**Development of petroleum applications and their benefits using artificial intelligence**

**Abstract**

**The application of AI and ML across various industries, such as manufacturing and petroleum, has led to innovative solutions that enhance productivity, accuracy, and decision-making capabilities. PCA was used to identify key GAI and MLA variables that influence the performance of the oil and gas value chain. SEM was employed to assess the regression equations related to their application. Recently, significant advancements in artificial intelligence (AI) technology have rapidly expanded within the petroleum industry, presenting enormous potential for growth and innovation. Generative Artificial Intelligence (GAI) and Machine Learning Algorithms (MLA) are becoming increasingly important in the oil and gas industry due to rapid advancements in society and technology. Principal Component Analysis (PCA) was utilized to identify critical variables influencing performance in the oil and gas value chain, and their effects were evaluated using Structural Equation Modeling (SEM). To effectively make decisions in the oil and gas value chain, it is essential to utilize advanced processing and analysis tools because of the vast amo unt of data generated by real-time monitoring of reservoirs and well operations. Machine learning (ML) is a powerful subset of artificial intelligence (AI) that utilizes models and algorithms to analyze historical data and extract insights. AI is a groundbreaking technology that enables machines to mimic human behavior.**

**Introduction**

**Recent findings indicate that artificial intelligence (AI) is transforming the energy sector, prompting many global companies to explore its applications within the oil and natural gas industry, which is a fundamental component of the global economy (Zakizadeh, Zand, 2024). Some of these companies have already begun utilizing AI and are experiencing unexpected results and insights in countries such as the United States and the Kingdom of Saudi Arabia. Additionally, some are striving to develop and innovate modern technologies in this area. The oil and gas industry plays a crucial role in the global energy production landscape due to its intricate nature and various challenges (Dongo, Relvas, 2025). In light of its numerous benefits, artificial intelligence has become a transformative technology in various sectors, including oil and gas (Stevens, 2018). Researchers have recently concentrated on applying AI technology within the oil and gas sector to enhance asset efficiency, boost production, reduce maintenance and repair expenses, and foster a culture of safety through various applications in exploration, transportation, and refining processes. The applications of AI mainly focus on the optimization of transportation and logistics, along with midstream operations like pipeline integrity management (PIM) (Gowekar, 2024). They additionally emphasize quality assurance in downstream processes, predictive maintenance for refining operations, and AI solutions for enhancing refinery efficiency. Investigators are also interested in investigating the ecological and safety applications of AI, which include AI-driven risk assessment and safety management, systems for real-time incident detection and response, and assessments of environmental effect and solutions (Rayan, 2023). This review article explores the future of the oil and gas industry in conjunction with emerging AI technologies within the energy sector. It underscores the crucial role of AI in transforming the petroleum industry by fostering innovation and enhancing efficiency, while also identifying areas that may benefit from further research and development (Hussein et al., 2024).**

**In the oil and gas industry, the use of Generative Artificial Intelligence (GAI) and Machine Learning Algorithms (MLA) is becoming increasingly popular. To explore how these technologies can improve productivity throughout the oil and gas value chain, Investigators tested the regression equations related to their application using structural equation modeling (SEM). Additionally, they employed Principal Component Analysis (PCA) to identify the key GAI and MLA factors that influence performance in the oil and gas value chain (Ochieng et al.,2024). The global energy sector increasingly recognizes that, given the rapid advancement of technology and society, it can improve its competitive edge and foster innovation by integrating modern digital technologies into its operations. In conclusion, artificial intelligence (AI) cannot yet think like humans, despite significant advancements and its ability to perform tasks once thought to be exclusive to humans. It is essential to understand both the potential and limitations of AI and to use it in a way that enhances, rather than replaces, human intelligence (Campbell et al., 2025).**

**The stages of oil and natural gas production.**

**Recent analyses indicate the various applications of artificial intelligence (AI) and machine learning (ML) in the oil and natural gas industry at each stage of production (Alagorni et al., 2015):**

