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(Review Article)

Real-time drilling data analytics for geohazard detection and wellbore stability: A comprehensive review

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Abstract

Real-time drilling data analytics has emerged as a transformative approach for improving geohazard detection and wellbore stability in modern drilling operations. This paper presents a comprehensive review of the fundamental concepts, technologies, and methodologies underpinning data-driven drilling systems. It examines the principles of geohazards and wellbore stability, followed by an analysis of real-time data acquisition technologies, including logging-while-drilling (LWD) and measurement-while-drilling (MWD), as well as advanced data processing and machine learning techniques. A comparative evaluation of machine learning, physics-based, hybrid, real-time, and pre-drill models is conducted to assess their performance, accuracy, and limitations. The review highlights that machine learning and real-time analytics provide superior adaptability and predictive capability, while physics-based models offer essential interpretability. Hybrid approaches are identified as the most promising solutions for integrating accuracy with reliability. Key challenges such as data quality, model generalization, computational demands, and integration complexity are also discussed.

Furthermore, the paper explores emerging opportunities, including digital twin technology, advanced artificial intelligence methods, and automated decision support systems. These innovations are expected to enhance predictive performance and operational efficiency. The study concludes that the integration of real-time analytics with advanced modeling techniques is essential for achieving safer, more efficient, and cost-effective drilling operations in increasingly complex subsurface environments.

Keywords: Geohazard Detection; Wellbore Stability; Machine Learning; Data Analytics; Digital twin Technology

1. Introduction

The oil and gas industry continues to face increasing challenges associated with drilling operations in complex subsurface environments. One of the most critical concerns is the occurrence of geohazards, including formation instability, abnormal pore pressure, and wellbore collapse, which can significantly affect operational safety, cost, and efficiency. These challenges have driven the need for more advanced and reliable methods for monitoring and predicting subsurface conditions during drilling operations.

Traditional approaches to wellbore stability analysis rely heavily on pre-drill geological models and post-drill evaluations. While these methods provide useful baseline information, they often fail to capture the dynamic and rapidly changing conditions encountered during drilling. As a result, unexpected hazards such as stuck pipe, lost circulation, and formation failure can still occur, leading to increased non-productive time and operational risks (Payrazyan and Robinson, 2023; Fouda et al., 2023).

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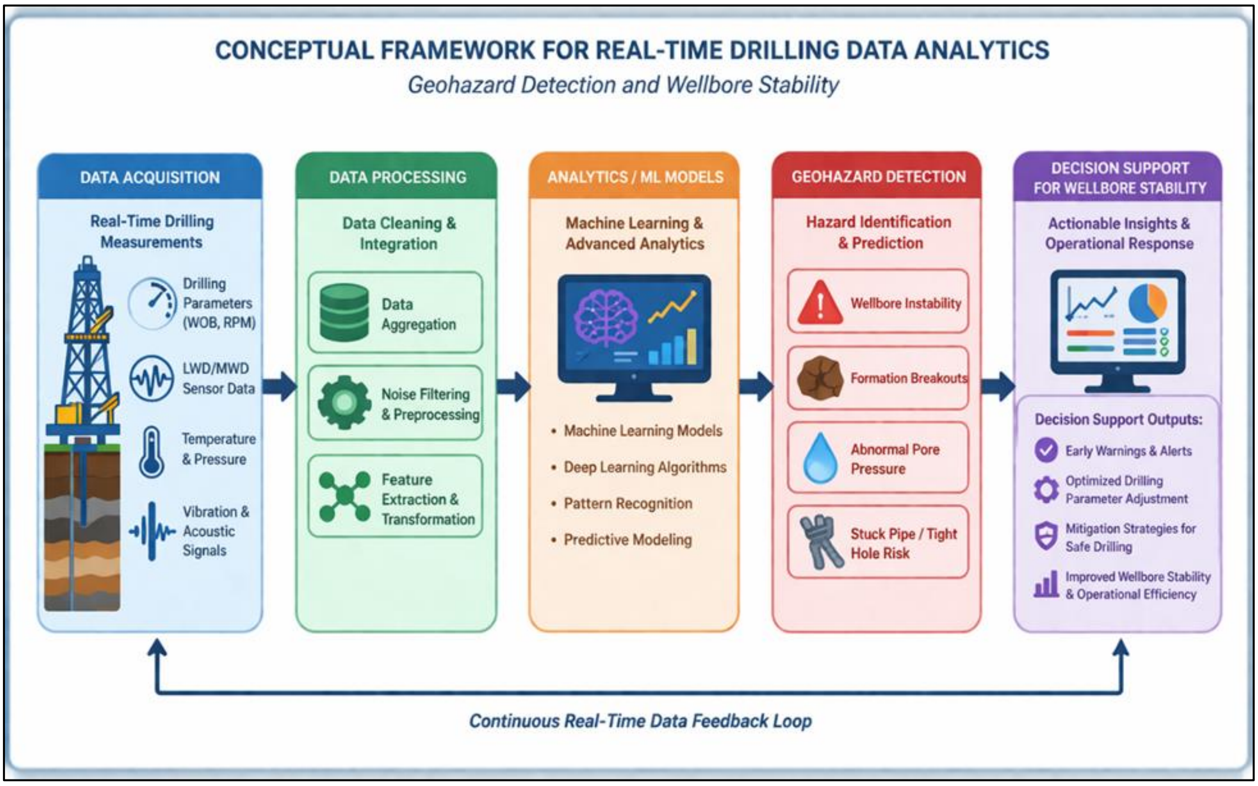
In recent years, the integration of real-time drilling data analytics has emerged as a transformative solution to these challenges. Advances in logging-while-drilling (LWD) and measurement-while-drilling (MWD) technologies now enable continuous acquisition of subsurface data, including drilling parameters, formation properties, and geomechanical indicators. These data streams, when combined with machine learning and advanced computational models, allow for real-time prediction of lithology, pore pressure, and wellbore stability conditions (Bai et al., 2023; Ding et al., 2025).

