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Understanding AI Application Dynamics in Oil and Gas Supply Chain Management and Development: A Location Perspective

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Abstract

The purpose of this paper is to gain a better understanding of Artificial Intelligence (AI) application dynamics in the oil and gas supply chain. A location perspective is used to explore the opportunities and challenges of specific AI technologies from upstream to downstream of the oil and gas supply chain. A literature review approach is adopted to capture representative research along these locations. This was followed by descriptive and comparative analysis for the reviewed literature. Results from the conducted analysis revealed important insights about AI implementation dynamics in the oil and gas industry. Furthermore, various recommendations for technology managers, policymakers, practitioners, and industry leaders in the oil and gas industry to ensure successful AI implementation were outlined.

Keywords: Artificial Intelligence; Development; Supply Chain; Oil and Gas; Petroleum Industry, Energy.

1. Introduction

In today's uncertain and volatile demand as well as the evolution of alternative energy sources, oil and gas firms have been forced by great pressure to speed up the pursuit of productivity in this climate, thus boosting production, reducing costs, and optimizing profits [1]. To help in this pursuit, the application of Artificial Intelligence (AI) in the oil and gas industry is quickly evolving at present, as the idea of AI steadily enters different phases of the industry like smart drilling, smart development, smart refinery, and smart pipeline [2]. According to the Evensen et al. (2021) [3] study, existing AI investments within firms in the oil and gas industry have yielded a 32% average return on investment. Over the last three years, there has been a 3% decrease in expenses and a 3% growth in income. This corresponds to an extra \$570 million in earnings for a \$10 billion corporation with a 10% profit margin. AI investments have also slashed the time it takes for new products and services to reach the market by 31 days.

The authors also stated that over the last three years, nearly 75% of AI champions in the oil and gas industry have generated more value than planned from their AI investments, when compared to their peers. The percentage of value generated through AI investments for different business objectives, is shown in Figure 1. The oil and gas supply chain is divided into 3 sectors: upstream, mid-stream and downstream. The upstream field of the oil and gas industry is the most capital-intensive and critical division of the three, since this is where crude oil and natural gas are extracted [4]. The midstream involves transportation and distribution, and like any other field, is an important aspect of the oil and gas industry, but the industry is unique from other sectors because of the highly sensitive quality of shipped and

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delivered products [5]. The downstream sector is responsible for the refining of oil and gas, as well as the distribution of end goods [6]. Activities in each of the three locations are captured in Figure 1.

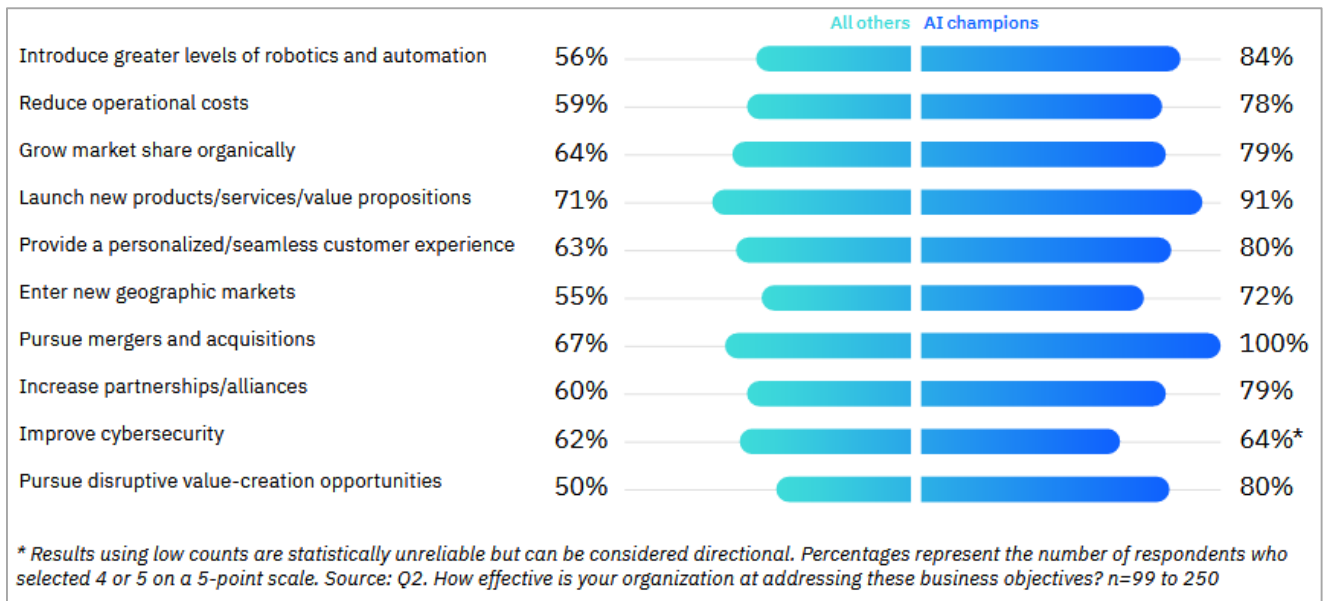


Figure 1. Levels of business objectives achieved, AI vs. traditional [3]

According to the International Energy Agency (2017) [7], digital technologies, such as AI, have the potential to reduce production costs by 10 to 20%. Biscardini et al. (2018) [8] estimated that the use of digital technologies like AI in oil and gas upstream operations could result in savings in capital and operating expenditures of \$100 billion to \$1 trillion by 2025. The potential increase in efficiency through digitalization is shown in Figure 2.