**Stage 1 (Exploration): This phase involves activities such as exploration, seismic surveying, drilling, and field development. Geologists must gather and analyze large amounts of data, including seismic, satellite, GPS, and remote sensing information, to identify potential drilling sites. During this traditional exploration process, oil companies invest significant time in analyzing data models. They will only proceed with drilling when these models suggest a strong possibility of finding oil or gas in the target areas. AI is utilized in the development and implementation of drilling support systems. It collects data from various sensors and devices during operation, well planning, well safety assessments, predictive analysis, drilling optimization, reservoir management, and other related systems. This use of AI can lead to an average reduction in the time spent in these phases by 20% to 40%, while also decreasing the probability of errors by up to 90%** (**Yang et al., 2024).**

**Stage 2 (Transportation): The second stage of the process, known as transportation, involves pipeline systems for natural gas and oil, as well as gas processing, liquefied natural gas production, and restructuring stations. In this stage, artificial intelligence plays a crucial role by creating reliable and continuous monitoring systems to ensure pipeline safety. AI also helps extend the lifespan of the infrastructure and utilizes simulation and predictive models to reduce operating and maintenance costs (Bharadiya, 2023).**

**Stage 3 (Refining): The third step, refining, involves transforming oil and condensates into marketable products that meet specific requirements, such as gasoline, diesel, or raw materials for the petrochemical sector. This stage also includes external refinery locations, such as distribution stations and storage tanks (Jung et al., 2025).**

**Beneficial of oil and gas industry from AI**

**Artificial intelligence (AI), which is currently the most impactful general-purpose technology, is rapidly growing across various sectors, presenting vast opportunities for progress and innovation (Cockburn et al., 2018; Brynjolfsson, et al., 2018). While AI is often associated with technology-driven sectors, its benefits extend beyond these industries. Sectors that have been slower to adopt digital technologies, such as mining, oil and gas, and construction (Kohli, Johnson, 2011; Kane et al., 2015), are increasingly becoming reliant on AI solutions. The oil and gas industry began actively exploring AI applications several years ago, though discussions on its use in the sector date back to the 1970s (Khan et al., 2015; Li et al., 2020; Chen et al., 2024). In order to maintain the profitability of oil and gas extraction, innovative operational strategies and business models are necessary in the exploration and production of hydrocarbons, due to the prevalence of "hard-to-extract" oil and gas reserves over the last ten years. When effectively trained on petroleum field data, AI systems can significantly enhance the speed of asset assessments while also improving their objectivity and reducing reliance on expert opinions (Kumari, 2024).**

**Categories of the petroleum industry and AI**

**The petroleum industry is divided into three categories: upstream, midstream, and downstream (Fig. 1). The upstream sector encompasses exploration, field development, and the extraction of crude oil and natural gas, representing the subsurface (mining) aspect of the industry (Koroteev Tekic, 2021). Midstream involves the transportation of oil and gas (Anshu et al., 2024), while downstream pertains to the refining process that generates fuels, lubricants, polymers, and various other products. The exploration of oil and gas reserves encompasses a series of procedures aimed at developing a three-dimensional geological model of an oil or gas field or reservoir. This process involves analyzing and processing the data collected from geophysical and petrophysical investigations. Geophysical and petrophysical investigations typically consist of three components: core analysis, well logging, and reservoir-scale seismic surveys. Seismic traces consist of records from sensors generated during seismic surveys. These traces are time series that illustrate the magnitude of elastic waves reflected from the boundaries between various layers of subsurface formations, initiated by a vibrator on the surface. The time series data, along with the spatial coordinates of the vibrator and the associated sensors, are processed using a distinctive reconstruction method that yields noisy three-dimensional images depicting sections of the reflecting surfaces. Seismic cubes refer to the three-dimensional images used in geophysical analysis. Seismic interpreters examine these cubes to gain insights into subsurface structures. Additionally, they may be involved in determining the parameters for earlier phases of reconstruction. Interpreters select specific points, lines, and surfaces within the 3D cube that are clearly connected to the boundaries between different layers of the subsurface formation. This process is essential for effectively segmenting the 3D images (Mao et al., 2019). The complete process, ranging from reconstruction to the segmentation of 3D cubes, is time-consuming and demands expertise. To gain a clearer understanding of subsurface features, geologists utilize the segmented 3D cubes to determine the locations for the initial exploratory wells, a process that can extend beyond a year while ensuring accurate seismic investigation data is processed.**

