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DEVELOPING DATA-DRIVEN DECISION MAKING FOR THE OIL AND GAS INDUSTRY

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ABSTRACT

The oil and gas industry is undergoing a significant transformation driven by big data analytics and artificial intelligence (AI). This paper summarizes the various methodologies and technologies available to the hydrocarbon community to deliver new tools and methods to move from traditional look-up tables to data-driven insights, reducing more and more the dependence on intuition while the amount of available data is drastically increasing. Many companies in the oil and gas industry operate with extremely advanced technology to optimize the performance of assets. Taking advantage of digital and information technology has allowed companies to deliver significant dividends in the recent past. Despite these advances, many organizations struggle to drive real value from the vast amount of structured and unstructured data available. This approach has the potential to improve efficiency, safety, and decision-making across the entire exploration and production value chain. However, challenges remain in implementing these new technologies, including the need for cultural change, workforce development, and robust data management practices.

Key Points: Big data, Data-driven decision making (DDDM), Artificial Intelligence (AI)

1. INTRODUCTION

The possibilities are numerous, and the present application covers various solutions with different levels of complexity (Manimuthu et al., 2021). One can imagine solutions in different classes of problems. New paradigms using modern sensor and communication technologies are expediting the growth of big data solutions in the oil and gas industry (Osinga et al., 2022).But big data has intrinsically high variability and complex relationships that require trained professionals working on the data to unlock its previously hidden value (Yang et al., 2021).Or, the plants need to be able to turn the big data into useful information to make a trained system and be able to make decisions based on the analysis (Andronie et al., 2022). This highlights the importance of expertise in handling big data, alongside the development of robust systems for data analysis (Rath, 2020). By bridging this gap, the industry can leverage DDDM to its full potential (Bakar et al., 2023).

The ability to capture, transfer, and store the huge volume of information generated by our daily activities has reached levels previously unimaginable (Wang et al., 2020). In the recent past, industrial plants had few sensors to capture equipment health. Today, the scenario has changed greatly with many digital applications allowing better understanding and prediction of plant behavior (Batko & Ślęzak, 2022). Furthermore, numerous tools are available to transform such a large volume of big data into useful information for asset management (Gür, 2022). As a result, asset decision-making has evolved from perceptions derived from small samples to data-driven decision-making (Javaid et al., 2021). This is a new world for owners and operators of industrial assets, including those in the oil and gas industry, their suppliers, and third-party service providers (Han et al., 2021). A dramatic cultural transformation will result.

Importance of Data-Driven Decision Making in the Oil and Gas Industry

Big data analytics and AI promise to transform the oil and gas industry, but specific applications are not yet widespread (Mohammadpoor & Torabi, 2020]). There are numerous opportunities to make the oil and gas industry safer and more efficient by developing new applications. These opportunities spread across the entire exploration and production value chain, from seismic interpretation to drilling, production, reservoir engineering, and field development plans, and extend to corporate functions like supply-chain management and finance (Arinze et al., 2024).

The challenge is to transform how the industry operates, so that data-driven methods become routine rather than the exception. It is not sufficient to develop special applications that require considerable data preprocessing and cleaning and hours of expert intervention with the results. Rather, the goal is to rewrite the corporate standard operating procedures (Mohammadpoor & Torabi, 2020). such that, for a set of well-defined tasks, the results are routinely produced by big data analytics or a machine learning model.

Data-driven decision making (DDDM) is becoming essential in the current era of digital transformation (Li et al., 2022). Innovations in big data, machine learning, and artificial intelligence (AI) offer significant potential to improve decision making. DDDM is the process of evaluating data-related variables directly with a variety and breadth of data instead of by expert opinion or intuition. This includes parameters that describe the state of the natural world, but it also includes the risks related to human activities and changing operating conditions and equipment states. (Bharadiya, 2023).

Challenges and Opportunities in Implementing Data-Driven Decision Making

Data-driven decision making (DDDM) is an essential component of sustainable business performance (Li et al., 2022). Investments in DDDM can provide a very positive return by improving the granularity, timeliness, accuracy, and reliability of decision information, and also through the delivery of this information to end users. These advantages can translate to many business opportunities or to business survival in the face of current industry challenges (Stowe et al., 2023). However, investing in a new paradigm of decision-making can also be risky, notably when enterprise budgets are constrained and when investment is driven by hype rather than business relevance and preparedness (Sarioguz & Miser, 2024).

