Artificial Intelligence and Machine Learning in Maritime Shipping

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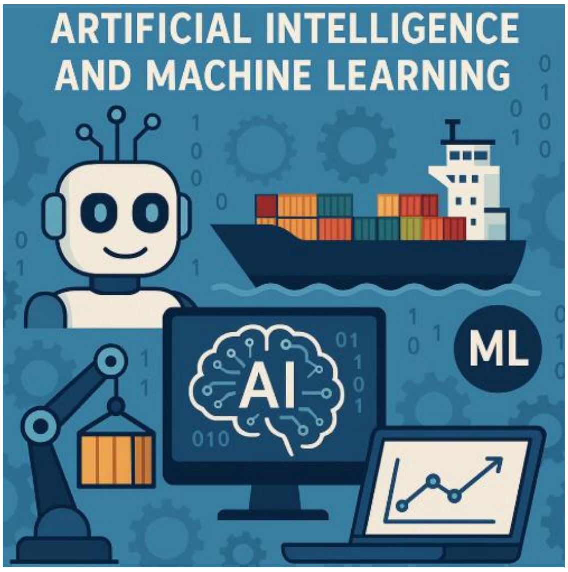
Abstract: ***"Artificial Intelligence" (AI), "Data Science" (DS), and "Machine Learning" (ML) have become ubiquitous terms in our vernacular, and many people have bandied them about for some time now. But many more people, like people, as well as professionals and researchers from varied fields, do not have a concrete understanding of what those terms entail. There are innumerable definitions, descriptions, and derivations of those terms. Thus, it must be acknowledged they can sometimes mean different things to different people. How are those related or different concepts defined, and what do they mean? As our world becomes more interconnected and interdependent-we see more rapid development and availability of new tools and methods to overcome challenges.***

Keywords: Artificial Intelligence (AI), Data Science (DS), and Machine Learning (ML), Automated Decision - Making Systems (ADMS)

1. Introduction to AI and ML in Shipping

Indeed, the rapid growth of shipping, the global movement of goods, tighter profit margins, and shorter turnaround times—from local to global markets—have become important manifestations of globalization. Industry, the environment, and society are all affected both positively and adversely regarding shipping, logistics, and transportation. AI, whether used by marine engineers, computational fluid dynamicists, design engineers, or naval architects, can take a variety of forms. Automation—especially with implementing AI algorithms—has become standard. Development of new sensors, new actuators and drives, and ever - improving computational power has allowed for innovations in systems—whether data - driven, simulation - based, hybrid, or analytic—in a variety of domains, including autonomous vessels, ship design and analysis, trajectory or route optimization, autopilots, and shipping traffic.



2. Historical Context

The idea of vessels being operated remotely or indirectly controlled has been so for a considerable time. In nautical lexicon, such remote - controlled vessels are referred to as "autonomous vessels", a term very much equivalent to the more common term "Unmanned Surface Vessel" (USV) used in military settings. These vessels envisage the remote - controlled operation of vessels but without seamen on board. The term "autonomous shipping" has nevertheless become used to argue the position that these vessels are being operated without the need of seamen on any part of the vessel.

The advances of artificial intelligence (AI) and machine learning (ML) offer a transformative advantage to the maritime community for improving efficiencies, enhanced access for reporting and encouraging better behavior from crew, protecting assets such as ships and cargo whose operations are deployed in remote, hostile environments. The Declaration supported research in establishing pan maritime AI and ML infrastructures that facilitated members and stakeholders making ethical, safe, and effective use of these new technologies in their future development.

While of major potential utility, AI and ML are not magical or serendipitous in their impact. Investment in the useful application of AI and ML by the maritime community is required to ensure that it delivers the value that is likely to be invested in it. Apart from the obvious advantages envisaged on efficiency and business optimization in vessel operations, these technologies hold major transformative potential in core maritime functions of ship safety, security, protection of crew, cargo and ships, reducing human error in shipping operations that have historically led to potentially adverse consequences, such as those involving loss of life.

