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RESEARCH ARTICLE

AI-ENABLED REAL-TIME DRILLING OPTIMISATION FOR SMART OIL AND GAS FIELDS IN SAUDI ARABIA: INTEGRATING MWD/LWD, AUTOMATED WELL PLANNING AND PREDICTIVE WELLBORE RISK MANAGEMENT

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Abstract

Artificial intelligence promises to improve drilling decisions, but field deployment remains constrained by delayed measurements, uncertain geology, inconsistent data quality and safety-critical operating limits. This critical review examines how measurement-while-drilling and logging while drilling information can support drilling rate optimisation adaptive well planning and predictive wellbore risk management within Saudi oil and gas operations. Thirty peer-reviewed publications issued between 2020 and 2025 were assessed through a structured, question led synthesis. The evidence was organized around measurement integrity, formation interpretation, optimisation architecture, trajectory revision, hazard prediction and deployment assurance. Published studies demonstrate substantial progress in rate-of-penetration forecasting, activity-aware influx detection and integrated geological-engineering planning. Nevertheless, model performance is generally assessed within particular fields or datasets; prospective validation, uncertainty calibration and evidence of avoided incidents remain less developed. The review proposes a bounded, human-supervised decision architecture in which physics-based constraints, data-quality controls and explicit operational authorisation separate algorithmic recommendations from drilling actions. This architecture accommodates heterogeneous Saudi reservoirs while retaining traceable decisions and established well control responsibilities. A practical evaluation protocol is proposed using offset-well testing, temporal validation, alert lead time, constraint violations and verified non-productive time. Resilience is framed as maintaining safe operational options under evolving uncertainty, rather than simply increasing drilling speed.

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Introduction:-

Drilling increasingly occurs within an information-rich yet uncertain operating environment. Downhole sensors, surface automation and sophisticated reservoir models provide different views of the same evolving well, often at different time intervals and spatial resolutions. The difficulty is not merely converting data into predictions. Engineers must reconcile interpretations, determine which actions remain safe and establish whether recommendations improve outcomes when formation properties depart from historical experience. For Saudi Arabia,

these questions matter across mature developments, heterogeneous carbonate reservoirs, directional wells and operations constrained by pressure margins, equipment limits or costly interruptions. Digital transformation therefore requires credible decision governance as much as advanced algorithms.

The literature documents a transition from static empirical drilling correlations towards data-driven forecasting and optimisation. A broad account of intelligent drilling identifies hybrid physical and machine-learning methods, scarce labelled examples and uncertain generalisation as continuing research challenges [1]. Reviews of penetration-rate management similarly establish the breadth of predictive techniques, but model rankings vary with geology, variables and testing design [2]. Such variation undermines claims that one algorithm constitutes a universally optimal solution. In operational settings, the chosen model must also recognise data latency, drill-string dynamics, transient circulation and the consequences of an incorrect recommendation.

Rate of penetration (ROP) remains an informative efficiency indicator, not a complete objective. High instantaneous ROP can coincide with excessive vibration, damaging torque, poor hole cleaning or a reduced ability to detect pressure disturbances. A credible optimisation strategy must therefore consider mechanical specific energy, trajectory compliance, hazard exposure and the likelihood of future non-productive time. Studies of ensemble prediction across lithologies show the promise of combining estimators [3], whereas comparisons of conventional and learning-based models highlight dependence on preprocessing and validation design [4]. Prediction uncertainty, explicitly investigated through Bayesian methods, provides a further reason to avoid treating point estimates as operational guarantees [5].

This review advances a different purpose from studies that catalogue smart-oilfield technologies. Its aim is to define an evidence-led route from while-drilling measurements to constrained drilling decisions for resilient Saudi field operations. Four objectives guide the argument: to evaluate the complementary information content of surface, MWD and LWD streams; to compare forecasting and optimisation methods by operational credibility; to connect automated trajectory planning with dynamic wellbore-risk assessment; and to specify validation, governance and performance measures for staged deployment. The central research question asks under which conditions continuous data integration can improve decisions without displacing established engineering accountability.