This section provides large analytics tools that can help us with developing data-driven decision making in the oil and gas industry. As a base for these analytics tools, we will find the necessary information about data-driven decision making: technology, history, trends of oil and gas industry, and big data in the oil and gas industry (Li et al., 2022). We will observe big data opportunities and challenges, data management, and big data case studies in the oil and gas industry (Elgendy et al., 2022). It is known that data-driven decision making is believed by many to be a major component of the next industrial revolution. It provides opportunities for organizations based on an effective use of data (Awan et al., 2021). There are several factors that drive organizations to become more data-driven, and these factors include emerging technologies and techniques for data storage and processing.

Technologies and Tools for Data Collection and Analysis

As data scientists, we have to recognize that these technologies and tools can play a supporting role in our efforts (Mohammadpoor & Torabi, 2020). It is important to remember that these technologies are only effective when placed within appropriate organizational structures, and when utilized by well-trained professionals and models. Further, no matter how attractive and flashy emerging tools and technologies may be, we need to begin by thinking of what deliverables are needed and where the data may lie. In other words, thinking in a structured manner allows us to capitalize on the many exciting new technological developments for measurement and analysis that can support well-defined business objectives. With the explosion of the Internet of Things, we can now readily gather data. This data can come in many different forms, representing many kinds of different physical phenomenon or qualitative representations (Koroteev & Tekic, 2021). Data has been referred to as the new oil in comparison to the discovery in the early 20th century that petroleum had great intrinsic value

In order to structure data collection and analysis efforts, we typically turn to key technologies and specialized tools. The choice of technology or tool is highly dependent on the nature of the data you are measuring (Sircar et al., 2021) .If the application is sensor-based or time-series in nature, a category of technologies will govern such data collection, management, and analysis . Alternatively, if the application is around unstructured data, such as written and published content, videos, and other non-traditional formats, there are emerging specialized tools and methods for such measures Birch et al., 2021.

Case Studies of Successful Data-Driven Decision Making in the Oil and Gas Industry

The best-known work on spatial geostatistical variography is by Isaaks and Srivastava, who compile a thorough survey of the most popular types of semi variograms used in practice (Sahu et al., 2020). A new momentum through the geostatistical modeling beyond the average, variance, and simple high-low inferential approach accelerates first through the earth science concerns about natural structure and second through a promising collaboration with information theory (Anand et al., 2021).

FirBrAI project researchers built Sherlock, an infrastructure and application work for managing model and realization-based uncertainty for modeling and simulation of static features such as rock properties (Zawadzki et al., 2024) .They assert a number of important experiences, two of which are that the connection between the geostatistical modeling and fluid flow simulation must be preserved and that any software solution should be vendor-independent Zawadzki et al., 2024 The mechanism arising from the Shannon uncertainty of sample estimates on the reliability of predictions for unseen cases provides a way to evaluate the uncertainty present in the prediction model output Hilal et al., 2024. Stakeholders of this output then better understand the region over which the actual results will fall Hilal et al., 2024.

While traditional oil and gas geostatistical modeling often generates a single best guess for a reservoir or rock property, it rarely provides a view of their associated uncertainties (Kianoush et al., 2023). Historically, the startup cost to move to a more probabilistic modeling approach was large, and companies either elected to ignore uncertainty or relied on smaller-scale solutions to address uncertainty it (Strebelle, 2021). Simulation grids that are large enough to realistically and accurately simulate the complexities that occur over thousands of feet are difficult and time-consuming to build and impose even larger computational demands to provide a set of fluid flow scenarios (Yu et al., 2023). However, Darcy's Law, kernel sizes, and geometrical realizations of the property of interest at a fixed support do not require a simulation grid to be large (Mehdipour et al., 2023). If properly upscaled, they properly preserve the global through its built-in local accuracy (Fajana, 2020). This need to preserve is not only a result of the computational burden and demanding resources of flow simulators but also from a bigger desire to make the most of the spatial consistency and to have associated fluid properties be consistent (Yousefzadeh et al., 2023).