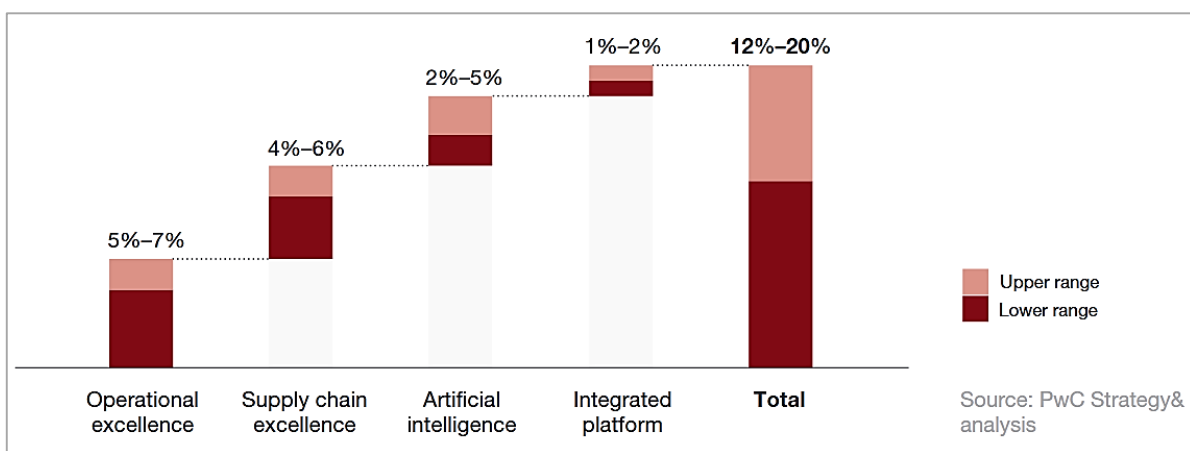


Figure 2. Efficiency increase from digitalization [8]

Worldwide, within offshore oil and gas companies, unplanned outages caused by damage or failure can cause output lags of tens of thousands of barrels of oil per day, as represented in Figure 3. An average offshore oil and gas company has 27 days of unplanned downtime per year, resulting in yearly losses ranging from \$38 million to \$88 million [9]. Additionally, offshore platforms are often only operating at 77% of their potential, this gap amounts to almost ten million barrels per day, or over \$200 billion in annual revenue [10].

This is where AI-enabled predictions and natural language processing (NLP) can help elevate traditional predictive analytics to optimize production. By monitoring and forecasting equipment breakdowns and highlighting the commercial effect of unplanned loss of production capacity, AI can assist in reducing costly downtime [9].

Advanced analytics, when used correctly, can produce returns of 30-50 times investment in just a few months [10]. Data from seismic surveys, geology evaluations, and reservoirs can be analysed by an AI system utilizing technologies like machine learning, artificial neural networks, expert systems, and fuzzy logic [9]. This analytical technique has the

potential to increase the global average subterranean recovery factor by up to 10%, equating to an additional \$1 trillion in BOE (Barrel of oil equivalent) [11].

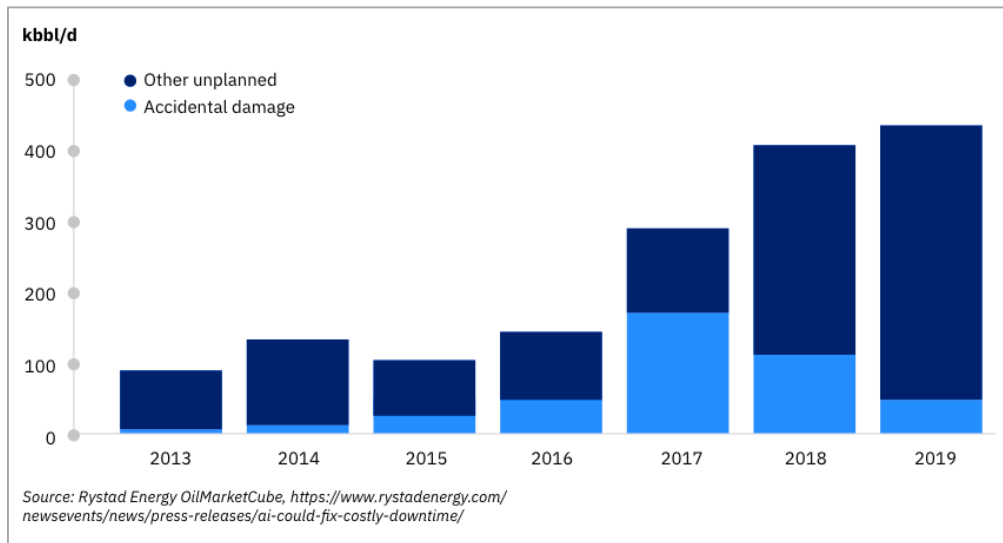


Figure 3. Global average of barrels of oil lost daily due to downtime [9]

This paper attempts, using a literature review approach, to better understand the applications and challenges dynamics of artificial intelligence (AI) in the oil and gas supply chain from a location perspective (as described in Figure 4). Many of the previous related work were concerned with the “what” and “how” questions regarding AI in oil and gas supply chain, while this paper focus to answer more the “where” question. We aim to get a broader understanding of the usage of AI technologies within oil and gas supply chain locations i.e., upstream, midstream and downstream. Along these locations, this paper will specifically focus on four main AI technologies, namely machine learning and hybrid algorithms, natural language processing, computer vision and robotics. These technologies were selected as they cover the widest range of potential AI applications within any supply chain.