Review Methodology:-

A structured critical literature review was adopted because the research question spans several linked technologies rather than a single intervention suitable for pooled statistical estimation. The evidence search covered peer-reviewed studies published from January 2020 through December 2025. Search expressions combined drilling optimisation, ROP prediction, MWD, LWD, geosteering, automated well planning, stuck pipe, lost circulation, bottomhole pressure, kick detection, uncertainty and machine learning. Publisher records and DOI-indexed scholarly pages were used to cross-check bibliographic identity. The thirty selected publications span methodological reviews, field-data investigations, computational studies and engineering demonstrations. The selection was purposive and thematic; consequently, it should not be interpreted as an exhaustive census of all indexed research.

Inclusion required a clear drilling or well-planning application, an identifiable publication date within the specified interval, and sufficient methodological information to evaluate inputs, outputs or deployment relevance. Studies confined to reservoir production optimisation without a direct connection to drilling decisions were excluded. Each publication was read against five analytical questions: which measurements inform the model; which uncertainty or hazard is addressed; how the prediction informs action; what validation is reported; and whether the operational outcome is observed or merely inferred. Contradictory findings were retained rather than averaged into an unsupported universal performance estimate.

Evidence was synthesised in four interacting domains: geological perception, drilling-performance decisions, trajectory adaptation and risk assurance. Particular attention was paid to whether datasets were split randomly, chronologically or by well, since observations from adjacent depths are highly correlated. Models tested on records from the same well cannot automatically demonstrate transfer to another well, field or drilling assembly. The review also distinguishes laboratory experiments, retrospective field analyses and prospective operational trials. Where publications report improved prediction scores but not independently verified avoided losses, the latter benefit is treated as a research hypothesis. This separation is essential when proposing safety-critical applications.

Critical appraisal and evidence hierarchy:-

The synthesis distinguishes evidence of technical feasibility from evidence of operational benefit. A simulation can demonstrate that an optimisation scheme satisfies assumed constraints; it cannot establish whether actual crews will accept its recommendations or whether additional telemetry will remain reliable under drilling vibration and heat. Retrospective field data offer a stronger account of realistic operating variation, but recorded responses reflect human interventions and may be affected by selection bias. Prospective shadow testing provides a more persuasive intermediate test because predictions are generated before outcomes are known. Controlled field implementation offers the strongest opportunity to evaluate impact, provided comparison intervals and safety oversight are specified in advance. This hierarchy avoids presenting every published accuracy metric as equivalent evidence of operational readiness. It also identifies where an apparently mature algorithm requires further evaluation before integration into live drilling decisions.

Data Architecture and Downhole Observability:-**Measurement integrity and contextualization:-**

MWD typically supplies directional and drilling-dynamics observations, whereas LWD contributes formation-facing measurements such as resistivity, density and related logging responses. Surface systems add flow, pressure, torque, rotary speed, hook load and equipment states. Integration is technically attractive because these signals capture complementary mechanisms; it is also difficult because sensors occupy different locations and operate with unequal acquisition rates, bandwidth and uncertainty. Prior to model training, measurements should be aligned by both time and measured depth, accounting for circulation delay, sensor-to-bit offset and interruptions in downhole telemetry.

The appropriate unit of analysis is not necessarily a row in a digital log. During drilling, reaming, connection-making and tripping, identical pressure or torque changes may signify entirely different conditions. Input windows should therefore include activity labels, tool configurations, bit and hydraulic characteristics, and an explicit record of missing values. Numerical interpolation may improve continuity but can conceal genuine transients or introduce future information into earlier predictions. A data-quality layer should retain raw values alongside corrected streams, recording transformations and the reasons for excluding suspect intervals.

Lithology prediction illustrates the value and limits of drilling measurements. Gradient-boosting models applied to MWD data can infer geological features, but measurement noise and formation heterogeneity require careful handling [10]. Another integrated classification study uses drilling signatures to identify lithology and reports operational relevance, although its performance remains conditional on the study setting [11]. Neither approach replaces geological verification. Rather, real-time classifications should update probabilistic formation hypotheses and identify where additional logging, cuttings analysis or expert interpretation is required. Disagreement among sources is useful evidence of uncertainty, not an inconvenience to be smoothed away.