**Role of deep learning in the seismic-related process**

**The exploration of this seismic-related process has increasingly incorporated contemporary deep learning-based pattern recognition systems, resulting in a ten- to thousand-fold acceleration in interpretation (Cunha et al., 2019). However, the probability that AI algorithms will enhance the physical components of initial seismic surveying at an asset—specifically, the quantity, cost, and arrangement of sensors remains low. The ability of machine learning algorithms to interpolate, combined with the mathematical foundations of recommender systems, can provide suitable recommendations for minimizing the expenses associated with secondary surveys while ensuring that the value of the collected information remains mostly intact (Portugal et al., 2018). Well logging is a method used to gather detailed information about the underground layers along a drilling hole. On the other hand, seismic images provide a broader view, covering many kilometers and giving insights about the shape of the underground rock and its physical features down to smaller distances of about tens of meters. Besides other functions, the well-logging sensors can assess electrical resistivity, neutron density, natural gamma-ray intensity, and their reaction to magnetic stimulation. Property vectors along the wellbore result from well logging activities. To interpret these vectors correctly, petrophysicists use well logging data to assess porosity and permeability, classify the rock types along the wellbore, and estimate the relative fluid saturation (the proportion of oil relative to gas and water) throughout the wellbore. The process of petrophysical interpretation is often time-consuming, and its success largely hinges on the expertise of the interpreter. This challenge was particularly evident to the authors while developing a machine learning-based automated interpretation system for oil companies. Utilizing AI-assisted technologies provides a straightforward method to accelerate the interpretation process and, potentially even more crucial, to remove the subjective component (Meshalkin et al., 2018;** **Wood, 2019). Seismic interpretation is enhanced by incorporating insights from petrophysical interpretation. Geologists and petrophysicists add porosity, permeability distribution, and fluid saturation values to the seismic cube based on data from near-wellbore zones (Erofeev et al., 2019;** **Gasda, Celia, 2005).**

**Upstream**

**Downstream**

**Midstream**

**Refinery**

**Production of fuels.**

**Plastics & Lubricants.**

**Petrochemicals.**

**Exploration**

**Field development**

**Seismic surveying.**

**Well logging.**

**Core analysis.**

**Transportation**

**Pipelines.**

**Ships.**

**Road vehicles.**

**Manufacturing**

**Process storage**

**Production**

**Production operation**

**Artificial lift.**

**Fluid separation.**

**Well treatment.**

**Trading & Storage**

**Field**

**Development**

**Reservoir Engineering.**

**Drilling & completion.**

**Infrastructure.**

**Whole Sales &**

**Retail**

**Figure 1: Oil and gas industry sectors.**

**Importance of the application of AI in field development**

**The use of artificial intelligence (AI) has increased in the petroleum sector in recent years. Machine learning, deep learning, and neural networks are techniques within artificial intelligence that analyze large volumes of data to provide insights that can improve decision-making. Artificial intelligence can be utilized to detect abnormalities, predict and improve production rates, and identify the optimal locations for wells. Additionally, it can enhance wellbore stability, optimize drilling parameters, and reduce costs in drilling and completion operations. Future studies should focus on developing more reliable and accurate AI algorithms and integrating them with traditional engineering methods to enhance the effectiveness and efficiency of petroleum engineering operations.**

**Three major reasons for using AI in reservoir engineering. The first aspect concerns computations performed with standard reservoir modeling software. These tools numerically solve partial differential equations that characterize the physics of reservoir flows. A 3D grid, typically containing between one million and several billion cells, is utilized to carry out these computations (Simonov et al., 2018; Temirchev et al., 2020). The second aspect is upscaling, a process that involves integrating data from various geophysical study scales into a single geological reservoir model before progressing to hydrodynamic reservoir models. A key aspect of the upscaling process is its technical nature. There is no universally accepted scientific framework for upscaling, so many reservoir engineers use methods that they believe are effective (Barker, Thibeau, 1997;** **Farmer, 2002). The third one relates to history matching, similar to upscaling. This process may involve using deep learning or machines to enhance speed and reduce bias in history matching. Mathematical modeling is often the most significant and effective simulation technique for understanding subsurface interactions between water, oil, and gas, as well as for analyzing fluid flow and solute transport (Dai et al, 2016; Yand et el, 2014; Jia et al.,2017). However, it is important to note that the physical flow rates, transport parameters, and geochemical reaction rates can vary dramatically—by orders of magnitude—over time or distance. This phenomenon is commonly referred to as the "scale effect." In the presence of heterogeneity and preferential flow paths, enhancing the accuracy of model parameter estimates can significantly improve the reliability of model predictions (Willmann et el, 2008; Rovey2009).**

