial intelligence (AI) applications in the maritime industry. The authors use the Bibliometric tool in R software. To do so, the authors use certain keywords namely “artificial intelligence” OR “Big Data” OR 'business intelligence' OR “data analytics” OR “machine learning” AND “maritime” OR “shipping” or “port”). The most remarkable conclusion reached by the authors is that scientific research on the broad topic of Big Data and AI in the maritime industry is strongly increased during the period (2015-2019).

3. Review Results

After reviewing the above-mentioned literature we found that the intelligent supply chain management solutions may improves the business processes. Any company has faced many problems and is looking for new ways to optimize funds and reduce production costs. As ways to improve, companies are likely to pay as much attention as possible to websites, marketing techniques, and application development. Continued improvement of supply chain returns is likely to bring more benefits to the company, the following statements are considered as a solution for business processes:

- **Digital transformation solutions**

Digital transformations will help companies around the world become more efficient and transparent. Modern supply chains are getting access to more information and technology than ever before, creating a new digital supply chain. However, an increasingly digital supply chain has grown based on the use of “smart technologies,” such as intelligent software solutions, the Internet of Things (IoT), artificial intelligence, big data, and Blockchain that are transforming manufacturing and logistics by providing a new level of insight, and opportunities to improve overall operations.

- **Software solutions for intelligent supply chain management**

There are a lot of different supply chain management software solutions that provide technologies and features for tracking, and controlling excess inventories, demand forecasting, and inventory planning. Thus, when a company feels that the current supply chain management resources are not enough, it must look for intelligent software solutions. There are important requirements that the company must pay attention to, such as the time to implement the tool in the company's operations and the possibility of integration with their ERP system. Moreover, the level of software flexibility according to the company's business needs also plays an important role. Utilities like Streamline provide a solution that is purposefully tailored to a company's needs. This software is essential for managing a business of any size by estimating future demand, optimizing inventory, and releasing frozen capital. To illustrate, Streamline uses time-series analysis, discrete demand models, and a human-like decision-making algorithm that determines the appropriate model for each product.

This approach is highly resistant to over-fitting. It does not try to meet irregular demand, but at the same time, it can capture all observed dependencies such as seasonality, trends, and level changes. Streamline aims to choose the simplest model that still captures dependencies in the data and is the only way to produce an accurate prediction. The trade-off between the simplicity of the model and its fit to the data ultimately results in the highest possible accuracy. An intelligent SCM solution should provide you with unparalleled visibility into your inventory, including associated costs and documentation, as it moves through your supply chain. It should also provide the most granular level of detail and allow you to manage issues by exception. And this is exactly how to streamline works.

- **Internet of Things (IoT) technology in logistics**

The Internet of Things is used by companies to simplify operations by connecting various web-enabled devices at the same time. Business markets from agriculture to manufacturing face problems at every step in the production and transportation processes. Many challenges can make or break a supply chain such as delays in transportation, lax monitoring of goods, theft, operator errors, and outdated IT failures. All of these factors threaten profits and add to cost pressure, which remains constant, regardless of the business.

Especially when it comes to perishables, the consequences are beyond minimal. According to the Internet of Things, the full 30% of all products and perishable products never make it from farm to fork. It is a frustrating state of waste and yet an opportunity to apply high technology to a pain point affecting growing populations and areas where food insecurity is widespread.

Taking into account all the above facts, the value of a connected logistics platform is indisputable. Known as Logistics 4.01TP5, the next generation of the successful Supply Chain Management 1TP5 will leverage edge computing and the Internet of Things (IoT) to produce real-time automated feedback mechanisms, awareness, and response. It will also put cyber security and secure data handling at an excellent level. It also enables logistics organizations to achieve transparency, efficiency, maintenance, automation, shipment safety, and cost optimization in all supply chain operations.

- **Artificial intelligence in demand forecasting software**

AI enables the supply chain with the ability to streamline nearly every process in the chain to the end user, allowing the opportunity to make decisions simultaneously based on real-time data.

One of the keys to artificial intelligence is its ability to learn and adapt. Using deep learning technology, AI is ideal for processes that are delicate and prone to human error. To illustrate, AI can improve inventory levels or order fulfillment by analyzing data and learning from past events. Moreover, this technique can use huge amounts of historical data to learn from mistakes. If an error occurs, it will not be committed again. Essentially, AI can make better decisions more quickly. This simplification can be applied across your supply chain for amazing results. Another aspect with great potential for AI is improving logistics. Such a smart solution can be applied to driverless cars which can reduce lead times and human labor costs. These vehicles are also more efficient and have a higher level of driving precision than humans. Several companies are working on launching an electric semi-truck with some self-driving capabilities such as Tesla, Nissan, and others. These innovations have a huge potential to revolutionize transportation in the supply chain industry in general and will impact other suppliers in particular.