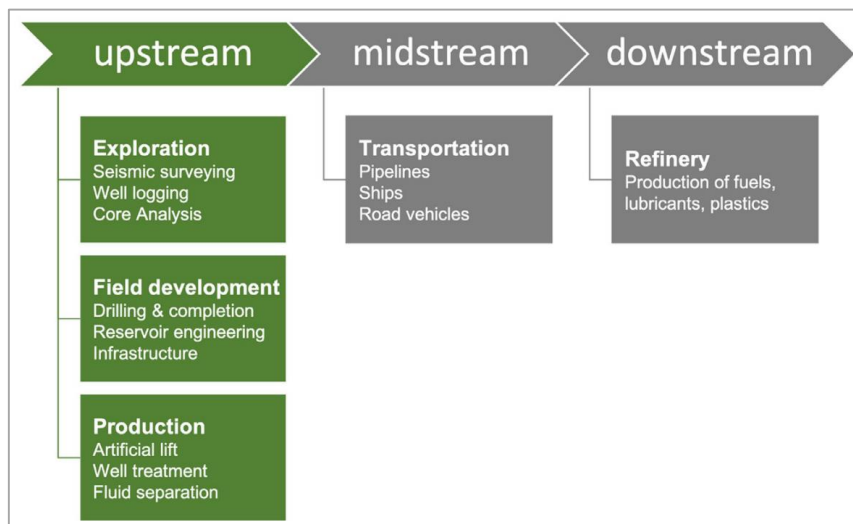


Figure 4. Upstream sector of the oil and gas industry [12]

2. Research Approach

The research methodology used in this research is based on literature review of the current body of knowledge and using secondary data from a variety of sources such as peer-reviewed papers, surveys, reports and websites. The science direct database is used for the literature review, and papers were selected by using specific set of keywords and filters.

The structured literature review involved five steps. In Step 1, a general literature search was performed to show the total number of journal articles on “Artificial Intelligence in Oil and Gas Industry”. In Step 1, the studies were found by using these combinations of keywords: TITLE (“Artificial Intelligence”) AND TITLE (“Oil and Gas”).

Based on the search a total of 2098 relevant results were found, these studies included articles from the year 1998 to 2021. Step 2 involved narrowing down the search results to capture the total number of journal articles on “Artificial Intelligence in Oil and Gas Industry Supply Chain”. In Step 2, the studies were found by using these combinations of keywords: TITLE (“Artificial intelligence”) AND TITLE (“Oil and Gas”) AND TITLE (“Supply Chain”). Based on the search a total of 346 relevant results were found, these studies included articles from the year 1997 to 2021. Step 3 attempted at narrowing down the search results even further by location and explore the total number of journal articles on “Artificial Intelligence in Oil and Gas Upstream”, “Artificial Intelligence in Oil and Gas Midstream” and “Artificial Intelligence in Oil and Gas Downstream”. In Step 3, the studies were found by using these combinations of keywords: TITLE (“Artificial intelligence”) AND TITLE (“Oil and Gas”) AND TITLE (“Upstream” OR “Midstream” OR “Downstream”).

Based on the search a total of 296 relevant results were found for the Upstream sector, 24 for Midstream and 294 for Downstream, these studies included articles from the year 1992 to 2021. In Step 4, 40 papers were selected to represent relevant studies that captured the selected AI technologies along the whole oil and gas supply chain. It is important to acknowledge the following points regarding the adopted review process. First is that the intent was not to conduct a comprehensive literature review for the whole body of knowledge; rather, this paper objective is to gain some insights regarding the AI location dynamics with oil and gas supply chain using representative sample of the research work. Second, it is clear from Figures 5(a) to 5(c) that the interest in AI application in the oil and gas supply chain is exponentially rising in the recent years among academicians. Third, the number of papers downstream that really focused on AI technologies considered in this paper within the focus of downstream activities identified also in this study (mainly refinery) are far less than the number reported using the search engines (294). Most of the papers at this category are actually referring to activities regarding demand management and forecasting which are important activities but do not align with the downstream definition in this work. A sample of this group is captured though in this analysis for purpose of completion. The literature review selection criteria are shown in Figure 6.