3. Current Trends in Shipping Technology

The advent of the Fourth Industrial Revolution has ushered in a global paradigm shift that reshapes everyday life and has far - reaching implications and consequences for the entire world. It has brought to life concepts that were in the realm of science fiction for decades, such as autonomous vehicles, smart robotics, artificial intelligence, augmented reality solutions, and many more. These emerging technologies are becoming omnipresent in our imperceptible lives and demonstrate tremendous potential to create vast advantages and augment quality and efficiency for the complex, fragmented, and consequently risky global supply chain.

4. Applications of AI in Shipping

While AI technologies are still not widely adopted in commercial shipping, during the last years several solutions have emerged, and the market is on the verge of new growth. The domain likely to be the first to reap the full benefits of AI would be ship management, “a data - heavy and low - margin business”. Applications including predictive maintenance, cargo loading optimization, personnel training simulation, and travel route scheduling are already benefiting from the technology, and new solutions are under development.

More traditional applications such as route planning and optimization, as well as fuel consumption optimization for vessels, “are likely to be among the first use cases benefitting from enhanced automation capabilities based on AI technologies”. Where remote monitoring and predictive maintenance and repair are concerned, “many of the building blocks of an AI - powered maintenance support capability already exist”.

4.1 Autonomous Vessels

The first kind of intelligent maritime system that comes to mind are autonomous vessels, which have no crew on board. Such ships, if well and truly developed, would have a positive impact on operating costs. The entirety of a ship’s operating costs are categorized into fixed cost and voyage cost. Operating costs can be reduced, or rather avoided, by reducing the need for port calls. Currently, these reduce the ship’s efficiency by taking one port out of the practical trading adage, “A ship earns money when it spends its time at sea.” Voyage cost is expensive due to the size of the crew, which is reported to typically account for 25 percent of costs offshore.

The advent of autonomous shipping is no longer a question of ‘if’, but ‘when’. For the first level, shore - controlled ships, the advantage is so obvious that the technology is already in practical use. A company employs an advanced maritime transport system while shipping crude oil along another route, the first lane of the coastal sea fleet commercialization of remote control infrastructure enabled a seafarers relief program. Limited introduction of the second and the third levels, i. e. vessels that can conduct courses for themselves with minimal human interference, are also currently under way. The world’s first ever test of a fully - functioning, remotely - operated drone - controlled ship is now reportedly well underway off the coast.

4.2 Predictive Maintenance

Predictive maintenance is a systematic strategy based on the theory of failure prevention. As more and more ships adopt increased levels of automation, they have increasingly less so - called “spares.” This has a particularly deleterious effect in shipping, where the time required to divert to a port to repair a minor malfunction can be lengthy and costly, with risks escalating further for critical sub - systems such as navigational equipment. The increasing demand for more fuel - efficient vessels is putting systems under stress and as these systems age, the risk of equipment failure increases. Decreasing the time between scheduled dry - dockings will help but without the aid of predictive maintenance to help guide dry - docking scheduling, there is a risk that some equipment may remain in a condition ripe for malfunction after too long a period, while other still - functioning systems may be too early to replace, thus potentially incurring additional risks. Furthermore, as shipping becomes increasingly interconnected and is reliant on low - margin logistics and just - in - time deliveries, the need to avoid unpredictable vessel downtime through better scheduling of maintenance at appropriate intervals is becoming more acute.

Predictive maintenance employs the technology of machine learning to build models that understand what data constitutes “normal” ship performance and then is able to calculate “health scores” that identify any component or ship system that is beginning to deviate from the dominant patterns. The data can come from physical sensors or can also come from “virtual” sensors, which calculate parameters such as pressure loss, that may be significant for predictive maintenance, but which may not have a conventional sensor to monitor them. By employing machine learning to track more data parameters at higher frequencies, it is possible to identify combinations of factors that indicate incipient failure of a component. While ship manufacturers and human data forensics experts can certainly identify parametric signatures associated with particular failures, teams applying predictive maintenance algorithms are able to track and analyze exponentially larger datasets.