Data fusion and geological confidence:-

MWD and LWD measurements should not be combined by indiscriminate concatenation. Their depths of investigation, physical sensitivities and spatial footprints differ, so the same boundary may appear at different apparent depths. Fusion requires a geological state representation that preserves uncertainty in bed orientation, fault proximity and tool response. Bayesian updating or ensemble conditioning can accommodate competing interpretations without forcing a premature single classification. Where LWD observations are absent, synthetic lithology estimates from surface signals may support operational awareness, but cannot be assigned the same confidence as direct formation measurements. Hybrid empirical–learning models offer an instructive precedent for preserving conventional drilling knowledge alongside statistical prediction [12]. The intended benefit is not an artificially smooth geological picture; it is a transparent account of what is observed, inferred and presently unresolved.

Latency and the decision horizon:-**Table 1. Evidence synthesis across linked drilling decision functions.**

Decision function	Principal signals	Modelled output	Critical validation question
Formation interpretation	MWD, LWD, offset logs	Lithology and target uncertainty	Across-well agreement; calibration [10–12]
Drilling efficiency	WOB, RPM, torque, ROP	ROP and mechanical energy	Forward-well evaluation; physical limits [3–9]
Trajectory adaptation	Surveys, LWD and geometry	Target exposure; collision margin	Geological ensembles; steering constraints [13–16]

Decision function	Principal signals	Modelled output	Critical validation question
Stuck-pipe surveillance	Torque, drag, movement, pressure	Depth-dependent warning	Lead time; unseen-well event capture [17–19]
Fluid-loss surveillance	Pit volume, flow and hydraulic state	Loss likelihood and severity	Confirmed events; nuisance alarms [20,21]
Well-control support	Flow, pressure, activity	Influx warning and escalation	Missed events; response latency [24–30]

An automated system must distinguish data arrival time from the geological time at which a measurement was acquired. The more slowly an observation reaches the surface, the shorter its usefulness for high-frequency control. Fast adjustments to weight on bit or rotary speed may rely on recent surface and near-bit data, while trajectory revisions use slower formation interpretation and survey updates. A practical architecture therefore separates rapid control support, periodic advisory optimisation and longer-horizon planning. Each loop requires its own refresh interval, confidence threshold and fallback behaviour. Claims of real-time operation are incomplete unless the full sensing-to-action delay is reported.

Data ownership and engineering handover:-

A multi-vendor drilling installation can generate technically valid but semantically inconsistent records. Equipment tags may change after maintenance, different contractors may record weight on bit at different sampling rates, and unit conversion errors can propagate silently into model recommendations. Before commissioning an analytical service, the operator should specify a canonical variable dictionary, a unit convention and traceable interface tests. Each predicted value should carry the model version, data window, applicable operating regime and an uncertainty or confidence indicator. This metadata enables engineers to distinguish a new geological signal from a software change. It also supports shift handovers: incoming crews can review why an advisory threshold changed, whether a sensor was temporarily unavailable and which recommendations were explicitly rejected.

Predictive Drilling Performance:-

Machine-learning models approximate nonlinear relationships among operational settings, formation properties and ROP. Geomechanics-informed work shows why geological heterogeneity should enter performance predictions rather than be treated as random noise [6]. Ensemble approaches can improve robustness when their constituent estimators make complementary errors [3], but increased sophistication is not intrinsically advantageous. A comparison against simple, transparent models is necessary to establish whether additional complexity offers a measurable benefit. Model selection should also recognise the cost of recalibration, availability of input sensors and interpretability for drilling supervisors.

