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Analysis the Role of Data Analysis in Business Decision Making in the Oil and Gas Industry

Hajer aldossari

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- 9. Chapter 1: Introduction

10. 1.1 Research Background

Data analysis refers to structured activities that collect, clean, integrate, and interpret data to produce insights that guide operational and strategic actions (Bernardo et al., 2024). In oil and gas, data sources include real time sensors, historians, drilling control systems, maintenance work orders, laboratory results, and logistics and inventory records (IOGP, 2021). Business decision making in oil and gas refers to selecting actions that balance safety, asset integrity, production targets, cost control, and regulatory requirements across interconnected systems, such as wells, facilities, pipelines, and supply networks (Awan et al., 2021). The sector operates with high capital intensity and tight operating margins, so decision errors often raise downtime, increase non productive time, and escalate cost per barrel (Krygier et al., 2020).

11. Digitalization trends increase data volume and data variety across upstream, midstream, and downstream activities (IOGP, 2021). Operators also report measurable value from deploying analytics and AI across the value chain. ADNOC reported US\$500 million in value generated from AI solutions deployed during 2023, linked to operational and decision improvements across multiple functions (ADNOC, 2024). Such evidence supports stronger interest in analytics maturity as a decision driver in modern asset management.

12. 1.2 Research Problem

Organizations often collect large volumes of operational data yet face fragmented systems, inconsistent data definitions, and limited end to end integration across operational technology and enterprise technology (IOGP, 2021). These conditions reduce confidence in analytics outputs and slow response during abnormal operations, such as drilling dysfunction, rotating equipment degradation, and supply disruption (Hegde et al., 2020).

13. 1.2.1 Theoretical Gaps

Research on analytics capability frequently links capability to firm performance, yet sector specific pathways that connect analytics maturity to decision performance metrics in oil and gas remain less consistent across upstream decision contexts, such as drilling and maintenance (Awan et al., 2021; Azmi, 2024). Literature also highlights governance and data foundation constraints, yet more work remains on integrating governance, platform interoperability, and decision behavior into one model (Bernardo et al., 2024; Moradi et al., 2024).

14. 1.2.2 Practical Gaps

Asset teams often operate with partial visibility across wells, facilities, maintenance, and materials. Data silos delay diagnosis and reduce decision speed during time critical events (IOGP, 2021). Cyber incidents also disrupt data availability and operational continuity, which weakens decision performance even when analytics tools exist (NIST, 2024). Halliburton reported a cyber incident affecting certain systems during 2024, which illustrates operational exposure in connected environments (Reuters, 2024).

15. 1.3 Research Significance

1.3.1 At the Theoretical Level

The research builds a sector grounded model that links data analysis maturity to decision performance, while including decision culture as a mediator and cybersecurity posture and data quality as moderators (Bernardo et al., 2024; NIST, 2024).

16. 1.3.2 At the Practical Level

The research supports managers who need measurable decision outcomes in drilling, production, and maintenance, using operational KPIs linked to uptime, NPT, forecast accuracy, and unit cost (Krygier et al., 2020; Werneck et al., 2022).

17. 1.4 Research Questions

RQ1. How does data analysis maturity influence decision performance in upstream oil and gas operations

RQ2. Which maturity dimensions, data quality, integration, tools, skills, governance, show the strongest association with decision performance

RQ3. How does decision culture mediate adoption of analytics outputs in operational decisions

RQ4. How do data quality and cybersecurity posture change the strength of the maturity to performance relationship

18. 1.5 Research Objectives

RO1. Define and operationalize data analysis maturity for upstream operations (Bernardo et al., 2024; IOGP, 2021).

RO2. Define and measure decision performance using operational and financial indicators relevant to upstream assets (Krygier et al., 2020; Werneck et al., 2022).

RO3. Test direct, mediating, and moderating relationships using a structured empirical method (Hair Jr. et al., 2021).

RO4. Produce a practical roadmap for analytics capability building aligned with governance and cyber controls (NIST, 2024; Moradi et al., 2024).

19. 1.6 Research Hypotheses

H1. Higher data analysis maturity associates with higher decision performance (Awan et al., 2021; Bernardo et al., 2024).

H2. Data quality positively influences decision performance and strengthens the maturity to performance relationship (Bernardo et al., 2024).

H3. System integration positively influences decision speed and decision performance (IOGP, 2021; Correia et al., 2022).

H4. Decision culture mediates the relationship between data analysis maturity and decision performance (Awan et al., 2021; Moradi et al., 2024).

H5. Stronger cybersecurity posture strengthens the relationship between maturity and decision performance by protecting data availability and operational continuity (NIST, 2024; Reuters, 2024).