Furthermore, the application of artificial intelligence and deep learning techniques has significantly improved the accuracy and speed of geohazard detection. These methods enable the identification of complex patterns and relationships within large datasets, supporting early warning systems and proactive decision-making during drilling operations (Hamoudi et al., 2026; Geng et al., 2025). Real-time analytics platforms have also been developed to integrate multiple data sources, providing automated insights that enhance operational safety and efficiency (Hasan et al., 2025; Richard et al., 2022).

The conceptual framework presented in Figure 1 illustrates the integrated workflow of real-time drilling data analytics for geohazard detection and wellbore stability. It begins with continuous data acquisition from drilling operations through sensors and logging-while-drilling systems, capturing critical parameters such as pressure, temperature, and vibration. These data are then subjected to data processing, including cleaning, integration, and feature extraction to ensure accuracy and usability (Fouda et al., 2023; Richard et al., 2022). Subsequently, advanced analytics and machine learning models are applied to interpret complex subsurface conditions and identify hidden patterns within the data. These models enable the real-time detection of geohazards, such as wellbore instability, abnormal pore pressure, and formation failure, thereby supporting proactive risk mitigation (Bai et al., 2023; Hammouri et al., 2026). Finally, the framework delivers decision support outputs, providing actionable insights that enhance drilling safety, optimize operational parameters, and improve overall efficiency.



Sources: (Bai et al., 2023; Hamoudi et al., 2026)

Figure 1 Conceptual Framework for Real-Time Drilling Data Analytics for Geohazard Detection and Wellbore Stability

Despite these advancements, several challenges remain, including data quality issues, integration of heterogeneous datasets, and the need for robust and scalable analytical frameworks. Additionally, there is a lack of comprehensive comparative studies that evaluate the effectiveness of different data-driven approaches for geohazard detection and wellbore stability.

Therefore, this review aims to provide a comprehensive and comparative analysis of real-time drilling data analytics techniques for geohazard detection and wellbore stability. The paper synthesizes existing research, evaluates different methodologies, and identifies key gaps and future research opportunities to support safer and more efficient drilling operations.

2. Fundamentals of Geohazards and Wellbore Stability in Drilling

Understanding geohazards and wellbore stability is fundamental to safe and efficient drilling operations. Geohazards in drilling environments refer to subsurface conditions that can negatively impact drilling performance and well integrity. These include formation instability, abnormal pore pressure, fault zones, fractures, and weak or unconsolidated formations. Such conditions can lead to operational challenges such as borehole collapse, stuck pipe, lost circulation, and kicks, all of which increase non-productive time and operational costs (Payrazyan and Robinson, 2023; Khan et al., 2024).