The training target demands scrutiny. Observed ROP is partly a consequence of human control decisions, equipment deterioration and operational restrictions; historical datasets therefore do not represent unconstrained experiments. A model may learn that low ROP accompanies unstable conditions without distinguishing cause from prudent risk mitigation. Predictive optimisation that simply searches for inputs associated with high historical ROP can recommend settings outside the range where the model has credible support. Uncertainty-aware prediction [5], explicit operating envelopes and out-of-distribution detection help expose this problem. Sensitivity analysis should test whether small plausible errors in WOB, torque or formation classification alter the recommended action materially.

Multi-objective studies offer a stronger formulation than speed maximisation alone. One framework jointly addresses ROP and mechanical specific energy using predictive estimators, evolutionary optimisation and preference ranking, with model updates from operational data [7]. More recent reinforcement-learning research combines perception and symbolic models for dynamic drilling decisions [8]. These contributions demonstrate computational possibilities, not unrestricted authority to issue rig commands. In a safety-critical system, objectives must remain subordinated to pressure, torque, vibration, equipment and well-control constraints. The optimisation output should include rejected alternatives and the controlling limit, allowing engineers to understand why a faster option was not selected.

Saudi-linked research on horizontal drilling reinforces the importance of local well geometry and formation context for ROP modelling [9]. Models transferred from vertical intervals or unrelated fields should initially be treated as provisional. A staged training approach can combine pooled historical data for broad representation with locally calibrated corrections and independent tests on subsequent wells. Evaluation should report absolute error, bias by

formation, uncertainty calibration and performance during transitions, rather than one aggregate accuracy figure. Operational utility then requires comparison with decisions made by existing crews under equivalent constraints.

Optimisation under constraints and distribution shift:-

Optimisation recommendations are only as dependable as the model over the candidate action space. If the optimiser explores combinations of high rotary speed and weight on bit that never occurred in historical drilling data, a smooth predictive surface may create fictitious gains. The first safeguard is a feasible-region filter derived from equipment ratings, hydraulics, vibration limits and operating practice. The second is a support check, flagging recommendations distant from the training distribution. A third safeguard uses several model families or posterior samples to test whether candidate rankings remain stable under plausible uncertainty. Where rankings reverse, the system should abstain or request supervised experimentation rather than promote the most optimistic prediction. This makes the optimisation problem fundamentally different from regression benchmarking: decision quality depends on avoiding unsafe extrapolation and quantifying the cost of being wrong.

Automated Well Planning and Geosteering:-

Automated planning changes the spatial character of drilling optimisation. Instead of selecting the next mechanical setting, the system estimates a path through uncertain targets while satisfying dogleg, torque-and-drag, anti-collision, casing and operational constraints. Integrated optimisation of well placement, trajectory and facilities demonstrates the computational value of linking decisions traditionally assigned to separate disciplines [13]. Geological and engineering objectives can also be combined in intelligent trajectory generation [14]. However, the ability to produce a feasible mathematical path is not equivalent to proving drillability with the actual bottomhole assembly and formation response.

LWD interpretation should enter the planning loop as updated evidence about bed boundaries, lithological changes and the location of the productive interval. Machine-learning-assisted directional planning indicates how simulation and steering models can inform revised paths [15]. Work on optimisation under geological uncertainty further shows the benefit of representing more than one plausible subsurface realisation [16]. A safe planning workflow evaluates candidate trajectories against an ensemble of geological interpretations rather than a single deterministic map. Where competing interpretations imply conflicting steering choices, the model should request additional evidence or recommend a conservative option that preserves future correction capacity.

Closed-loop planning also needs limits on autonomy. Survey uncertainty, toolface response and hydraulic consequences cannot be eliminated by an impressive trajectory prediction score. Before a new route is approved, the proposed path should pass independently implemented geometry, collision, dogleg, torque-and-drag and pressure checks. The system should preserve the prior approved plan, log each revision and explain the assumptions that changed. Human authorisation remains especially important when a trajectory recommendation changes casing strategy, target exposure or the likelihood of encountering an uncertain pressure zone.