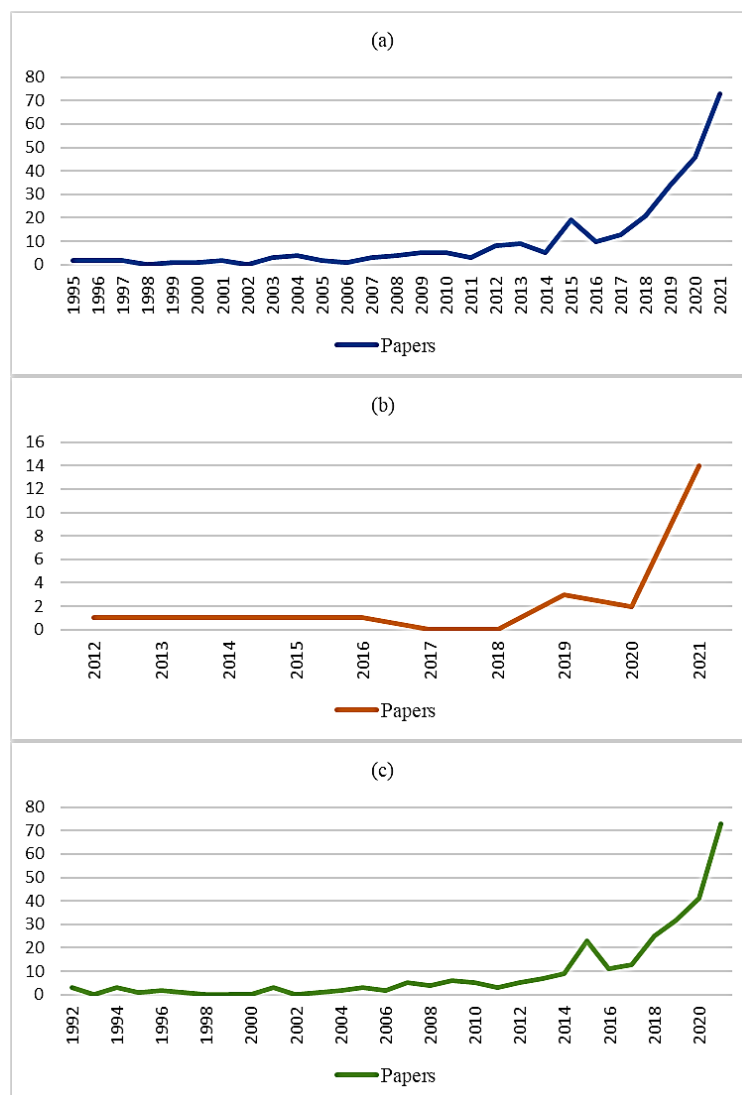


Figure 5. No of papers per year for (a) upstream, (b) midstream and (c) downstream

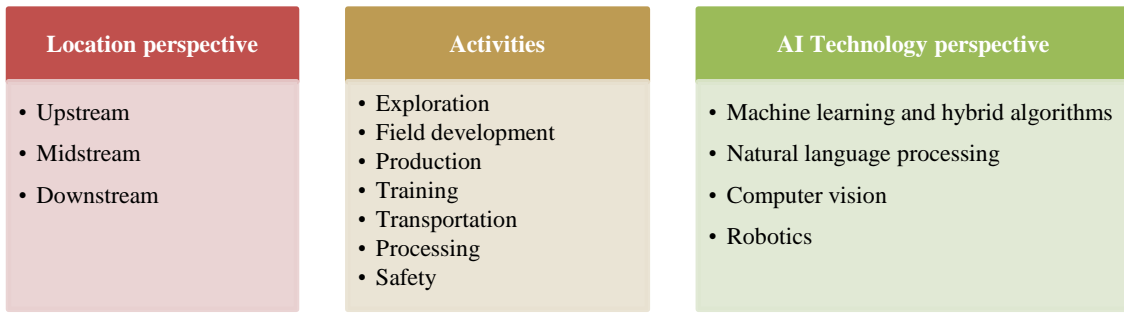


Figure 6. Literature review selection criteria

3. A Location Perspective of AI in Oil and Gas Supply Chain

In this section, we summarize the main findings from the considered literature papers regarding the AI technology benefits and challenges in oil and gas supply chain. As mentioned earlier, the summary will follow the location perspective since this is the focus of this paper.

3.1. AI in Oil and Gas Upstream

In the upstream sector of the oil and gas industry, the three critical areas are exploration, field development, and production. In exploration, machine learning (ML) models have been used to automate data collection, transmission and analysis for activities such as seismic surveying, well logging and core analysis, thereby reducing costs, lowering errors and improving efficiencies [12].

Many research work have focused on the applications of AI technologies within field development, for activities such as drilling, reservoir engineering and infrastrucutre. Machine learning models and its hybrids reveal successful applications in drilling for prediction of optimal mud properties and drilling parameters to improve safety, drilling efficiency and cost effectiveness [13-17]. Similarly in reservoir engineering and infrastructure, ML and its hybrids are used for estimation and optimization purposes in activities such as estimating dew point pressure and optimizing waterflooding which helps to maximize hydrocarbon production, optimize oil production and maximize finanacial profits [2, 18, 19].

In the area of production, ML models and its hybrids are mainly used for the monitoring, prediction, forecasting, selection and detection of various characteristics and components critical for optimal production. This includes, choke valve flow-rates, production at ultra-high water cut stages, precipitation of asphaltene, sand production, separator selection, faulty events, production forecasting and predictive maintenance [20-29].

Furthermore, in the upstream sector, computer vision technology has been used for training technicians and field operators using a virtual reality environment. This has helped to both reduce the cost and time of training, while at the same time improving safety [30].

3.2. AI in Oil and Gas Midstream

In the midstream sector, the main functions are transportation and distribution. Pipes and tanks are two of the most important systems used in the transport and storing of oil and gas in the industry [5].

Many of the considered papers discussed the applications of ML algorithms for the modelling, monitoring, assessment and optimization of gas pipelines. Particularly, ML has been used to: find optimal balance between operation benefit and transmission amount in pipelines [31, 32], to develop continuous and dependable monitoring systems to assure pipeline safety and help extend their lifespans [33, 34], and finally to improve specific operation, design and risk assessments using predictive models and simulations to reduce maintenance and operational costs [35, 36].

Pipes and storage tanks, especially those continuously used for long-distance transport and long-term storage, need periodic inspection and maintenance. It is costly and unsafe to humanly inspect these components, so automated inspection and handling of these components is very desirable. Research conducted evaluated the applications of robotics for this purpose, in the form of in-pipe inspection robots, tank inspection robots, unmanned aerial vehicles, autonomous underwater vehicles and under-water welding robots [5, 37, 38].

3.3. AI in Oil and Gas Downstream

In the downstream sector, the main functions are refining of oil and gas, as well as the distribution of end products, ML algorithms and hybrid versions of them were found to be more capable than conventional models and reveal

successful applications for accident prediction relating to repair & maintenance in refineries. They can also assist in prediction and estimation of various chemical processes, which directly affects the efficiency and safety of downstream processing during product recovery [39-41].