**Ways to Reduce Bias in Machine Learning:**

**Four ways is recorded: 1) Use a more complex model: The overly simple model is a major contributor to high bias. Its ability to understand complex data is limited. To address this, we can increase the number of hidden layers in a deep neural network to enhance the model's sophistication. Additionally, for non-linear datasets, we might consider using a more advanced approach, such as polynomial regression. 2, Increase the number of features: By adding more features to train the dataset will increase the complexity of the model. And improve its ability to capture the underlying patterns in the data. 3. Reduce Regularization of the model: Model generalization can be improved, and overfitting may be prevented through regularization methods such as L1 or L2 regularization. If the model shows considerable bias, its performance may be improved by reducing or removing regularization. 4, Increase the size of the training data: Increasing the training data set can help reduce bias by providing the model with more examples to learn from.**

**Application of AI in petroleum safety**

**The numerus hazards present in the oil field include physical hazards, chemical hazards, environmental hazards, and operational hazards. In addition to utilizing AI for risk mitigation and cost reduction, it is important to recognize its significant impact on safety protocols. The oilfields present numerous hazards, including heavy machinery, uncovered rotational equipment, high pressure, extreme temperatures, and aggressive chemicals, all of which make the work environment dangerous for employees (Park, Kang, 2024). There are many deep learning-based IT tools available that help safety officials identify instances of violence against safety standards. These tools utilize deep learning pattern recognition to analyze video streams captured by cameras, alerting personnel if an employee is not properly equipped for specific tasks. Predictive analytics informs operators about equipment conditions, enabling proactive measures to prevent disasters that could harm the environment, safety, and public health (Liu et al., 2022). The following are the different deep learning-based IT tools available for safety officials, Safety culture AI Tool, CHATGPT AI Tool, Jasper AI Tool, Grammarly AI Tool, Wondershare Filmore AI Tool, Murf AI Tool, Asana AI Tool, Krisp AI Tool, Mailbutler AI Tool and Deektopus AI Tool.**

**Transformative potential of AI**

**Artificial intelligence (AI) has the potential to greatly transform the petroleum industry by addressing several critical issues. It can improve exploration success rates through enhanced data analysis and predictive modeling. AI can also streamline manufacturing processes, leading to lower operating costs and increased production output. Additionally, it enhances safety and reduces environmental impacts through real-time monitoring and predictive maintenance (Gruetzemacher R, Whittlestone, 2022; Wang et al., 2025) (Figure 2).**

**Figure 2: Potential of AI in addressing critical issues facing the petroleum sector.**

**Conclusion**

**This study provides a comprehensive analysis of AI optimization methods used in the exploration and production of petroleum. The application of AI techniques has yielded impressive results in predicting, estimating, and optimizing various objectives, such as oil production rates and reservoir characterization. Deep learning methods for identifying new patterns have gained popularity in seismic operations due to their ability to accelerate interpretation by a factor of 10 to 1000. However, the physical aspects of the seismic process seem to be beyond the reach of artificial intelligence. On the other hand, these methods contribute to optimizing secondary surveys. Machine learning and mathematical processing offer effective predictive capabilities that can provide more cost-efficient suggestions for secondary surveys while minimizing the risk of compromising the value of collected data. AI-powered techniques can significantly reduce the subjective elements of data interpretation and speed up the process. In addition to potential applications in future seismic operations, machine learning could be used to efficiently generate a substantial amount of well-logging data. This advancement could simplify the integration of machine learning into standard logging practices. However, systems that prioritize the needs of oil companies often allocate less funding to the operational aspects of well logging. A similar strategy can also be utilized to enhance core analytical processes. Artificial lift planning, well treatment, and predicting oil and gas production rates are examples of how AI and machine learning (ML) are being implemented to optimize fluid output. These methods improve decision-making related to production by generating accurate forecasts and practical solutions for various processes in the petroleum sector. The application of AI and ML has significantly reduced both operational and computational time, as well as associated costs.**

**DISCLAIMER (ARTIFICIAL INTELLIGENCE)**

**The authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.**

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