4.3 Cargo Optimization

Carrying the greatest possible payload is not only a source of profit for shipping companies, but also impacts on safety at sea, the environment, and other stakeholders. Maximizing load capacity and payload is anything but a straightforward operation. Even a basic relationship between a ship's length and width and the possible volume of container hold space doesn't consider overhanging containers, ship stability during heavy seas, weight distribution, ballast water treatment systems, and efficiency of discharging ports with cranes or other means that take longer to load or unload higher containers. Carrying the most containers at the lowest overall cost is an algorithmic challenge demanding advanced software skill.

Considerable movement of empty containers occurs around the world caused by demand fluctuation. This creates inefficiencies that AI and machine learning could optimize. Empty return shipping containers taking up large amounts of cargo space require costly repositioning. Adding the costs of port handling fees, these empty containers attempting to minimize repositioning costs add costs to agents responsible for scheduling shipments via air or ground transportation. AI could define the lowest cost, delivery - time - efficient journey for ground trucks and helicopters to transport containers of goods to be shipped back in the hold of its intended journey.

AI optimization could be applied to improve seaplane, rail, and truck delivery of containers and container goods across the globe. Careful monitoring of POS and sales could enable other nodes in the logistic supply train to share information on who may be shipping more goods returning empty and staffed to ship back than others. This would optimize delivery, minimizing return shipping containers and empty runs in the lowest time at the lowest cost. Wouldn't it be great if everybody involved in shipping profit, no matter how marginally, when a container finally docked at port? Machine learning could be used to address repeating imbalances.

4.4 Route Optimization

Automated route optimization in shipping has become a basic and important function for shipping companies. The optimization of a specific route is not only complicated but also dynamic because it has to consider many dynamic factors affecting running costs and running time. In addition to the demand for dynamic and automated route optimization, ship owners also hope for optimization tools for customer - centric approach.

5. Applications of Machine Learning in Shipping

Artificial Intelligence and its offspring machine learning are making their inroads into shipping business. Companies turn to data and data - driven decision support. Data from ships has in the past been used to improve ship designs, marine engineering, and environmental implementation. In recent years, however, data from ships is being used to improve operational implementation and support operations. There are reports of the use of predictive maintenance when the sensors on a ship can signal when the equipment is going to break down. The next big data direction is demanding forecasting. The availability of big data is one significant motivation in using data analysis to predict demand; however, companies want the wisdom to improve forecasts to make sense to invest.

Ship routing and scheduling present a complex optimization task that is like the Traveling Salesman Problem in discrete space; it has been solved via a combination of heuristic functions, heuristics, and classical search methods due to the curse of dimensionality. Simulation - based optimization methods like policy gradients and genetic algorithms have been tested to significant success. Route planning in continuous space is often performed via route decomposition for practical reasons. Autonomous ship navigation is a holy grail in marine robotics. A reverse approach to the problem is mapping, where a ship can generate a map from the data. Both autonomous ship navigation and mapping have been achieved by employing reinforcement learning on data.

5.1 Demand Forecasting

When faced with the commonplace product demand uncertainty that every organization must tackle, a typical response from a shipping firm, port or shipping service node operator, is to invest in more capacity in order to satisfy a higher demand level than expected and avoid the risk of incurring a demand shortage that usually results in loss of business. Searching for near optimum values for such capacity investments is made by complex simulation models that need a range of average demand values as their input. Consequently, a logical starting point for the demand simulation is some method for demand forecasting, focusing on the relevant aspects of the long - term demand generation process, which is very complicated. As the forecast errors cannot be reduced to zero, capacity management will need to handle the errors. Proactively using a model for high - quality forecasting gives decision makers better information, reduces forecast errors and can support them in reducing the negative impacts of forecast errors during the period when capacity is fixed.

5.2 Risk Assessment

The risk assessment information gathered from the cargo documentation is helpful for the authorities to be more efficient and effective in their inspection operations. Risk evaluation uses historical data based on risk assessments for shipments arriving at designated entry ports, and therefore it will improve over time. Thus, as the risk assessment results get better, more room will be accommodated for inspection of the shipments assessed as low risk, permitting a more efficient allocation of available resources to invest in the inspection of the high - risk shipments.