Ethical and Legal Considerations in Data Collection and Usage

This section is devoted to ethical and legal considerations pertinent to data collection and utilization in the context of the onshore oil and gas sector (Arinze et al., 2024) It is essential to acknowledge from the outset that while data-driven decision-making offers huge benefits, it is necessary to understand and mitigate potential risks and challenges associated with the collection and processing of various types of data (Abd et al., 2023). From an onshore oil and gas perspective, it is important to consider and describe the extent to which different processes comply with the appropriate guidelines and legal requirements (Singh et al., 2023). These may vary between different regions and countries (Joel and Oguanobi, 2024). Heightened consideration needs to be given to this within the context of global multinational companies seeking a standard approach (Perdeli et al., 2021). Ensuring that each process conforms to the legal, regulatory, and commercial requirements applicable to each country in which the company operates is the fulfillment of those requirements (Obaigbena et al., 2024).

Building a Data Culture within Oil and Gas Organizations

Once technological capabilities are upscaled, data gets more relevant outputs, and real decisions get made, the organization can deal with the increased volume of data readily (Borodin et al., 2021). Processes are in place where data can effectively enable informed decisions. Data stories must be transparent and understandable across all stakeholder groups. This requires a mix of strategic hiring of talent and strategic development of the current staff (Wanasinghe et al., 2021). Executives, decision-makers, and divisions should be aware of what talent gaps they have, build a strategic plan to fill these gaps, and then execute that plan (Adebajo et al., 2023). The creation of a solid data-based culture that has its talent capable of filling any need within the data pipeline will greatly build public trust and confidence (Al-Jadir, 2021). Every leak gets cleaned out over time. The organization gets a cleaner data pipeline because they have hired, trained, and used the right data citizens (Bangera and Bhat, 2023).

Although a large culture change for many oil and gas companies, the move to a data-driven culture has long been required and will only become more necessary in the future (Dietz et al., 2021). This is about letting data guide the decision-making process and organization from the top down. Company executives and decision-makers must understand the power of data and want to incorporate data findings into how they operate (Zhao et al., 2023). Realizing the importance of properly cleaning, storing, and maintaining data is vital for data insight (Sattari et al., 2022). Visualizing and then understanding these data insights does require a different ingrained way of thinking making (Chenger and Pettigrew, 2023). This has less to do with being a data scientist and more to do with a person's readiness to use fact-based findings to make decisions (Teixeira et al., 2023).

Strategies for Overcoming Resistance to Data-Driven Decision Making

Engaging domain experts in all stages of innovation is important for deriving the most value from the work. The degree that decisions are data driven depends on the quality of the insights and the capacity for integration into business challenges or decisions, focusing on establishing trust and drawing clear connections between potential business impact and the work. Plots and business application conversations are often the most effective strategy. A data-driven workflow one that observes the outcome and consequences of decision making when generating new data help teams experiment faster and course correct. Small tests can help calibrate risk of predictions, refine data models, and ensure insights are addressing genuine business challenges. Combating perceptual mismatch: "I can't see how they impact the earth.

Building data-driven decision making relies on leveraging people in addition to technology (Chenger & Pettigrew, 2023). Most companies have many people in different roles, positions, and backgrounds who have vast knowledge about their companies and the domain, but they might not understand the domain of data science (Agbaji, 2021). By involving people in compelling business challenges, the anchors of their hard work and learning in the physical world (well data, well production, logs, seismic, all other subsurface data) are readily understood. Insights from the data - anchored in the earth and helping business decisions (Hurmelinna-Laukkanen et al., 2021).

Integrate the insights into decision making over the workflow. The business challenge and unit performance should be an important focus from project scoping through to final result integration into business decisions over the workflow (Hurmelinna-Laukkanen et al., 2021).

Insights from the models can significantly be augmented with other insight about what goes on in the reservoir and the wells.

However, these individuals may not possess a strong understanding of data science principles.

Here are some strategies to overcome resistance to data-driven decision making:

1. **Engage Domain Experts Throughout the Process:** Involving domain experts at all stages of innovation is crucial for extracting the most value from data initiatives (Lievens & Blažević, 2021). The level of data-driven decision-making hinges on the quality of insights generated and their integration with real-world business challenges and decision-making processes (Hurmelinna-Laukkanen et al., 2021).

   Focus on establishing trust and drawing clear connections between potential business impacts and the data science work being done (Ghosh & Wu, 2023). Visualizations and discussions about business applications are often the most effective strategies for achieving this (Brown et al., 2021).
2. **Iterative Data-Driven Workflow:** A data-driven workflow that observes the outcomes and consequences of decision-making when generating new data allows teams to experiment faster and make course corrections as needed (Compagnucci et al., 2021). Small tests can help calibrate the risk of predictions, refine data models, and ensure insights address genuine business challenges (Globocnik & Faullant, 2021).
3. **Addressing Perceptual Mismatch:** Sometimes, resistance stems from a lack of understanding of how data science impacts the physical world. Combating the perception of "I can't see how they impact the earth" is crucial (Hevner & Gregor, 2022).