ML and its hybrids have also been used in the downstream oil and gas industry for overall demand and consumption forecasting, where its use has helped improve predictability and accuracy of forecasted data and synchronizing it with different production activities [42, 43].

Additionally, in the downstream sector, computer vision technology has been used to monitor the various parameters associated with the processing of oil in refinery processing plants. The technology has been found to be successful in predicting the occurrence of unstable conditions, by monitoring oil flame dynamics within the refinery using cameras, thereby avoiding potentially dangerous situations and promoting safety by automating the control system [44].

3.4. Other Applications of AI along the Whole Oil and Gas Supply Chain

Several papers discussed how AI technologies can be used throughout the whole oil and gas supply chain. Shukla and Karki (2016a, 2016b) [5, 37] discuss how robotics, in the form of in-pipe inspection robots, tank inspection robots, unmanned aerial vehicles, wireless sensor networks, remote operated vehicles, autonomous underwater vehicles underwater welding robots can be used for onshore and offshore applications for activities such as site survey, drilling, production and transportation. According to them, these technologies can help automate several processes within the industry and can help improve health and safety standards and also improve efficiency.

Other work discussed how to improve overall safety and operational performance throughout the oil and gas supply chain from upstream to downstream. This can be realized using ML for activities such as process safety management (PSM), risk-based inspection (RBI), disaster assessments and production and maintenance related tasks. In these cases, ML has helped to expedite data collection and analysis processes in PSM, predict the vulnerability and disruption in disaster assessments, improve quality of conventional RBI by reducing output variability and increasing precision and accuracy [6, 45-47].

Single et al. (2020) [48] discussed the use of natural language processing, to help with the acquisition of knowledge related to accidents throughout the supply chain. The authors' results indicated that their proposed method was useful to discover causal accident relations from databases. The authors also stated that this technology, with the help of databases can be used to create a robust shareable knowledge structure that can be used across countries and companies, to help improve safety.

3.5. Challenges of Implementing AI in Oil and Gas Supply Chain

The considered literature also discussed AI implementation challenges. For example, in the upstream sector of the oil and gas industry, Koroteev and Tekic (2021) [12] highlights three main challenges. First, is the people since AI have to be highly customized based on the business context and data, firms will need in-house teams capable of supporting development of AI infrastructure and customizing AI tools. Second, is the data since successful AI applications requires access to large amounts of good quality data. Third challenge is the open collaboration among all echelons, which is a challenge due to the lack of open data source and cross-company, cross-border data sharing. Osarogiagbon et al. (2021) [13] pointed to safety challenges in the area of ML algorithms being applied for dangerous events in drilling operations. Apart from a lack of publicly available datasets, a lack of customized deep learning algorithms primarily in the field of drilling activity was also observed.

Al-Fattah and Aramco (2021) [42] discussed some of the serious challenges faced when building AI and ML models for forecasting crude oil demand. The challenges were due to the over-fitting, under-fitting, and/or memorization, which means that during the training phase, the model appears to produce excellent results, but does not perform as well in the testing phase, resulting in unacceptable forecast results. According to the author, some of the causes for these challenges are: (a) Insufficient data, and (b) inappropriate network configuration.

Hanga and Kovalchuk (2019) [6] presents other challenges in applying AI to oil and gas industry tasks. Some of the challenges that limit the implementation of AI in oil and gas industry are: (a) Lack of awareness and knowledge about the techniques technical capacity; (b) Shortage of development tools for efficient implementation and finally (c) Uncertainty and risk of acceptance of new technologies.

Shukla and Karki (2016b) [37] highlighted that some challenges regarding applying robotic solutions in the offshore oil and gas activities including inspection, manipulation and repair. Navigation and localization of the autonomous underwater vehicles were some examples of these challenges.

In the oil and gas midstream sector, Ben Seghier et al. (2021) [33] discussed data measurement problems due to the high cost of inspections, excavation requirements and the risk of vulnerable pipelines, particularly for the anticipation of high pitting corrosion depths in oil and gas pipelines.

Finally, the work of Lu et al. (2019) revealed several difficulties that the oil and gas industry will face when transitioning into the Oil and Gas 4.0 era [1]. Apart from the challenges mentioned earlier, some of other challenges include negative outlook as well as lack of general standardization and planning.

4. Literature Review Analysis for AI Location

To gain further insights about the AI implementation dynamics along the oil and gas supply chain, descriptive and comparative analyses were conducted for the reviewed body of literature. The analyses started with general quantitative overview and then was followed by specific analysis for each location in the supply chain.

4.1. Overall Comparative Analysis for AI Location and Technology Type

Out of the 40 considered studies for review that focused on the specific AI technologies in oil and gas supply chain perspective, 50% contributed to the upstream sector, 18% to the midstream sector, 15% to the downstream sector. In addition, 17% of the papers focused on all three supply locations, for the selected AI technologies in the oil and gas supply chain. The overall distribution is shown in Figure 7.