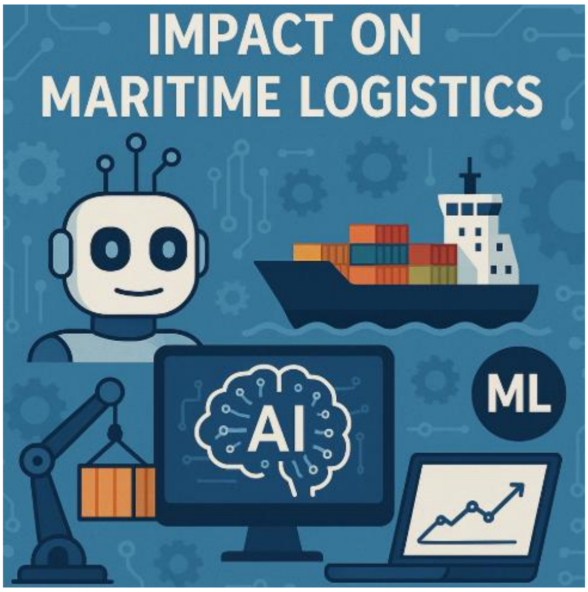
Several studies that made accurate risk assessments in shipping by using logistic regression and support vector machine techniques offered good promise for using other modern machine learning techniques, such as artificial neural networks or gradient boosting machines, that do not rely as much on strong assumptions as the former two. However, to benefit from machine learning, there is usually a need for a large - scale dataset to avoid overfitting. Still, industry players in the shipping business are often reluctant to provide their proprietary data, as the competition is often fierce. When proprietary real competition data are not available for the risk modeling study, simulated datasets, usually based on expert knowledge, can be generated to allow for the testing of more modern machine learning techniques. Such risk modeling of cargo shipments at large port terminals has become an active research area because, by improving risk prediction accuracy, risk - based inspection policies can further minimize costs for both the cargo shippers and the inspection authorities.

5.3 Fraud Detection

Fraud detection through data mining is a rapidly growing area of research, enabling a substantial and of course highly relevant application of data science in shipping. Given the extensive amount of data being generated in shipping operations such as freight contracts, charters, invoices, payments, and cargo transactions, as well as the involvement of a multitude of actors over a long time period, the chances for fraudulent behavior are also large, and the consequences would be severe.

6. Impact on Maritime Logistics

Due to the machinery's growing potential for rendering a lot of tedious work in the context of shipping planning, AI and ML solutions are increasingly taking over herewith, promising profound transformations on different levels of the industry. Such technology can take effect on evaluating future transport demand, on embedding and refining all shipping - related decisions within supply chain optimization models, sometimes coupled with insights stemming from complex technology portfolio decisions. As a result, better routed ships should use less fuel, commodities should take less time to be delivered, shoreside inventories should be kept lower, and transports would leave less impact on the environment.



6.1 Supply Chain Efficiency

The use of advanced algorithms within Artificial Intelligence (AI) and Automated Decision - Making Systems (ADMS) has a substantial impact on logistics systems. Multi - agent AI - based systems capable of robust decision support processes are currently pursued. These systems may have the ability to reason why and how to achieve the desired objectives while finding the right balance between cost and service levels when multiple service requests are involved; should automatically track all carrier performance so that adjustments in assignments are based on service history; should allow the use of a single, shared pool of vehicles and drivers owned by multiple carriers to ensure the rapid sharing of assets in cases of peak demand; and should monitor and control all transport real time from multiple control centers. ADMS and AI tools already have a short - time impact on logistics systems, where Transport and Logistics Service Providers (TLSPs) are faced with the high pull effect; Assisted business policy definition based and near - real time control - based systems have been tested, but MA - ADMS have yet to be implemented in Logistics and Transport Systems Operations Control Centers. They will be one of the key ingredients to enabling framework technology of Integrated Production and Transport Planning and Control for short to medium time/control cycles. AI - based systems can strongly contribute to the short - term transport cooperation strategy definition.