Wellbore stability is primarily governed by geomechanical factors, including in-situ stress conditions, rock strength, pore pressure, and drilling fluid properties. The interaction between these parameters determines whether the borehole remains stable or experiences failure during drilling. Recent studies have emphasized the importance of integrating geomechanical modeling with real-time data to better understand subsurface behavior. For instance, drilling dynamics data have been shown to provide valuable insights into stress distribution and rock response, enabling improved prediction of wellbore stability (Soroush and Qin, 2025).

Geohazards are often categorized based on their origin and impact. Mechanical hazards, such as borehole collapse and shear failure, are typically associated with weak formations or unfavorable stress conditions. Hydraulic hazards, including abnormal pore pressure and fluid influx, can lead to kicks or blowouts if not properly managed. Additionally, operational hazards such as poor hole cleaning and pack-off events are closely linked to drilling parameters and fluid dynamics (Raman et al., 2023; Payrazyan and Robinson, 2023). These hazards highlight the need for continuous monitoring and rapid response during drilling operations.

Traditional methods for assessing wellbore stability rely on pre-drill geological and geomechanical models, which use seismic data, offset well information, and laboratory measurements. While these approaches provide a foundational understanding of subsurface conditions, they are often limited by uncertainties in geological interpretation and the inability to adapt to real-time changes. As a result, discrepancies between predicted and actual conditions frequently occur, leading to increased operational risks (Fouda et al., 2023).

To address these limitations, modern drilling operations increasingly incorporate real-time monitoring techniques. Logging-while-drilling (LWD) and measurement-while-drilling (MWD) technologies enable continuous acquisition of formation and drilling data, allowing for dynamic assessment of wellbore conditions. Advanced imaging tools, such as ultrasonic logging systems, further enhance the ability to detect fractures, formation boundaries, and instability zones in real time (Khan et al., 2024). These technologies provide critical inputs for evaluating wellbore integrity during drilling.

In addition, recent advancements in data-driven approaches have improved the characterization of subsurface conditions. Machine learning models can analyze large volumes of drilling data to identify patterns associated with lithology, pore pressure, and instability events. For example, real-time rock characterization using multi-source data integration has been shown to enhance the prediction of formation properties while drilling (Bai et al., 2023). Similarly, data-driven lithology identification techniques based on drilling parameters provide improved accuracy compared to conventional methods (Ding et al., 2025).

Geohazard prediction has also benefited from the application of deep learning and probabilistic modeling techniques. These approaches allow for the assessment of uncertainty and the generation of predictive models that can anticipate hazardous conditions before they occur. Studies have demonstrated the effectiveness of machine learning in pore pressure prediction and geohazard mapping, which are critical for maintaining wellbore stability (Hammouri et al., 2026; Geng et al., 2025). Furthermore, stochastic methods provide a framework for managing uncertainties in subsurface conditions, supporting more robust decision-making processes (Quansah and Yakin, 2025).

Despite these advancements, challenges remain in fully understanding and predicting geohazards. The complexity of subsurface environments, coupled with the variability of geological formations, makes it difficult to develop universally applicable models. Additionally, integrating diverse data sources, including geological, geophysical, and drilling data, presents significant technical challenges. These limitations highlight the need for continued research into more accurate and adaptive models for geohazard detection and wellbore stability.

Overall, the fundamentals of geohazards and wellbore stability emphasize the importance of integrating geomechanical principles with real-time data analytics. A comprehensive understanding of these concepts is essential for developing advanced monitoring and prediction systems, which form the basis for the comparative analysis of data-driven approaches discussed in subsequent sections.

3. Real-Time Drilling Data Acquisition and Analytics Techniques

Real-time drilling data acquisition and analytics play a critical role in improving geohazard detection and maintaining wellbore stability. Modern drilling operations rely on continuous data streams generated from advanced downhole and surface sensors, which provide real-time insights into subsurface conditions and drilling performance.