20. 1.7 Research Model

The model positions data analysis maturity as the independent variable and decision performance as the dependent variable. Decision culture serves as a mediator. Data quality and cybersecurity posture act as moderators (Bernardo et al., 2024; NIST, 2024).

21. 1.8 Research Methodology Overview

The research uses a mixed methods design. Quantitative data tests hypotheses using survey constructs and operational KPIs. Qualitative interviews validate decision workflows and explain adoption barriers (Hair Jr. et al., 2021; IOGP, 2021).

22. 1.9 Scope of the Study

The scope centers on upstream operations, drilling, production operations, and maintenance reliability, plus selected midstream logistics interfaces that influence uptime through materials and transport (Krygier et al., 2020; Okeke & Zhang, 2024).

23. 1.10 The Suggested Project Structure

The project follows six chapters aligned with the table of contents, ending with appendices that include survey items, interview guide, KPI definitions, and a conceptual model diagram.

24. Chapter 2: Literature Review

25. 2.1 Introduction

Recent literature describes oil and gas digitalization as a shift from isolated datasets toward integrated platforms, analytics workflows, and governance mechanisms that support daily operational decisions (IOGP, 2021; Bernardo et al., 2024). Research also highlights ecosystem governance and interoperability challenges in shared platforms and open source data ecosystems used by the sector (Moradi et al., 2024; Correia et al., 2022).

26. 2.2 Data Analysis in Oil and Gas Operations

Drilling and production generate high frequency time series data, while maintenance and supply chain generate event and transactional data. Analytics value increases when teams integrate these data types and align outputs with operational KPIs (Boukredera et al., 2023; Okeke & Zhang, 2024). Predictive analytics reviews in oil and gas emphasize condition monitoring, failure prediction, and scheduling optimization as core value streams (Azmi, 2024).

27. 2.3 Business Decision Making in Oil and Gas

Operational decisions include selecting drilling parameters, planning maintenance interventions, prioritizing deferred work, and allocating production capacity under facility constraints. Decision performance depends on speed, accuracy, and execution alignment with safety and asset integrity (Krygier et al., 2020; Werneck et al., 2022). Analytics capability literature links data driven routines to performance through improved information processing and improved operational alignment (Awan et al., 2021).

28. 2.4 The Independent Variable, Data Analysis Maturity

Data analysis maturity represents the degree of capability across data foundations and analytics deployment.

Key dimensions include data quality, system integration, analytics tools and methods, team skills, and governance (Bernardo et al., 2024; IOGP, 2021). Platform and ecosystem governance influences data access rules, data lineage, and shared standards, which affect integration outcomes (Moradi et al., 2024; Correia et al., 2022).

29. 2.5 The Dependent Variable, Decision Performance

Decision performance represents measurable outcomes after decisions, such as reduced downtime, reduced NPT, improved production forecast accuracy, and reduced unit cost (Krygier et al., 2020; Werneck et al., 2022).

Enterprise evidence also links analytics deployment to measurable business value across the value chain (ADNOC, 2024).

30. 2.6 Relationship Between Data Analysis Maturity and Decision Performance

The literature supports three pathways. First, higher data quality and integration improve signal reliability for abnormal situation detection (Bernardo et al., 2024; IOGP, 2021). Second, predictive and prescriptive models support faster scenario evaluation and stronger parameter choices (Hegde et al., 2020; Boukredera et al., 2023). Third, governance and trust influence adoption, so decision culture and system trust shape performance gains (Moradi et al., 2024; Awan et al., 2021).

31. 2.7 Key Use Cases in Oil and Gas

2.7.1 Predictive Maintenance

Predictive analytics supports early identification of equipment degradation and supports planned interventions, which targets downtime reduction and throughput stability (Azmi, 2024). Cyber controls support reliability of connected monitoring and analytics services (NIST, 2024).

32. 2.7.2 Drilling Optimization

Machine learning based drilling optimization integrates drilling dynamics and operational signals to optimize rate of penetration while controlling dysfunction risk (Hegde et al., 2020). Industrial case evidence reports performance improvement when workflows embed AI recommendations into rig decisions (Boukredera et al., 2023). Well stability issues contribute to drilling NPT, so earlier detection and optimized practices improve decision performance (Krygier et al., 2020).

33. 2.7.3 Production Forecasting

Deep learning based production and pressure forecasting supports planning decisions such as choke management, compression allocation, and intervention selection (Werneck et al., 2022).

34. 2.7.4 Supply Chain Optimization

Analytics improves spares planning, logistics scheduling, and disruption response through improved forecasting and risk scoring, which reduces downtime drivers linked to material unavailability (Okeke & Zhang, 2024).