6.2 Inventory Management

Inventory management refers to the practice in which a business manages its ordering, storing, and use of its products. Inventory refers to the assortment of products that a company trades in, manufactures, and also raw materials that are either in use or idle. The goal of inventory management is to be able to serve customers promptly at a lower transaction cost. This means that the business needs to balance the holding cost of finished products or raw materials against lost sales and transaction costs.

A thorough analysis of what is meant by Big Data in shipping and its implications for the future are done. For the shipping industry in particular, these developments seem to come with a considerable delay compared to others industries. Furthermore, there are some very specific obstacles like confidentiality, investment in research and development, existent traditional structures and issue of investment. Possible opportunities coming from the need of coping with business processes, costs and stakeholder expectations include electronic commerce, maritime security, effect of financial constraints, environmental initiatives and Short Sea Shipping.

Usually, Big Data is characterized by Volume which associates with large amounts of data, Variety which describes the different types and sources of data, Velocity which refers to the speed of data - in - motion and Veracity meaning reliability of the processed data. For the Shipping and Maritime industry, the Volume is uncertain at present but mostly considered for future potential benefits. Variety is certainly an issue for the industry. Ships are sensors which provide vast amounts of physical data on the environment and their movements.

7. Big Data Utilization

Decisions in shipping are often taken with considerable neglect of the many millions of transactions every day that generate data relevant to almost every decision - making challenge. For charterers, owners, brokers, etc., the data enable a real - time comparison of an owner's offer with the current market, taking due account of a vessel's performance in terms of speed and fuel consumption, the company's reliability to comply with deadlines, absent from the contract, and a host of other intangible issues, plus taking account of the decision time structure governing the respective companies' decisions.

7.1 Real - time Monitoring

The real - time monitoring of the current state of the vessel is essential to implement effective decision - making strategies throughout the voyage. The effective functioning of the mesh of connected equipment, onboard or offshore, generating, collecting, and analyzing the data generated will eventually allow stakeholders to decide on the direction for the next stage of development, and which business opportunities to pursue.

Through the ongoing monitoring of the equipment state, the predictive maintenance application receives the data and alerts crews about a possible malfunction before critical failures occur. Modularity of the ship energy system allows carrying basic operations in islands disconnected from shore through the optimization of load demand of the island. Data collection in offshore conditions allows creating a predictive algorithm of the ship energy supply system for land bases. Crew efficiency assessments significantly affect operational costs.

8. Challenges in Implementing AI and ML

In the era of New Age Shipping, data - driven, technically assisted, digitization, and transition of Shipping towards an AI and ML - based approach is quickly advancing. However, the rapid movement is not without its bubble, where the speed of implementation is often greater than that of planning for tomorrow and integration of Tomorrow's AI within existing systems. Within an industry that has seen integrations and collaborations, where Shipping companies often operate in silos, the urgency could be counterintuitive, with AI tools often being stuck in the Early Adopters domain of the Technology Adoption curve.

There remain several problems that would need to be addressed from a Shipping perspective, where careful and often slower implementation may be more prudent than a flying start. Data Privacy Concerns, the potential of Data Biases growing, Data availability, training variables for FML, Adoption of AI in the core mindset of Employees and Stakeholders, Skill Gap in the Workforce, Navigational and Operational Safety Implications and Integration with existing Maritime Systems.

Data Privacy Issues would be a critical driver to the AI Adoption model. Unlike e - commerce and fintech sectors, the dearth of existing frameworks and laws governing maritime data storage, usage, sharing, access is severely limiting the movement of critical data towards Machine Learning Infrastructure. The adopting firm not only needs to develop adequate sharing measures and frameworks with stakeholders, but also has to ensure that private, confidential and highly sensitive data is protected. The potentially catastrophic implications of a Data Breach may be offset against the organizational motivation of AI adoption for Cost Savings.

8.1 Data Privacy Concerns

Artificial Intelligence and Machine Learning are programs where their data architecture relies on heavy data processes. The general public dissemination of data used to compile the models increases risks with regards to data privacy and the ability for AI or ML to breach people’s privacy. These data incursion concerns wary clients looking for AI or ML solutions. Another issue is how to design a model so it respects data privacy and why would a client engage in such a disruptive and expensive business transformation with uncertain payoffs or benefits? Most importantly, whose responsibility is it to secure individuals’ private data? The administrator of the system? The owner of the data? Or the community as a whole because the data is used for the progress of humankind? Currently, there is a lack of understanding about whose responsibility it is to ensure data privacy, thus it is left to individual’s discretion. Consent information is often not clear and understandable as terms can be extremely long and complex.