Here's how to address this:

- **Anchor Insights in the Physical World:** By focusing on business challenges that resonate with employees' existing knowledge and experience (well data, well production, logs, seismic, etc.), data insights become more readily understood (Chenger & Pettigrew, 2023). Frame data insights as tools that are anchored in the earth and can directly support business decisions.
- **Integrate Insights Throughout the Workflow:** Integrate data-driven insights into decision-making throughout the workflow, not just at the end (Agbaji, 2021). Business unit performance and the specific challenge being addressed should be a key focus from project scoping all the way through to integrating the final results into real-world business decisions (Zhao et al., 2023).
- **Augment Data Insights with Other Knowledge:** Insights from data models can be significantly enhanced by incorporating knowledge about well behavior and reservoir characteristics held by domain experts (Alsaeedi et al., 2021).

By employing these strategies, you can bridge the gap between data science and domain expertise, fostering a more collaborative and data-driven decision-making culture within your organization.

Training and Development of Data Literacy Skills in the Oil and Gas Sector

With the growing importance of digital and advanced analytical, including AI and Machine Learning, resources in the oil and gas sector, roles for the workforce will need to increasingly focus not just on technology expertise but on data-driven understanding, skills, (Zhao et al., 2023) and the right mindset to deliver a constant pivot towards value-drivers as the sector transitions to a more digitally enabled world (Chenger and Pettigrew, 2023). The ability to make effective data-empowered decisions throughout the oil and gas value chain will therefore be essential for a new oil and gas workforce (Nguyen et al., 2020). that is equipped to meet demanding challenges, ranging from the energy transition dynamics, decarbonization, disruptive technologies, risk and resources productivity improvement, and the data governance needed (Olawale et al., 2024).

Data literacy is imperative for the future workforce of the oil and gas industry sector (Reddicharla et al., 2022). Through support and technological resources, company leaders need to invest in training and preparation to build a new data-driven decision-making workforce (Ershaghi and Paul, 2020). Analytics skills such as engineering (both reservoir and software skills, engineers, and technical) background can bring valuable skills particularly to mid-career entrants (Agbaji, 2021). Simultaneously, new technical skills and data can be both upskilling for mid-level and grad-programmers or those in data engineering matric, business vertical domain which have data as part of their knowledge set (Okoroafor et al., 2022). Like the global educational community, industry, in collaboration with the broader education and training community, needs to embark on dedicated, sustained, and intentional activities to develop a future workforce with the data literacy needed to equitably realize the new energy future (Bello, 2021).

Integration of Data-Driven Decision Making into Operational Workflows

Changing the organization's mental models of information and work processes happens at three levels: technical routine, standard operating procedures, and expectations (Burke, 2023). At a technical routine level, employees receive the training, mentoring, information infrastructure, and problem-solving support resources necessary to incorporate a new data source or to use a metric or formula that better describes subsurface behavior (Moradi et al., 2021).

At a standard operating procedures level, the workflows, technical practices, work structures, and career paths (Bunker, 2020). to support or restrict modular integration and application of informational elements are modified to optimize the collaborative performance of transdisciplinary operations and planning (Kuratko et al., 2021). At an expectations level, the extensive communication of user and project (Hong et al., 2020). value, and the delivery of feedback on the enablement of new behaviors, stimulate corporate and individual curiosity and initiative in the extraction and realization of unrealized value (Schneider et al., 2022).