35. 2.8 Mediators and Moderators

Decision culture mediates analytics impact through trust, accountability, and incentives that shape adoption of model outputs (Awan et al., 2021; Moradi et al., 2024). Data quality moderates analytics value because poor data reduces model reliability (Bernardo et al., 2024). Cybersecurity posture moderates results because incidents disrupt data availability and operations, including incidents reported in oilfield services environments (NIST, 2024; Reuters, 2024).

36. 2.9 Literature Review Summary

The literature supports a positive link between analytics maturity and decision performance, with strong roles for governance, trust, and cyber resilience (Bernardo et al., 2024; NIST, 2024).

37. Chapter 3: Research Model and Hypotheses Development

38. 3.1 Introduction

This chapter translates literature into a testable conceptual model and hypotheses.

39. 3.2 Conceptual Definitions of Variables

Data analysis maturity includes data quality, integration, analytics tools, skills, and governance (Bernardo et al., 2024). Decision performance includes downtime reduction, NPT reduction, forecast accuracy improvement, and unit cost reduction (Krygier et al., 2020; Werneck et al., 2022).

40. 3.3 Research Model Description

The model asserts that higher maturity improves decision inputs and decision speed, which improves decision performance. Decision culture supports adoption as a mediator. Data quality and cybersecurity posture influence relationship strength as moderators (Awan et al., 2021; NIST, 2024).

41. 3.4 Hypotheses Development

3.4.1 Direct Effect Hypotheses

H1, H2, H3 focus on direct effects from maturity and dimensions to decision performance (Bernardo et al., 2024; IOGP, 2021).

42. 3.4.2 Mediating Effect Hypotheses

H4 tests decision culture as an adoption mediator (Moradi et al., 2024; Awan et al., 2021).

43. 3.4.3 Moderating Effect Hypotheses

H5 tests cybersecurity posture as a moderator due to operational continuity and data availability dependence (NIST, 2024; Reuters, 2024).

44. 3.5 Operational Definitions and Measurement Indicators

Independent variable indicators include data quality controls, integration coverage across OT and IT, analytics deployment depth, workforce skills, and governance practices (Bernardo et al., 2024; Correia et al., 2022). Dependent variable indicators include downtime hours, NPT hours in drilling, forecast error metrics, and unit cost measures linked to lifting and maintenance cost (Krygier et al., 2020; Werneck et al., 2022; Okeke & Zhang, 2024).

45. 3.6 Chapter Summary

The model and hypotheses align with prior findings on analytics capability, governance, and cyber risk in connected operations (Bernardo et al., 2024; NIST, 2024).

46. Chapter 4: Research Methodology

47. 4.1 Introduction

This chapter defines the research design, population, data collection, and analysis approach.

48. 4.2 Research Design

A sequential mixed methods design supports measurement and explanation. Quantitative testing estimates relationships across constructs. Qualitative interviews explain adoption barriers and workflow realities (Hair Jr. et al., 2021; IOGP, 2021).

49. 4.3 Target Population and Sampling

Target population includes upstream decision stakeholders, drilling engineers, production engineers, reliability engineers, maintenance planners, operations supervisors, and digital and data governance roles. Sampling uses stratified sampling across functions and asset types to improve representation (Hair Jr. et al., 2021).

50. 4.4 Data Collection Methods

4.4.1 Survey Instrument

Survey constructs measure maturity dimensions and decision culture using validated capability logic from analytics capability research and governance literature (Awan et al., 2021; Bernardo et al., 2024).

4.4.2 Interviews

Semi structured interviews validate decision workflows and clarify adoption barriers linked to trust, incentives, and governance (Moradi et al., 2024; IOGP, 2021).

4.4.3 Operational and Asset Data

Operational KPIs include downtime, drilling NPT, production forecast error, and unit cost metrics, aligned with upstream decision contexts (Krygier et al., 2020; Werneck et al., 2022).

51. 4.5 Measurement Scales and Constructs

Data analysis maturity forms a higher order construct with five dimensions. Decision performance forms a construct aligned with KPI outcomes. Decision culture measures trust, accountability, and routine use of analytics outputs (Awan et al., 2021; Moradi et al., 2024).

52. 4.6 Reliability and Validity Procedures

Composite reliability, convergent validity, and discriminant validity follow structured SEM evaluation guidance (Hair Jr. et al., 2021).

53. 4.7 Data Analysis Techniques

The research uses structural equation modeling for hypothesis testing and mediation and moderation estimation. Partial least squares SEM offers fit for complex models with formative and reflective constructs and applied field samples (Hair Jr. et al., 2021).