Some industries are especially vulnerable using AI and ML without data privacy protection systems.

8.2 Integration with Existing Systems

Integration of AI and ML methods with existing systems presents a significant difficulty for companies. Effective for intelligent decision - making, AI and ML may utilize several in - house and external databases while the company operates in established industry infrastructure. So, from a corporate perspective to what degree is the orchestration of the management of the organizations’ computer systems using AI algorithms to minimize costs and increase efficiency, through developing, building, constructing, and selling advanced algorithms, supporting programs, and hardware structures distinct from making improvements in tools and using the tools effectively?

8.3 Skill Gap in Workforce

Artificial intelligence (AI) and machine learning (ML) talk is currently everywhere. It is used to conduct complex tasks and drive cars. The hype surrounding the new capabilities has led to companies rushing to deploy these technologies. But ask any company that has implemented AI or ML: The hardest part is building a team that has the skillset to deploy the technology.

9. Future Prospects of AI and ML in Shipping

Disruption is no longer an option; it is a necessity. The intense pressure to meet climate - neutral targets is transforming the shipping landscape faster than anyone could have anticipated. As a result, it is vital that the maritime industry embraces and enables new technologies to assist in these changes. Artificial intelligence and machine learning have reached a level of maturity that new applications are swiftly emerging in an increasing number of sectors, including shipping. With the global shipping sector already facing decarbonization, this progress raises the question whether the timely adoption of AI and machine learning could facilitate a faster route towards the transformation of shipping into a more sustainable, safer, and more efficient industry, and as a consequence, overcome the perceived economic challenges linked to decarbonization. In the short term, such technologies could enable shipowners to reap the benefits of improved operational efficiency at neutral cost, as AI and machine learning would use the mountain of operational data already collected but not utilized by maritime players. In the long term, with a growing number of ships operating in a greener manner, relying on AI and machine learning technologies, the shipping sector would benefit from an overall reduction of capital and operational costs, as well as from optimized vessel routes.

9.1 Emerging Technologies

While many AI and ML systems in shipping remain at a premature stage of project development and investment, there is a growing sense of excitement over the tangible possibilities being harnessed in the industry. Use of advanced AI and ML systems is rapidly expanding in more traditional areas of shipping such as digital twins, cybersecurity, fuel efficiency, operational optimization, and big data analytics for trading and other decision - making functions, aided by further technological developments and investment in computational power and speed. These functions are well - established as areas where big data, data analytics, and predictive models are already reshaping the industry. And further development of other cutting - edge technologies with AI and ML are being pioneered for application in shipping, including these:

Natural Language Processing (NLP): NLP is a computer - driven mechanism that translates human information, such as a spoken word, text, or verbal command, into a language that a computer can interpret and translate back into human communication. NLP has application and implications for machine - augmented management and control of language - based and writing - based maritime functions, such as contractual obligations and compliance with other requirements. These maritime functions can involve such diverse areas as chartering, insurance, and maritime law – particularly for multinational companies such as multi - billion - dollar parcel logistics businesses, commodity trading companies, financial services firms, and industrial conglomerates with close ties to shipping and logistics operations. The adoption of NLP technology by shipping for these functions would be on par with the current widespread utilization in other business sectors of automated language translation and related software.

Meta - Learning and Self - Supervised Learning: These promising AI techniques are the cognizance and creativity to design or leverage models that can learn to recognize beforehand what might be observable or what functions might need to be performed, and how to efficiently adapt to different tasks with minimal labeled data. These functions can be learning prototypes or observations, and performing segmentation, zero - shot classification, goal - conditioned planning, perceiving human motion, reinforcement learning, reward modeling, or causal structure learning.