Geosteering as sequential decision-making:-

Geosteering should be considered a sequence of reversible and irreversible commitments. Small steering adjustments may preserve several later routes; large early corrections can consume dogleg allowance or limit access to the desired formation. The optimal decision is therefore influenced by option value, not solely by current target proximity. A decision system can compare trajectories by expected pay-zone exposure, uncertainty in bed position, predicted friction and remaining steering flexibility. It should also quantify whether waiting for another observation is preferable to an immediate correction. Such restraint is particularly valuable where telemetry delay and uncertain dip could otherwise trigger repeated steering reversals. The engineering contribution of automation is improved option appraisal under uncertainty, while the actual drilling command must continue to satisfy mechanical feasibility and responsible review.

Predictive Wellbore Risk Management:-**Stuck pipe and lost circulation:-**

Stuck pipe often emerges from interacting mechanical, hydraulic and geological mechanisms rather than a single measurable precursor. Data-driven indicators constructed from drilling records can track motion anomalies and pressure-related signals as risk changes with depth [17]. Classification-tree approaches translate historical events into relatively interpretable risk rules, but case-specific patterns should not be assumed universal [18]. Unsupervised anomaly detection has also been investigated to recognise early signs when labelled stuck-pipe examples are rare

[19]. These approaches are best positioned as additional surveillance layers supporting diagnosis, not replacements for established hole-cleaning, differential-sticking and well-control procedures.

Lost circulation presents a related but distinct problem. Models based on surface measurements and active-pit changes have been tested for predicting loss severity using multiwell data [20]. Other work combines logs and learning methods to characterise loss intensity [21]. Such predictions must be coupled with geological uncertainty, estimated pressure margins and operational activity. A pit-volume decline may reflect transfers, surface handling or sensor error rather than formation losses. For that reason, an alert should describe corroborating evidence and recommend a verification sequence before any consequential action. Different loss mechanisms require different responses; a single generic alarm is insufficient.

Hazard dependencies and competing actions:-

Wellbore hazards cannot always be managed independently. Increasing mud density may reduce one instability mechanism while increasing the risk of induced losses; raising pump rate may improve cuttings transport while changing downhole pressure and equivalent circulating density. Similarly, slowing penetration can support hole cleaning but prolong exposure to an unstable interval. A supervisory model should represent these couplings explicitly rather than combine unrelated alarm scores into a single opaque index. Scenario analysis can compare conservative operational alternatives and reveal why a locally attractive action becomes inferior once secondary consequences are included. The resulting recommendation should identify the primary hazard, relevant evidence, likely trade-offs and any missing measurements. This approach allows engineers to reject superficially efficient actions for well-documented physical reasons rather than relying on an unexplained model score.

Stability, pressure and influx:-

Wellbore instability models need to consider the relation between stresses, rock strength, mud properties and borehole geometry. A contemporary review distinguishes component-level machine-learning predictions from full-process stability models, while identifying data fusion and dynamic updating as emerging priorities [22]. Neural-network prediction of borehole enlargement provides a further example of combining observed drilling outcomes with physical understanding [23]. The underlying lesson is that a useful model estimates not only the chance of deterioration but also the sensitivity of that outcome to controllable variables and uncertain formation properties. For managed-pressure or narrow-window operations, bottomhole pressure must remain physically credible. A physics-constrained neural workflow seeks to improve prediction stability by incorporating hydraulic relationships [24]. That approach is preferable to unconstrained extrapolation when field conditions change rapidly, although even physics-guided predictions require calibration. Model outputs should be checked against independent pressure measurements and conservative pore-pressure and fracture-gradient bounds. The well-control decision tree must retain precedence over any machine-generated optimisation suggestion.

Early influx detection provides stronger evidence of risk-oriented learning than many efficiency applications. Classifying drilling activities before kick assessment can reduce confusion between normal operations and hazardous patterns [25]. Cost-sensitive models acknowledge the asymmetric consequences of missed warnings and false alarms [26]. Ensemble-based monitoring has also been explored using drilling and mud-system parameters [27]. Earlier Bayesian and neural studies show the feasibility of combining downhole evidence with probabilistic warning [28,29], while field-data investigations reveal practical sensitivity to measurement selection and risk definitions [30]. Yet detection accuracy cannot establish response effectiveness without verified alarm timing, crew action and well-control outcomes.