3.1. Data Acquisition Technologies

The foundation of real-time analytics lies in robust data acquisition systems, primarily logging-while-drilling (LWD) and measurement-while-drilling (MWD) technologies. These systems collect a wide range of parameters, including drilling rate, torque, weight on bit, pressure, temperature, and formation properties. LWD tools further provide formation evaluation data such as resistivity, density, and acoustic signals, which are essential for identifying lithology and detecting abnormal conditions (Fouda et al., 2023; Khan et al., 2024).

In addition, advanced sensing technologies such as ultrasonic imaging and acoustic telemetry enhance subsurface visibility, enabling early identification of fractures, weak zones, and formation boundaries. These technologies significantly improve the ability to monitor wellbore conditions in real time and reduce uncertainty during drilling operations (Khan et al., 2024).

3.2. Data Processing and Integration

Raw drilling data are often noisy, incomplete, and heterogeneous, requiring preprocessing before meaningful analysis can be performed. Data processing involves filtering, normalization, and feature extraction to improve data quality and usability. Integration of multiple data sources including geological, geophysical, and operational datasets is also essential for creating a comprehensive understanding of subsurface conditions (Richard et al., 2022; Fouda et al., 2023).

Real-time data platforms are increasingly used to automate these processes, enabling seamless data flow from acquisition systems to analytics engines (Fouda et al., 2023). These platforms support continuous monitoring and allow engineers to make timely decisions based on updated information.

3.3. Machine Learning and Advanced Analytics

The application of machine learning (ML) and artificial intelligence (AI) has significantly enhanced the capabilities of real-time drilling analytics by enabling the processing of large and complex datasets to uncover patterns and relationships that are difficult to detect using traditional methods. These techniques are widely applied in key areas such as lithology identification using drilling parameters (Ding et al., 2025), real-time rock characterization through multi-source data integration (Bai et al., 2023), pore pressure prediction and monitoring (Raman et al., 2023), and geohazard detection and mapping using deep learning models (Geng et al., 2025). Collectively, these applications support accurate real-time prediction of drilling risks, enabling early intervention and improved operational safety. Also, probabilistic and stochastic methods further enhance model reliability by improving uncertainty quantification, resulting in more robust and dependable predictions (Quansah and Yakin, 2025).

3.4. Real-Time Decision Support Systems

Real-time analytics are ultimately integrated into decision support systems that assist drilling engineers in optimizing operations. These systems combine processed data and predictive models to generate actionable insights, such as adjusting drilling parameters, modifying mud properties, or altering well trajectories.

Automated platforms have been developed to provide real-time hazard analysis and recommendations, significantly reducing human error and response time. For example, automated drilling hazard analysis systems can detect early signs of instability and recommend corrective actions to prevent incidents such as stuck pipe or wellbore collapse (Hasan et al., 2025; Parazoan and Robinson, 2023).

3.5. Summary of Real-Time Analytics Workflow

The overall workflow of real-time drilling data analytics is summarized in the table below.

Table 1 Teal-time drilling data analytics

Stage	Key Functions	Technologies/Methods
Data Acquisition	Collect drilling and formation data	LWD, MWD, sensors
Data Processing	Clean and integrate data	Filtering, feature extraction
Analytics	Interpret and predict conditions	ML, AI, statistical models
Decision Support	Optimize drilling operations	Automated systems, dashboards

Sources: (Hasan et al., 2025; Geng et al., 2025; Parazoan and Robinson, 2023)

Generally, real-time drilling data acquisition and analytics techniques represent a significant advancement over traditional methods. By enabling continuous monitoring, predictive modeling, and automated decision-making, these technologies improve operational safety, enhance efficiency, and reduce the risks associated with geohazards and wellbore instability. These developments form the basis for the comparative evaluation of different data-driven approaches discussed in the next section.

4. Comparative Analysis of Data-Driven Approaches for Geohazard Detection

This section provides a comparative evaluation of key data-driven approaches used in geohazard detection and wellbore stability, focusing on the differences between machine learning (ML) and physics-based models, as well as real-time and pre-drill prediction systems. It further examines performance, accuracy, and limitations based on insights from the reviewed studies.