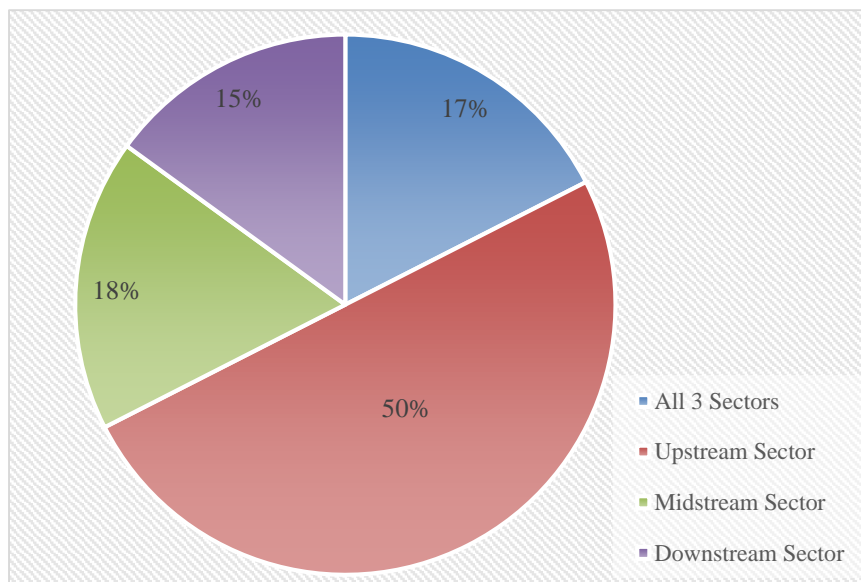


Figure 7. Literature review location focus quantitative analysis

Figure 8 captures the overall distribution for the same body of knowledge focusing on the selected AI technologies implementation along the whole supply chain. One can observe that 85% of AI technology implementation are related to machine learning and hybrid algorithms, 5% are related to computer vision, 8% are related to robotics and 2% are related to Natural Language Processing (NLP).

From Figures 7 and 8 we can point to some interesting observations. First, when compared to other locations, the highest concentration of research work is related to upstream while the lowest concentration of work is found to be focusing on downstream activities. This poses an important query for such distribution. The key to understand such distribution is related to the complexity of activities and operations at each location. Upstream activities are by far more complex and capital intensive and thus more information is needed to manage and reduce such complexity and its associated risks. AI is well suited to capture and process high plethora of information and thus it had been an attractive solution to oil and gas supply chains especially upstream.

Second, in terms of the type of AI technology used within the oil and gas supply chain locations, machine learning and hybrid algorithms are clearly the main adopted technology (85% of all papers focused on this specific AI technology). This should come with no surprise given the ability of ML and its hybrids to analyse various data in predictive and prescriptive manner assisting oil and gas supply chain managers in various decisions. ML as the paramount of AI technology will enhance the visibility of the whole supply chain leading to almost real time educated decisions saving time and cost as well as reducing risks in this critical industry.

Third, the results also suggest that more research is required to explore the lower adoption rates of AI at both midstream and downstream locations. The same need is also true to explore why some AI technologies like NLP for example in this study had captured less attention than other AI technologies in the oil and gas supply chain.

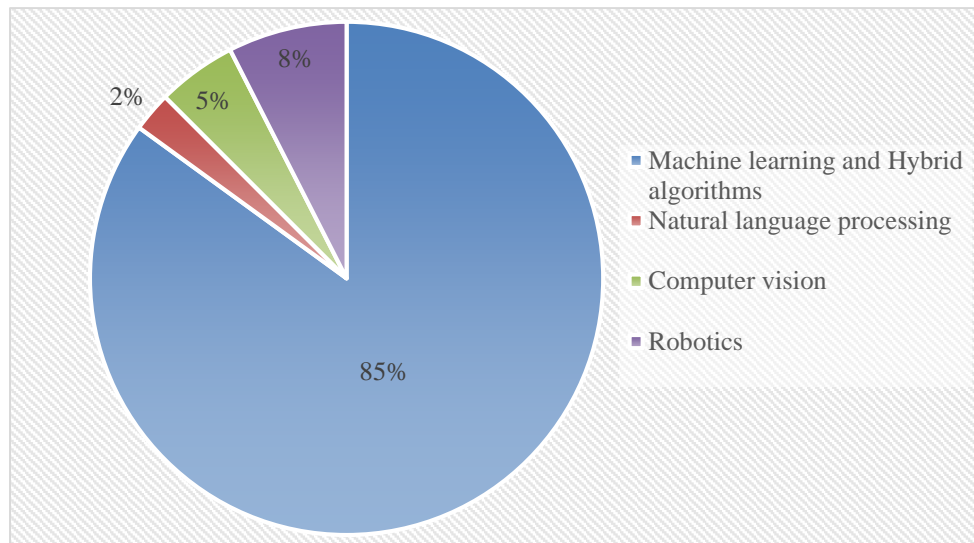


Figure 8. Literature review quantitative analysis for AI technology type

4.2. Descriptive Analysis for AI Location and Technology Type

In this section, a detailed description of the various AI technologies implemented at the different oil and gas supply chain locations is presented in a tabular format. The main objective is to provide a more granular insight beyond where AI technology is concentrated or its general type into how it relates to the different locations’ activities within the captured body of knowledge.

Table 1 lists the different AI technologies implemented within the different oil and gas activities upstream the supply chain. A total of 20 studies in the considered literature focused on AI applications upstream the oil and gas supply chain. Field development and production were the main activities with had ML-based solutions as the dominant applied AI technology. This is mainly due to the ability of ML technologies to assist in precise drilling, adaptive production as well as preventive maintenance. Using ML solutions like digital twins integrated with IoT can lead to overall optimal performance in these activities and significant cost reduction. Other research work upstream pointed to the importance of upskilling the current human resources to expedite and improve AI application in upstream activities.