Alarm design and operator response:-

Warning usefulness depends on precision at the relevant operating prevalence, not merely overall classification accuracy. Rare but consequential kick events can yield apparently attractive accuracy even when detection sensitivity is inadequate. Alarm evaluation should therefore report missed events, false alarms per operating day, median and lower-tail warning lead time, and how often crews could complete the intended response before escalation. Labels should distinguish suspected precursor states from confirmed incidents, because defining long warning windows retrospectively can exaggerate model success. Operational procedures must define acknowledgement, investigation, escalation and closure steps, with recorded reasons for overrides. A warning that cannot be interpreted, verified or acted upon in time is not a successful safety intervention, regardless of its offline model score.

An Integrated Saudi Deployment Framework:-**EVIDENCE-TO-DECISION ARCHITECTURE****Figure 1. Proposed sensing-to-authorisation architecture for supervised drilling optimisation.**

The proposed framework has five connected layers: trusted measurement, contextual geological interpretation, predictive services, constrained decision support and authorised execution. Measurement services retain sensor provenance, time alignment, calibration status and drilling-activity classification. Interpretation services combine MWD, LWD, geological models and uncertainty estimates. Predictive services generate ROP, mechanical-energy, trajectory and hazard estimates. A constraint engine then checks proposed changes against verified drilling limits and rejects unsafe or unsupported candidates. Finally, an accountable engineer reviews the recommendation before any action affecting well integrity or operating envelopes.

Figure 1 presents the flow of information and authority. Its defining feature is the separation between probabilistic inference and permission to act. A high-confidence model is not permitted to override a pressure limit; equally, a low-confidence hazard signal should prompt additional assessment rather than silent suppression. Figure 2 traces the escalation pathway from new observations to verification, constrained response and learning. Both designs allow an operator to begin with decision support before considering partial automation. They also provide audit points for incident investigation and independent model review.

Implementation in Saudi fields should be stratified by reservoir type, drilling system and operational maturity. On mature assets, the principal challenge may be incomplete historical logging or inconsistent activity labels. In extended-reach wells, trajectory, friction and cleaning constraints may dominate. Where pressure windows are narrow, early-warning reliability and response latency become decisive. A common digital platform can provide governance, but models and thresholds may need local calibration. Pooling every well into one undifferentiated training set risks concealing systematic errors among different formations and rigs.

The recommended pilot sequence starts with retrospective data audits, followed by untouched offset-well validation. The next phase runs models in shadow mode, recording what each system would have recommended without changing operations. Only after error, latency and alarm performance satisfy agreed criteria should engineers test advisory deployment with logged decisions. Controlled trials can then compare similar wells or matched sections, adjusting for lithology, depth, bit type and rig configuration. Success must include safety and reliability measures alongside ROP and cost indicators. Model rollback and independent intervention remain available throughout the pilot.

Risk-bounded performance indicators:-

PREDICTIVE WELLBORE-RISK DECISION LOOP



Figure 2. Decision pathway linking evolving wellbore evidence, verification, response and model learning.

Table 2. Staged validation gates for a risk-bounded Saudi drilling pilot.

Gate	Required activity	Decision evidence
1. Data readiness	Unit, time and depth reconciliation	Audited availability; missingness by sensor
2. Model credibility	Train by historical wells; lock future holdout	Well-level error; bias; confidence calibration
3. Safety assurance	Independent hydraulic and mechanical checks	Zero unauthorised constraint overrides
4. Shadow deployment	Record advice without applying commands	Latency; abstentions; false alerts/day
5. Supervised pilot	Engineer-approved, traceable changes	ROP and MSE at comparable formation
6. Risk outcomes	Externally review confirmed wellbore events	Missed warnings; lead time; response completion
7. Continuous control	Monitor drift, rollback and reauthorisation	NPT verified; audit completeness; version history