54. 4.8 Ethical Considerations and Data Security Controls

The research protects confidentiality and aligns data handling with cybersecurity risk management frameworks. Controls include role based access, anonymization, and secure storage for survey and operational data (NIST, 2024). Cyber incident evidence in the sector reinforces the need for strict controls (Reuters, 2024).

55. 4.9 Chapter Summary

The methodology aligns with the research model and supports rigorous testing and practical insight generation (Hair Jr. et al., 2021).

56. Chapter 5: Field Study, Proposed Application Setting

57. 5.1 Introduction

The field study setting provides a realistic context for measuring maturity and decision outcomes.

58. 5.2 Study Context and Asset Type

The proposed setting includes an upstream producing asset with a mix of wells, surface facilities, and rotating equipment such as compressors and pumps, plus a drilling program segment for NPT analysis (Krygier et al., 2020; Azmi, 2024).

59. 5.3 Process and Data Landscape

The data landscape includes SCADA and historian data, drilling time series, maintenance management data, and ERP inventory and procurement records. Integration maturity varies across assets in industry practice, which supports comparative analysis (IOGP, 2021; Correia et al., 2022).

60. 5.4 Key Decisions Covered in the Field Study

5.4.1 Maintenance Decision Workflow

Decisions include preventive versus condition based work, backlog prioritization, and outage scheduling. Predictive analytics supports early intervention planning (Azmi, 2024).

5.4.2 Drilling Decision Workflow

Decisions include drilling parameter selection, dysfunction response, and stability management. Optimization models support parameter decisions and NPT reduction (Hegde et al., 2020; Boukredera et al., 2023).

5.4.3 Production Planning Workflow

Decisions include forecast based planning, choke strategy, and facility constraint management. Deep learning forecasting supports planning accuracy (Werneck et al., 2022).

61. 5.5 KPIs and Performance Measures

Core measures include downtime hours, NPT hours, forecast error, and unit cost changes aligned with operational decisions (Krygier et al., 2020; Werneck et al., 2022).

62. 5.6 Expected Outcomes and Practical Value

Expected outcomes include higher decision speed through integrated data, lower downtime through predictive maintenance, lower drilling NPT through optimization, and improved planning through stronger forecasts (Hegde et al., 2020; Werneck et al., 2022; Azmi, 2024). Enterprise value evidence supports measurable benefits from scaled analytics (ADNOC, 2024).

63. 5.7 Chapter Summary

The field study design links analytics maturity to measurable operational outcomes in a realistic upstream context (IOGP, 2021).

64. Chapter 6: Proposed Project Plan and Outline

65. 6.1 Introduction

This chapter defines phases, deliverables, and governance for research execution.

66. 6.2 Project Phases and Deliverables

Phase 1. Literature review and construct definition, deliverables include variable definitions and draft survey (Bernardo et al., 2024).

Phase 2. Instrument design and pilot, deliverables include validated survey and interview protocol (Hair Jr. et al., 2021).

Phase 3. Data collection, deliverables include survey dataset, interview transcripts, and KPI extracts (Krygier et al., 2020).

Phase 4. Data analysis, deliverables include SEM results, mediation and moderation results, and field interpretation (Hair Jr. et al., 2021).

Phase 5. Reporting, deliverables include findings, managerial recommendations, limitations, and future research agenda (Awan et al., 2021).

67. 6.3 Timeline and Milestones

Milestone set includes completion of pilot testing, completion of field data access approvals, completion of quantitative analysis, completion of interview coding, and final thesis submission (NIST, 2024).

68. 6.4 Required Resources and Roles

Resources include access to operational KPI reports, survey platform, interview scheduling, and analytics software for SEM. Roles include research lead, SME reviewers from drilling and maintenance, and data governance reviewer (IOGP, 2021; Hair Jr. et al., 2021).

69. 6.5 Risk Register and Mitigation Plan

Risk 1. Limited access to operational KPI data, mitigation uses anonymized aggregates and data use agreements (NIST, 2024).

Risk 2. Low survey response rate, mitigation uses function level sponsorship and reminders.

Risk 3. Cyber and confidentiality exposure, mitigation follows NIST CSF controls for access and storage (NIST, 2024). Sector incident evidence supports this control focus (Reuters, 2024).

70. 6.6 Monitoring and Evaluation Plan

Monitoring uses milestone tracking and quality checks for data completeness and construct reliability, aligned with SEM evaluation guidance (Hair Jr. et al., 2021).

71. 6.7 Chapter Summary

The project plan supports structured delivery and protects data security while producing measurable results (NIST, 2024).

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