4.1. Machine Learning vs Physics-Based Models

Machine learning and physics-based (mechanistic) models represent two fundamental approaches to geohazard prediction, each with distinct strengths and limitations. Machine learning models rely heavily on large datasets, enabling them to learn complex relationships between drilling parameters and subsurface conditions (Ding et al., 2025). These models are particularly effective in predicting lithology, pore pressure, and wellbore instability in complex geological environments (Bai et al., 2023; Ding et al., 2025). However, they often function as "black-box" systems, making their predictions less interpretable.

In contrast, physics-based models are grounded in well-established geomechanical principles, such as stress distribution and rock strength. These models provide a clearer understanding of the underlying processes governing wellbore stability, making them more interpretable and reliable for validation purposes. However, their reliance on simplified assumptions and limited adaptability reduces their effectiveness in highly dynamic drilling environments (Soroush and Qin, 2025).

4.2. To better illustrate these differences, Table 2 presents a comparison of the two approaches.

Table 2 Comparison of Machine Learning and Physics-Based Models

Criteria	Machine Learning Models	Physics-Based Models
Data Requirement	Large datasets required	Moderate (physical parameters)
Interpretability	Low (black-box)	High (physical laws)
Adaptability	High	Limited
Real-Time Capability	Strong	Moderate
Accuracy (Complex Systems)	High	Moderate

Sources: (Bai et al., 2023; Ding et al., 2025)

Recent research highlights the emergence of hybrid approaches that integrate machine learning with physics-based constraints. These models combine predictive accuracy with interpretability, offering a more balanced and robust framework for geohazard detection (Hamoudi et al., 2026).

4.3. Real-Time vs Pre-Drill Prediction Systems

A second important comparison involves real-time analytics systems and pre-drill prediction models. Pre-drill models are developed using historical, geological, and seismic data, providing an initial understanding of subsurface conditions before drilling begins. While these models are essential for planning, their predictive capability is limited by uncertainties in input data and their inability to adapt to changing conditions during drilling. Real-time systems, on the other hand, utilize continuous data streams from LWD and MWD technologies to dynamically update predictions. This allows for immediate detection of anomalies and rapid response to potential hazards. Studies have shown that real-time systems significantly improve operational safety and efficiency by enabling proactive decision-making (Hasan et al., 2025; Fouda et al., 2023). The differences between these approaches are summarized in Table 3.

Table 3 Comparison of Real-Time and Pre-Drill Systems

Feature	Real-Time Systems	Pre-Drill Models
Data Source	Live drilling data	Historical/seismic data
Responsiveness	Immediate	Static
Accuracy	High (adaptive)	Moderate
Risk Mitigation	Proactive	Reactive
Complexity	High	Moderate

Sources: (Hasan et al., 2025; Fouda et al., 2023)

Overall, real-time systems provide a significant advantage in dynamic environments, where continuous updates are essential for effective hazard management.

4.4. Case Studies from Literature

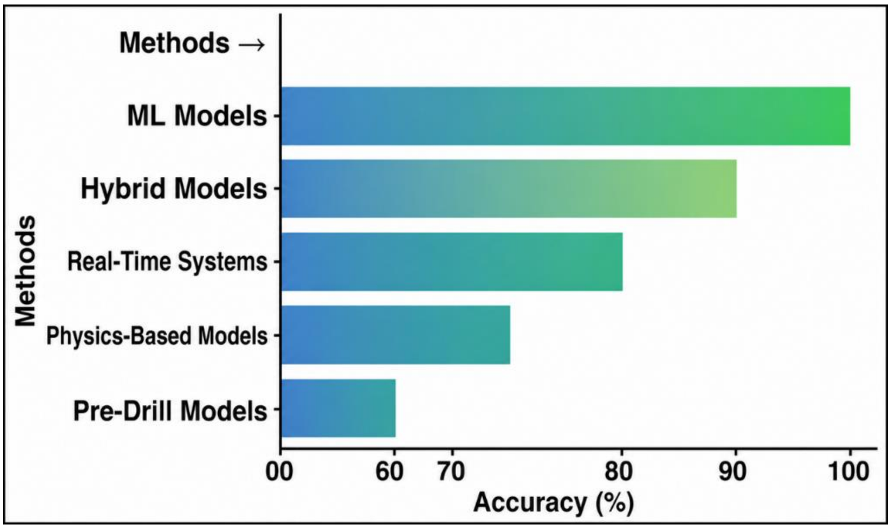
Evidence from the reviewed literature demonstrates the practical effectiveness of data-driven approaches. For example, real-time rock characterization models using multi-source data integration have significantly improved formation prediction accuracy during drilling operations (Bai et al., 2023). Similarly, machine learning-based lithology identification methods have outperformed traditional classification techniques, providing more reliable subsurface interpretations (Ding et al., 2025).