Table 1. Papers focusing on AI technologies applied to upstream activities

Supply chain location	Location activities	AI technology implemented	References captured
Upstream Sector	Field development (Drilling)	Machine learning – Supervised learning	Osarogiagbon et al. (2021) [13]
	Field development	Machine learning; Fuzzy logic; Swarm intelligence; Genetic algorithm; Hybrid	Li et al. (2020) [2]
	Field development (Drilling)	Hybrid [Machine learning - Supervised learning & Genetic algorithm]; Hybrid [Machine learning - Supervised learning & Swarm intelligence]	Mohamadian et al. (2021) [14]
	Field development (Drilling)	Machine learning – Supervised learning; Fuzzy logic; Swarm intelligence; Genetic algorithm; Hybrid (Multiple types)	Ossai and Duru (2020) [15]
	Field development (Drilling)	Machine learning - Multigene genetic programming	Agwu et al. (2021) [16]
	Field development (Drilling)	Machine learning – Supervised learning	Agwu et al. (2018) [17]
	Field development (Reservoirs)	Hybrid [Machine learning – Supervised learning & Swarm intelligence]; Fuzzy logic; Hybrid [Genetic algorithm & Fuzzy logic]	Ahmadi et al. (2014) [18]
	Field development (Reservoirs)	Machine learning – Reinforcement learning	Hourfar et al. (2019) [19]
	Production	Machine learning - Supervised learning; Genetic algorithm used as an optimizer	Rashid et al. (2019) [20]

Production	Machine learning - Supervised learning; Swarm intelligence used as an optimizer	Aminu et al. (2019) [21]
Production	Machine learning – Supervised learning; Bayesian optimizer	Marins et al. (2021) [22]
Production	Machine learning - Supervised learning	WANG et al. (2020) [23]
Production	Hybrid [Machine learning - Supervised learning & Genetic algorithm]	Naseri et al. (2016) [24]
Production	Machine learning - Supervised learning	Ayala H et al. (2009) [25]
Production	Machine learning - Supervised learning; Genetic algorithm used as an optimizer	Sadi and Shahrabadi (2018) [26]
Production (Forecasting)	Machine learning – Supervised learning	Al-Shabandar et al. (2021) [28]
Production (Forecasting)	Machine learning – Supervised learning	Sheremetov et al. 2013 [29]
Production (Artificial Lift)	Machine learning – Supervised learning	Syed et al. (2020) [27]
Exploration, Field development, Production	Machine learning; Hybrid modelling [Physics-driven models and data-driven models]	Koroteev and Tekic (2021) [12]
Training	Computer Vision	Garcia et al. (2019) [30]

Table 2 captures the research work considered focusing on midstream of the oil and gas supply chain. Transportation through pipelines was the main activity discussed with ML-based solution again as the leading technology. Many of the suggested AI solutions addressed the pipeline maintenance and monitoring using historical data. This highlights the importance of data availability as a fundamental requirement and in many cases challenge for successful AI implementation in midstream activities.

Table 2. Papers focusing on AI technologies applied to midstream activities

Supply chain location	Location activities	AI technology implemented	References captured
Midstream Sector	Transportation (Pipeline)	Machine learning – Multiple types	Ben Seghier et al. (2021) [33]
	Transportation (Pipeline)	Machine learning - Supervised learning; Fuzzy logic	Neuroth et al. (2000) [35]
	Transportation (Pipeline)	Robotics	Ibrahimov (2018) [38]
	Transportation (Pipeline)	Swarm intelligence	Wu et al. (2014) [31]
	Transportation (Pipeline)	Machine learning - Supervised learning; Adaptive Neuro-Fuzzy inference System; Fuzzy Inference System; Genetic algorithm used as an optimizer	MohamadiBaghmolaei et al. (2014) [32]
	Transportation (Pipeline)	Machine learning - Genetic programming	Nazari et al. (2015) [36]
	Transportation (Pipeline)	Machine learning - Supervised learning	Saade and Mustapha (2020) [34]

Table 3 demonstrates the lower emphasize the considered research had on downstream sector. The few articles reviewed highlighted the importance of big data ML and computer vision techniques to be applied for accident prediction (safety) and intelligent refining (operation) in refineries.

Table 3. Papers focusing on AI technologies applied to downstream activities

Supply chain location	Location activities	AI technology implemented	References captured
Downstream Sector	Downstream processing	Machine learning - Supervised learning	Eze and Masuku (2018) [39]
	Accident prediction in refineries	Machine learning - Supervised learning; Fuzzy logic; Genetic algorithm; Metaheuristic algorithm; Hybrid (Multiple types)	Zaranezhad et al. (2019) [40]
	Refinery process	Machine learning - Supervised learning	Arce-Medina and Paz-Paredes (2009) [41]
	Refinery process	Computer vision	Silva et al. (2015) [44]
	Consumption forecasting	Hybrid [Machine learning - Supervised learning & Genetic algorithm]	Li et al. (2018) [43]
	Demand forecasting	Hybrid [Data mining & Genetic algorithm & Artificial neural network]	Al-Fattah and Aramco (2021) [42]

A group of the considered research work were focusing on AI technologies that can offer solutions for issues along all three locations. Table 4 summarizes the findings of this group where robotics, ML and NLP were the suggested AI technologies. Robotic solutions were investigated for both onshore and offshore operation performance improvements. ML models were also discussed to enhance prediction and assessment of risks and disasters along the whole oil and gas supply chain. NLP was used to improve data acquisition, to help discover causal accident relations from databases.