The complexity of an operational workflow in E&P poses significant challenges to the integration of any new data-driven technology (Jakobsen, 2022). The efficient incorporation of data requires a strong partnership between end users, technology development, system integration, and change management teams (Trevathan, 2020). This enhanced feedback loop structure should be designed to transcend traditional compartmentalized professional responsibilities, span different technical disciplines, include data analysts and infrastructure designers, and be designed for the constant validation and re-validation of end-user value (Balachandran and Padmanabhan, 2023). The iterative feedback loop optimization process has to be swift in response to changing regulatory, information, and commercial environments (Sumarto et al., 2024)

Measuring the Impact and ROI of Data-Driven Decision-Making Initiatives

Organizations can measure the maturity progress of their data-driven decision-making initiatives on both a quantitative and qualitative basis (Korherr et al., 2022). Due to the difficulty of quantifying the value of data science, modeling, and analytics, most organizations track on a qualitative basis only and look to measure the business impact of only those specific projects whose primary purpose is to step change and be transformational for the business (Johnson et al., 2021). These may include predictive maintenance applications on large or mission-critical assets, advanced analytics around pricing, scheduling, manufacturing optimization, and other market demand and sale forecasting applications (Gökalp et al., 2021). Organizations may look at forecasting the impacts of seasonality, ensuring that descriptive and diagnostic capabilities are part of larger implementation efforts targeted to build the statistical demand models (Gökalp et al., 2021).

It is important to use the Business-Side Maturity Model, applied to the data-driven decision-making oriented project as a representative of the organization's broader efforts to further the consistency, commitment, methodology, skills, business influence, and management of their data science and analytics teams (Awan et al., 2021).Use evidence and findings from all representative data-driven initiatives to tell a story to the business and highlight deficiencies and best practices, persistently enabling transformation and competitive advantage (Dodman et al., 2021).

In the previous sections of this paper, we examined many of the important elements and principles necessary to establish a mature data-driven decision-making environment within the oil and gas industry practices (Berntsson and Taghavianfar, 2020). As organizations begin to establish a process for how they can continuously mature, it is important that they also are able to understand how they are making progress and feel certain that what they are doing is valuable. (Agbaji, 2021) The most valuable quality initiatives are not always tied directly to the highest potential value in terms of ROI, but it is important to embrace that measuring ROI is indeed an important element of a continuous process improvement routine (Shah et al., 2022). Being successful in high-visibility efforts tied to ROI can serve to drive additional executive sponsorship and establish the tenor of future data-driven initiatives throughout the organization (Vuttipittayamongkol et al., 2021)

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Future Trends and Innovations in Data-Driven Decision Making for Oil and Gas

Expectations related to the increasing amounts of data and increases in the processing speeds becoming possible have led to renewed interest and development in methods and algorithms classed generally under the subject area of AI (artificial intelligence) (Prestidge, 2022). As the oil and gas industry strives for a completely digitally driven business model, the difference between business requirements and business needs becomes clear (Georgiou et al., 2021). Data management and proper indexing of each data come on top (Botha, 2022). As the strength of business in the oil and gas industry becomes linked with computational modeling, understanding becomes crucial (Alsaeedi et al., 2021). Flood performance evaluation is, in that respect, vital in assessing the expected value of a waterflood and instrumental in meeting the requirement of understanding (Sharma and McDonald, 2023).

Although the contributions to this special section cover a significant part of the data-driven decision-making toolkit and methodologies, it is well understood that future trends and innovations will continue to develop (Monteiro, 2022). As such, we foresee several interesting themes in the development of data-driven decision support methods and their applications to the oil and gas industry in the future. Our snapshot can be divided into three broad areas, namely, that of technology, AI involvement, the role and nature of the data in the analysis process, and that of the temporal dimension, i.e. the role of time as it relates to the changing state of the system (Evseeva et al., 2023). These, in turn, lead to a number of interesting thematic directions for research (Sarioguz & Miser, 2024).

2. CONCLUSION

Computational experiments can use large-scale experimental data to show a good relationship between self-organizing semantic maps of mineral, physical, and rock strength properties. These results illustrate the potential of large-scale experimental data to evaluate the potential for hydrocarbon exploration based on massive data-rich subsurface samples. In this case, thanks to the use of mannequins in the work on the database and the use of geoscience applications, the company has notable successes. The database is supported by the company's data traceability project. The system of data traceability has helped manage information management problems and could be complemented by the use of semantic mediation in the development of the same company.

In order to make informed business decisions in the oil industry and use the data, it is necessary to have managers who not only make decisions using the results of data analysis but can also interpret the results of the work of professionals who worked with this data. It is necessary to combine the efforts of several specialties to obtain useful results. This involves a combination of efforts from geologists, geometers, technology specialists, etc. Over the years, many companies have not been able to effectively manage and manage information. Computational power is growing, and computational modeling has become an increasingly important tool for solving a wide range of problems. The use of simulated models has accelerated breakthrough discoveries in many industries including oil and gas.

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