Deep learning approaches have also been successfully applied to geohazard mapping, enabling more precise identification of high-risk zones in complex drilling environments (Geng et al., 2025). In addition, automated hazard analysis platforms have demonstrated the ability to reduce drilling risks by providing real-time recommendations (Hasan et al., 2025) . Machine learning models for pore pressure prediction have further enhanced early warning capabilities, supporting better well control and safety (Raman et al., 2023).

These case studies collectively highlight the growing effectiveness of data-driven techniques in improving drilling performance and reducing geohazard risks.

4.5. Performance and Accuracy Comparison

The performance of different approaches varies significantly depending on their ability to process data and adapt to changing conditions. In general, machine learning and hybrid models demonstrate the highest levels of accuracy, particularly in complex environments where traditional methods may struggle. Real-time systems also outperform static pre-drill models due to their ability to continuously update predictions. Figure 2 provides an illustrative comparison of the relative accuracy of different approaches.



Source: Author's construct.

Figure 2 Conceptual comparison of accuracy across different modelling approaches

This figure shows that machine learning and hybrid models achieve the highest predictive accuracy, while pre-drill models provide baseline estimates with lower reliability.

4.6. Cumulative Impact of Data-Driven Approaches

The integration of multiple data-driven techniques leads to cumulative improvements in performance and risk reduction. As systems evolve from standalone physics-based models to fully integrated hybrid and real-time analytics frameworks, their predictive capability increases significantly. This trend is illustrated in Figure 3, which presents a conceptual cumulative Performance Gain in Increasing Integration.

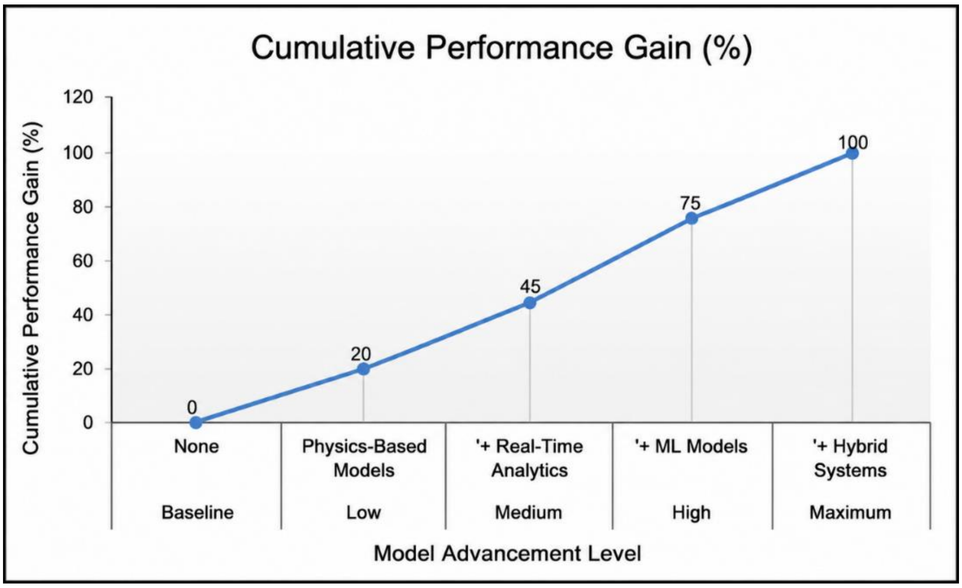


Figure 3 Conceptual representation of performance gains with increasing integration of data-driven approaches

The figure demonstrates that combining multiple techniques results in progressive improvements in prediction of accuracy and operational efficiency.

4.7. Summary of Comparative Insights

Overall, the comparative analysis indicates that machine learning and real-time analytics provide superior performance in geohazard detection and wellbore stability prediction. Physics-based models remain important for interpretability and validation, while hybrid approaches offer the most promising solution by combining the strengths of both methodologies. Additionally, the integration of multiple data sources enhances predictive capability and operational efficiency.