9.2 Regulatory Considerations

AI systems or hardware, cyber security concerns the vulnerability of systems to hacking, and accountability concerns regarding who bears the responsibility in the case of an accident. Such consideration of accountability raises further interesting issues once one considers the extent to which such developments currently are or should be liable for traditional tort actions and owe such a duty of care to those potentially affected. Further concerns also arise with regard to the impact that the further increased replacement of human labour in certain roles might have on the sustainability of the relevant transport modes, as well as on their regulatory frameworks.

10. Case Studies

The chapters above illustrated how Artificial Intelligence and Machine Learning could be utilized in different areas of shipping. A lot of algorithms were presented and a broad discussion about these algorithms followed. However, some might ask if these ideas have reached real implementation in the shipping industry? In order to help answer this question, this chapter summarizes initiatives using AI and ML on real maritime use cases, some were very successful, others weren't but each of them has some lessons learned for shipping safety, efficiency, and sustainability. These road - tested cases provide knowledge about the opportunities and limitations of AI in shipping and its promise of helping the industry to meet its targets set in the decarbonization roadmaps. The information content of this chapter provides the groundwork for the researchers and start - ups who continuously develop novel algorithms to implement their latest results in future maritime use cases.

11. Ethical Considerations

Despite the obvious advantages of artificial intelligence and machine learning, it is imperative to consider the collateral consequences of the implementation of such systems. This is particularly true for specific sectors, where the direct impact on people's lives is considerable and where the risk that private interests will prevail over collective interest could be considerable. The maritime shipping sector abounds with these elements of fragility.

11.1 Impact on Employment

Unresolved ethical questions arise when contemplating the impact of AI and ML on various labor markets. The development of AI has long been championed with the promise of removing laborious, unskilled, or even dangerous tasks from humans, and instead allowing them to pursue higher societal goals. Nevertheless, a strong possibility exists that the uptake of AI in various sectors may actually lead to heightened inequality or to some sections of the workforce, particularly the most vulnerable, losing out as low - skilled positions are eliminated faster than new jobs are created. In shipping, this scenario of mass unemployment or radical job displacement remains a possibility, particularly given the alarming number of recent studies pointing to the vulnerability of a large proportion of existing jobs to automation.

11.2 Environmental Concerns

The maritime transport sector has seen the implementation of various innovations and proposes novel technologies to automate conventional processes, including Artificial Intelligence and Machine Learning applications. As global waterborne trade continues to expand, with an increasing number of fleets plying the oceans across the globe, it has become essential to improve the performance of maritime transport. These technologies aim to enhance the quality of services and achieve cost and time reductions. Moreover, they are also expected to reduce the burden on the natural environment by diminishing energy consumption and curbing harmful gas emissions. Compared to the

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overwhelming utilization of fossil fuels for land and air transport, maritime transport is more ecofriendly since it relies less on consuming fossil fuels relative to the overall cargo transported across long distances. Global legislation has mandated the use of SOx scrubbers and NOx emissions technology to curb moves for zero emissions. These new requirements have pushed investment flows and the creation of start - ups in this space until at the time of writing. The Marine Insurance and P&I Clubs have attempted collaborations with other organizations but urge the maritime industry to educate itself on the environmental consequences of the industry, particularly when it comes to greenhouse gas emissions. In addition, the challenge to insurance also touches the traditional insurance business models, which base much of their pricing structure on observed past data, as the adoption of these novel technologies must evolve rapidly to ensure the safety of ships and their crews.

12. Conclusion

Shipping has undergone a digital transformation in recent years, thanks to several advancements. At the same time, shipping is still one of the oldest industries and has the largest percentage of work hours which utilize human abilities. Although historical problems exist permanently, including the problem of low profit margins and unsustainable practices, nowadays additional issues such as supply chain disruptions, trading conflicts, changes in trading patterns, and piracy of data are challenges shipping is currently facing. Innovation can help to master these challenges. Therefore, artificial intelligence, machine learning, and related technologies will be introduced in shipping in the upcoming years. It is expected that many more operational, tactical, and strategic decisions will be supported and automated, driven by new operating models and available data including autonomous ship operation and optimization and risk assessment and mitigation.

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