- **Blockchain technology to improve business**

There are many different ways to implement this well-known technique. Aside from the hype and great promise of dramatically reducing transaction costs, for blockchain

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technology to be realistic, it has the potential to be used in logistics to record and track the vast majority of transactions. One of the biggest problems with data nowadays is the recording and storage process. On the other hand, information about a company's transactions is stored privately with the main ledger often not available for all activities. On the other hand, this data is often distributed across company divisions or hired workers internally, making coordinating transactions a time-consuming and error-prone effort. Instead, in a blockchain system, there is no need to hire third parties to verify transactions or transfers. Moreover, in blockchain-based systems, all transactions are secured and verified within seconds as the ledger is copied into a large number of identical databases. As a result, shortly blockchain will help overcome these problems in logistics and increase efficiency in supply chain operations. The main benefit of using this technology is to achieve data transparency and access to relevant stakeholders along the value chain, thus creating a "single source of truth".

Table 1. Overview of some empirical studies related to AI and PMI Methods from Papers reviewed

Authors	Year	Al procedures	Application area	Database Sources
Zarzuelo et al	2010-2019	Port 4.0 Smart port Global supplychain, Port innovation, Port connectivity, Internet of things	Shipping container recognition	JCR, SCOPUS,
Munim et al	1995–2019	artificiel intelligence, business intelligence, analytics, machine Learning, maritime, shipping, port'	Shipping demand forecasting	Web of Science
Zeng et al	1990 -2018	adoption (diffusion, adoption, assimilation), information systems (information system, information technologies, ERP, RFID, EDI, ICT), and supplychain management	Vessel traffic and route planning	Web of Science, and ProQuest.
(Abebe, Shin, Noh, Lee, & Lee, 2020)	2020	Decision Tree (DTR), Gradient Boosting (GBR), Extreme Gradient Boosting (EGBR), Random Forest (RFR), and Extra Trees (ETR)	Predicting ship speed over the ground	Applied Sciences
(Adi, Iskandar, & Bae, 2020)	2020	Deep Reinforcement Learning	Vessel traffic and route planning	MDPI
(Al Hajj Hassan,	2020	Reinforcement Learning	Shipping demand	Science Direct

Mahmassani, & Chen, 2020)			forecasting	
(Chen, Liu, Achuthan, & Zhang, 2020)	2020	Deep Separable (DS) - Visual Geometry Group (VGG) network and Adversarial Spatial Transformer Network (ASTN) - Faster Region-based Convolutional Neural Networks (R-CNN)	Shipping container recognition	INDER-SCIENCE publisher
(Chen, Ding, & Zhang, 2020)	2020	Convolutional Neural Network-Ship Movement Modes Classification (CNN-SMMC) algorithm	Vessel traffic and route planning	Science Direct
Du, Pei, et al	2019	Novel hybrid learning method - Variational Mode Decomposition (VMD), Extreme Learning Machine (ELM), Butterfly Optimization Algorithm (BELM),	Container throughput forecasting	Science Direct
(Fikioris, Patroumpas, & Artikis, 2020)	2020	Genetic Algorithm (GA)	Optimizing vessel trajectory compression	IEEE Publisher
Filipiak, et al	2020	GA with Spatial Partitioning, CUSUM (cumulative sum) algorithm	Vessel traffic and route planning	Springer Nature
(Gao, Chang, Fang, & Fan, 2019)	2019	Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN)	Container throughput forecasting	Hindawi Publisher
(Han & Yang, 2020)	2020	Big data-driven mathematical framework	Vessel traffic and route planning	Springer Nature
(Hoque & Sharma, 2020)	2020	Ensembled Deep Learning Approach	Maritime anomaly détection	Springer Nature
(Ji & Lu, 2020)	2020	DDBN-OCSVM Framework	Maritime anomaly détection	IOS Press
(Jimenez,	2020	Computational artificial	Predictive	Science Direct

Bouhmala, & Gausdal, 2020)		intelligence model	maintenance	

4. Conclusion

Intelligent supply chain management solutions provide a wide range of opportunities to improve business processes and increase revenue. A smart approach to supply chain optimization starts with better and smarter software, which will resolve inventory forecast gaps and improve demand planning. When these factors do not have an extensive impact on business development, speed and accuracy will become a point of change. Technologies such as IoT, AI, Big Data and Block chain will enhance the company and facilitate further operations. Moreover, these technologies will empower businesses and significantly improve efficiencies at all levels of service delivery, but we still have a long way to go. Always remember that there is no single panacea for all issues with logistics, inventory planning, and broadcasts, plus where one tool will give the best results, the other won't. You never know until you try. Additionally, we presented a literature review related to the application of AI in SCM. To do so, two stages were applied. The first stage focused on the presentation of theories and methods related to IA and SCM. In addition, it addressed the empirical studies carried out on the application of AI in SCM in four main areas (marketing, production, logistics and supply chain). Given the existing literature, we found that the existing literature is largely focused on the SCM, thus leaving the research screening at a very limited level.

To fill this gap and to further research, we resorted to the literature on the application of AI in Ports and Maritime Industry. Certainly, we presented in the second part some studies on the subject. Although scientific research in this area is beginning to develop, especially during the period 2015-2019, it is still insufficient. This insufficiency could be attributed to the lack of adoption of some types of AI in the port and maritime industry. Therefore, there is little coverage in the literature on the subject. In addition, among the limitations of research related to the contribution of AI in the Port and Maritime Industry is that it is largely based on bibliometric review. In this context, it is to be recommended to researchers set up a systematic.

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