These findings highlight the need for continued development of integrated, scalable, and interpretable systems, which will be further explored in the next section on challenges, opportunities, and future directions.

5. Challenges, Opportunities, and Future Directions

5.1. Key Challenges in Real-Time Drilling Data Analytics

Despite the significant progress made in real-time drilling data analytics for geohazard detection and wellbore stability, several challenges continue to limit its full effectiveness and widespread adoption. One of the primary issues is data quality and availability. Real-time drilling data are often affected by noise, missing values, and inconsistencies due to harsh downhole environments and limitations in sensor technologies. These issues can significantly impact the accuracy and reliability of predictive models, particularly those based on machine learning (Richard et al., 2022). Furthermore, the integration of heterogeneous datasets ranging from geological and geophysical data to operational drilling parameters remains complex. Variations in data formats, sampling frequencies, and measurement uncertainties create additional challenges in achieving seamless data fusion.

Another major limitation is the generalization capability of machine learning models. Many models are trained using specific datasets and may not perform effectively when applied to different geological formations or drilling conditions. This restricts their scalability and applicability across diverse operational settings. In addition, the lack of interpretability in many machine learning algorithms presents a significant barrier, particularly in safety-critical applications where engineers require transparent and explainable outputs to support decision-making (Hammouri et al., 2026).

Computational demands and infrastructure constraints further complicate the implementation of real-time analytics systems. These systems require high processing power, reliable communication networks, and low-latency data transmission, which can be difficult to achieve in remote or offshore drilling environments. Ensuring system stability and reliability under such conditions remains a critical challenge. Collectively, these limitations highlight the need for more robust, scalable, and interpretable solutions in real-time drilling analytics.

5.2. Opportunities and Future Research Directions

Despite these challenges, there are significant opportunities for advancing real-time drilling data analytics. One of the most promising directions is the development of hybrid modeling approaches that integrate machine learning with physics-based models. These approaches combine the predictive strength of data-driven techniques with the interpretability of physical models, leading to improved accuracy and reliability (Soroush and Qin, 2025). Such integration is expected to play a key role in addressing the limitations of standalone models. The emergence of digital twin technology also presents a transformative opportunity. Digital twins enable the creation of real-time virtual replicas of drilling systems, allowing for continuous monitoring, simulation, and optimization of operations. By integrating real-time data with predictive analytics, these systems can significantly enhance decision-making and operational efficiency.

Advancements in artificial intelligence and deep learning are expected to further improve geohazard detection capabilities. Techniques such as neural networks and reinforcement learning can process large and complex datasets, enabling more accurate prediction of subsurface conditions and early detection of potential hazards (Geng et al., 2025). These methods are particularly valuable in handling the high-dimensional data generated in modern drilling operations.

Another important opportunity lies in the development of automated and intelligent decision support systems. These systems can provide real-time recommendations for optimizing drilling parameters and mitigating risks, thereby reducing human error and improving response times (Hasan et al., 2025). As the industry moves toward digitalization, such systems are expected to become increasingly integral to drilling operations.

Future research should focus on improving model scalability, interpretability, and data integration techniques. Enhancing sensor technologies, reducing computational costs, and developing standardized data frameworks will also be essential for advancing the field. Collaboration between academia and industry will play a crucial role in translating these innovations into practical, field-ready solutions.

In summary, while challenges remain, the continued evolution of data-driven technologies, combined with emerging innovations such as hybrid models and digital twins, provides a strong foundation for the future of safe, efficient, and intelligent drilling operations.

6. Conclusion

This review highlights the critical role of real-time drilling data analytics in improving geohazard detection and wellbore stability. By integrating advanced data acquisition systems, machine learning, and physics-based models, modern approaches enable more accurate, adaptive, and proactive decision-making during drilling operations. Comparative analysis shows that hybrid and real-time systems outperform traditional methods, despite challenges related to data quality, scalability, and interpretability. Emerging technologies such as digital twins and intelligent decision support systems present significant opportunities for future advancements. Overall, continued innovation and integration of data-driven techniques are essential for enhancing safety, efficiency, and reliability in drilling operations.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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