A Saudi operator evaluating an intelligent-drilling pilot should adopt a balanced scorecard rather than a singular commercial target. Efficiency indicators can include ROP by comparable lithological interval, mechanical specific energy, bit life and verified drilling hours. Trajectory indicators should include target-zone exposure, dogleg compliance, correction frequency and survey-to-plan deviation. Safety indicators should cover pressure-margin excursions, unplanned loss events, stuck-pipe precursors and alert performance. Digital reliability indicators include data availability, end-to-end latency, model abstention frequency and software rollback success. Interpretation requires stratification: an apparent ROP gain may reflect a softer formation rather than better control. All measures should be defined before the trial, with a documented baseline, comparability checks and independent sign-off on incident classifications. Table 2 translates these concerns into practical evidence requirements for deployment decisions.

Discussion and Research Priorities:-

The literature supports a substantial technical opportunity, but its evidence is uneven. Prediction studies commonly describe retrospective accuracy, while planning studies frequently rely on simulations or simplified constraints. Risk studies are more directly aligned with operational safety, yet rare events create severe class imbalance and uncertain labels. A high area under a classification curve can coexist with unacceptable missed warnings, excessive nuisance alarms or insufficient response time. The strongest future studies will evaluate the complete detection-to-decision

pathway, not only model discrimination. Prospective comparisons should identify whether earlier warnings produced appropriate action and whether those actions reduced actual exposure.

Three research priorities follow. First, transferability should be examined through independent-well, independent-rig and time-forward tests, with uncertainty reported by geological interval. Second, hybrid models should undergo physical consistency tests under deliberately perturbed sensor values, unusual operating states and missing-data scenarios. Third, human factors require direct evaluation: recommendation clarity, alarm fatigue, handover practice and accountability can determine whether a theoretically superior system improves outcomes. Cybersecurity, access controls and model-version traceability are equally important where data and decisions move between rig, remote operations centre and enterprise platforms.

This review has limitations. It uses a purposive set of thirty recent studies rather than a complete bibliometric census; differences in tasks, datasets and metrics preclude defensible pooling of effect sizes. Evidence drawn from other countries and drilling environments cannot establish expected gains in Saudi Arabia. Nor do the reviewed studies jointly validate the five-layer architecture proposed here. The contribution is therefore a critically grounded design and evaluation agenda, not a claim that a particular integrated platform has already achieved specified field-wide benefits.

Limits of economic extrapolation:-

Commercial assessments of drilling intelligence frequently multiply small predicted time savings by large annual rig costs. This calculation is highly sensitive to assumptions about achievable utilisation, geological comparability and whether faster drilling changes subsequent operations. A defensible business case should model uncertainty in both benefits and deployment costs, including sensors, communications, engineering supervision, training and ongoing recalibration. It should also distinguish time saved on the critical path from improvements that do not change total well delivery. A risk-adjusted analysis can assign consequences to false alarms, unnecessary intervention, lost circulation and well-control escalation without assuming that all hazards are equally likely. In this framing, an intervention that marginally reduces speed while avoiding severe operational exposure may represent the economically superior decision. The financial conclusion must follow validated field outcomes, not precede them.

Conclusions:-

AI-enabled drilling optimisation is most credible when measurement quality, geological uncertainty, physical feasibility and operational authority are treated as one engineering problem. Recent research provides credible components: MWD-informed lithology recognition, uncertainty-aware ROP models, integrated trajectory design, multi-objective optimisation and probabilistic warnings for wellbore hazards. The evidence does not justify replacing well-control expertise with unconstrained autonomous decisions. For Saudi oil and gas fields, the proposed contribution is an auditable sequence from validated signals to risk-bounded recommendations and supervised action, evaluated through independent wells and prospective performance measures. Future work should prioritise early-warning lead time, false-alarm burden, out-of-distribution robustness, safe trajectory compliance and independently verified non-productive time. Prospective studies should document whether model advice remains trustworthy during equipment changes, sensor failures, geological surprises, procedures and handovers between rig and remote teams. Reliable decisions, rather than maximum instantaneous drilling speed, provide the defensible measure of intelligent-field resilience.

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