Table 4. Papers focusing on AI technologies applied to activities along the whole supply chain

Supply chain location	Location activities	AI technology implemented	References captured
	Onshore	Robotics	Shukla and Karki (2016a) [5]
	Offshore	Robotics	Shukla and Karki (2016b) [37]
	Predict and assess disasters	Machine learning – Supervised learning	Sattari et al. (2021) [45]
All 3 locations	Predict and assess disasters	Machine learning – Supervised learning	Sakib et al. (2021) [46]
	Oil and Gas industry tasks	Machine learning; Multi-agent Systems	Hanga and Kovalchuk (2019) [6]
	Risk based inspection	Machine learning	Rachman and Ratnayake (2019) [47]
	Accident exploration	Natural language processing	Single et al. (2020) [48]

5. Conclusions and Recommendations

This paper attempted to understand some of the dynamics related to the application of artificial intelligence (AI) in the oil and gas industry through a supply chain location perspective. Using a literature review approach that was followed by a comparative and descriptive analysis, the nexus of where oil and gas supply chain location and AI technology intersect was highlighted through a representative body of knowledge. Results from the conducted analysis suggest the following observations and recommendations:

- Current research focuses on the AI applications at upstream of the oil and gas supply chain more than other locations. This actually reflects the industry practice and can be due to two main reasons. First, is the fact that upstream activities are the most capital-intensive and second, they have a significant complexity level. AI technologies are ideal to offer different solutions that can save costs, reduce complexity, improve productivity, efficiency and safety within these upstream activities.
- Midstream activities were mainly concerned with the impact AI technology can have on improving pipeline transportation this included investing in intelligent pipelines that ensures the tracking and tracing of oil delivery and at the same time well maintaining the safety of these ongoing growing lines (the length of pipelines worldwide grows by 3–4% per year). This also applies to various equipment used at this midstream transportation stage.
- As for downstream, different AI solutions were suggested to develop intelligent refinery systems. The role of AI integrated with IoT is reemphasized in these new refineries that utilize data gathered by IoT and delivered to AI digital models to optimize refinery plants settings and operations for various products. Some research at this location also highlighted the importance of improving sales prediction using AI forecasting models to align refinery production plans with real demand signals as much as possible.
- The research points to the evolution of the oil and gas supply chain towards more automation and intelligence (Oil and Gas 4.0). This will be demonstrated through various intelligentization of the supply chain echelons including precise drilling, automated production, smart maintenance and intelligent refining to name a few. It is important in this regard to mention that a fundamental requirement for such evolution as outlined by the research work is a successful digitization of the whole ecosystem.
- The digitization requirement of the oil and gas supply chain infrastructure highlight the challenge of data availability. The considered research suggested some strategies to manage this challenge through integrated IoT solutions as well as developing standardized platforms for data sharing and guidelines. This should be the effort of both the private as well as the public sectors through industry regulations and government policies that awards for transparency and ensure fairness.
- Within the considered literature body, machine learning ML-solutions were the leading AI technology type across all supply chain locations. This is mainly due to their versatility, and ability to assist in offering educated decisions in this very complex and costly environment. Furthermore, these decisions can be almost at real time using techniques like digital twins that had been growing recently in the oil and gas industry. The second popular AI techniques were robotics solutions. Interestingly, within the considered literature body, NLP technologies to were rarely used and still needed more investigation to explore their potential in this industry.
- The review also revealed that some challenges facing AI implementation throughout the oil and gas supply chain. These were mainly: (a) Lack of open-source quality data related to oil and gas; (b) Lack of open collaboration and standardization; (c) High cost of implementing AI and (d) Lack of interdisciplinary talent.
- From the above challenges, various strategies are recommended. For the lack of open-source quality data, simulations can be used instead of raw data as an alternative. Another suggestion would be for regulatory

authorities to create rules and guidelines for data governance that promote broad access to and exchange of quality data specifically for the oil and gas industry. This will allow future researches to do in-depth studies and contribute to improving the efficiency, productivity and sustainability of existing and future oil and gas Industry. Furthermore, this could also help mitigate the lack of open collaboration and standardization.

- In terms of the high cost of implementing AI, in addition to cost reduction techniques, more research needs to be conducted to explore the optimal investment portfolio and planning. This will require some effort in terms of valuation approaches that apply to all digital investment decisions. This includes determining the best business model that will ensure growth utilizing AI technology, capturing risk resilience improvement and estimating present value not just by discounting the expected savings and subtracting the investments required but also by examining second-order competitive effects. Finally assessing how customer service improvement can lead to higher market share should be art of this valuation process.
- Skilling and upskilling the current workforce in the oil and gas supply chain was a clear need in most of the research work reviewed. AI requires a new set of skills that industry and education institutions alike need to offer through more training and degrees. This should be at all levels starting from simple data analysis to sophisticated system design and modeling operations. Without such effort to close the current skill gap, the implementation of AI will continue to suffer from its current slow pace.
- Few researches touched on ethical and social issues related to AI implementation. This is an indication to the need to further look into these matters along all locations to explore concerns regarding for example labor replacement and data privacy and integrity to name a few.

It is important to acknowledge that although the results of this study are the limited by number and scope of papers considered, however, the findings are general enough to offer valid insights for AI in the oil and gas supply chain. Future research is needed to explore how the AI technologies can be implemented at the same rate of upstream into midstream and downstream. Specific AI solutions are up for further investigation to realize their potential in the oil and gas supply chain including NLP and augmented and virtual reality. AI integration with blockchain, IoT and cloud computing is a further area of hot research especially with the rising discussion of Oil and Gas 4.0. Finally, more field work is needed to align the research work with the real need and current application of the oil and gas supply chain practices.

In conclusion, this work aimed at highlighting the importance of the *where* question as much as research and practice are concerned with the “*what*” and “*how*” questions regarding AI implementation in oil and gas supply chain. Studying this question can help in offering oil and gas supply chain practitioners and technology managers multiple insights regarding AI implementation evolution, investment priorities profile as well as optimal solutions for operation excellence.

6. Declarations

6.1. Author Contributions

A.D., and T.V. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

Data sharing is not applicable to this article.

6.3. Funding

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6.4. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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