

**Evaluating the Efficiency and Effectiveness of
AI-Driven Sales Forecasting in the Oil and Gas
Sector: A Mixed-Methods Study of Mid-Sized
Companies in Central and Eastern Saudi Arabia**

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Dedication

I respectfully dedicate this work to my dear parents, whose unwavering support and enduring inspiration have shaped every stage of my life. To my mother, whose encouragement and boundless care have always been a source of strength, and to my father, who instilled in me the values of perseverance, integrity, and diligent effort.

To my beloved wife, whose partnership, encouragement, and steadfast support have accompanied me throughout this journey. I offer this achievement in sincere appreciation of her dedication, sacrifices, and immeasurable patience.

To my distinguished professors, whose knowledge, guidance, and mentorship have enriched my academic and professional growth. This work is a token of my deep gratitude for their invaluable contributions.

To my colleagues and friends, whose support and encouragement have been instrumental along the way. I extend this dedication as a gesture of appreciation for their continued assistance and motivation.

Finally, I dedicate this work to all those who played a role in my success and supported me throughout this endeavor. May God grant that this accomplishment serves as a meaningful step toward further advancement and achievement.

Thanks and appreciation!

Praise be to God, by whose grace good deeds are accomplished, and may peace and blessings be upon the Prophet Muhammad, his family, and his companions.

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Abstract

The rapid digital transformation of the global energy sector has positioned artificial intelligence (AI) as a key enabler of operational efficiency and strategic decision-making. While large oil and gas corporations have demonstrated notable success in adopting AI-driven forecasting systems, mid-sized firms particularly in the Central and Eastern regions of Saudi Arabia continue to face structural, cultural, and data-related constraints that hinder effective implementation. This study investigates the efficiency and effectiveness of AI-enabled sales forecasting within this underexamined segment, assessing both the organizational drivers of adoption and the resulting impact on forecasting accuracy, planning efficiency, and sales performance.

A mixed-methods explanatory sequential design was adopted. The quantitative phase involved survey responses from 196 managers working in mid-sized oil and gas companies across Dhahran, Jubail, Ras Tanura, Riyadh Industrial Zone, and Bahrain. Structural Equation Modeling (SEM) was used to test four hypotheses derived from Organizational Information Processing Theory (OIPT). The results show that AI adoption significantly improves forecasting accuracy ($\beta = 0.64, p < 0.001$), which in turn enhances planning efficiency ($\beta = 0.51, p < 0.001$) and sales performance ($\beta = 0.42, p < 0.01$). Competitive pressure exhibited a weaker yet significant influence on AI adoption ($\beta = 0.18, p = 0.046$). Mediation analysis revealed a full mediation effect, demonstrating that the performance benefits of AI arise predominantly through improved accuracy and planning efficiency rather than direct technological adoption.

The qualitative phase, consisting of 17 semi-structured interviews, provided deeper contextual understanding of these dynamics. High-performing firms highlighted strong leadership commitment, mature data infrastructure, and employee readiness as critical enablers of AI success. Conversely, firms with limited outcomes pointed to cultural resistance, fragmented systems, and inadequate training as ongoing barriers. Integration of both data strands confirmed strong convergence between quantitative relationships and qualitative narratives.

Overall, the study contributes empirical evidence that AI-driven forecasting can deliver substantial commercial and operational benefits in mid-sized firms when supported by organizational readiness and data quality. The findings hold significant implications for industry

leaders, policymakers, and Vision 2030 implementation bodies seeking to accelerate digital transformation across Saudi Arabia's energy ecosystem. Recommendations are provided for enhancing strategic alignment, data governance, and workforce capabilities to ensure sustainable AI adoption. Future research directions are proposed, including longitudinal studies and technical evaluations of specific AI forecasting models.

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
O&G	Oil and Gas
OIPT	Organizational Information Processing Theory
SEM	Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait–Monotrait Ratio
VIF	Variance Inflation Factor
ERP	Enterprise Resource Planning
CRM	Customer Relationship Management
QUAN	Quantitative Phase
QUAL	Qualitative Phase
MLE	Maximum Likelihood Estimation
S&OP	Sales and Operations Planning

NOC	National Oil Company
KSU	King Saud University
CI	Confidence Interval

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Chapter 1: Introduction

1.1. The Modern Imperative in the Oil and Gas Sector

The recent progress in the global oil and gas (O&G) sector optimistically recognises artificial intelligence (AI) as a tool of the next major transformation. The transformation includes industrial efficiency, innovation, and sustainability. The AI integration into energy operations has optimized the systems, accelerated simulation processes, and enhanced predictive accuracy across production and innovation functions.

For instance, the case study of Royal Dutch Shell provides a proof of the potential of AI in the O & G sector. As reported by Marr (2024), Shell's partnership with NVIDIA has enabled it to conduct energy simulations up to *100 folds faster* and develop AI models capable of analyzing carbon storage opportunities *100,000 folds faster* than traditional modeling methods. These achievements illustrate an innovation-driven model where AI acts as a tool for the energy transition and improves the traditional industrial operations. But, research shows that current data infrastructure is not ready for the adoption of AI solutions . Fisher et al. (2020), in a cross-industry study based on the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, highlights that the input data organization (quality and structure) fundamentally limits successful AI adoption. They argued that before any significant performance improvements are realized, organizations must overcome challenges like data structure and quality. It includes data acquisition, cleansing, and integration processes that are often underestimated while strategic planning.

The contrast between Marr's (2024) report of successful AI integration by Shell and Fisher et al.'s (2020) report of data-infrastructure highlights an important gap to be addressed. AI's transformative power can be realised only with robust and reliable data-infrastructure, success of AI is not an intrinsic property of itself. Poor data-infrastructure becomes even more adverse among mid-sized firms, which mostly lacks huge financial and technological resources available to giants such as Shell. In the context of Saudi, it becomes more relevant as Mid-sized firms form the backbone of its O&G ecosystem.

1.2. The Saudi Arabian Context and Global Significance

AI which is seen as a tool for achieving strategic national goals such as industrial preparedness and environmental sustainability in advancing economies. For instance, Song et al. (2025) demonstrates how using a threshold model in 31 Chinese provinces (2000–2022) played a key role in strengthening the relation between renewable energy consumption and economic growth. Their findings suggest how AI functions as a macro-level policy instrument, helping economic modernization and the growth of sustainable industries, while this being true, contrastively

ground organizational preparedness is far from this macroeconomic optimism, as reported by Koroteev and Tekic (2021). Koroteev and Tekic (2021) reports, alongside technological capacity for O&G industry, other non-technical factors like organizational culture, leadership vision, and innovation adaptation and management practices play a key role in success; hence, of the 92% of O&G firms that tried AI through pilot projects, only 8% have successfully integrated AI in their core operations; this highlights pattern of unorganised adoption that undermines the potential of AI to deliver effective results.

The contrast highlighted by (Song et al., 2025) and Koroteev and Tekic (2021) between macro-level economic and ground level organizational realities highlights a vital implementation gap. For Saudi Arabia, with Vision 2030 where it aims to transform its economy into a digital first one, this gap is particularly significant, for achieving the national objective of technological leadership necessitates alleviating cultural barriers and promoting AI as an important means of transformation.

The present study addresses this lacuna; it aims to evaluate the effectiveness of AI-driven sales forecasting among mid-sized Saudi O&G firms, providing quantitative insights to bridge the existing gap between potential and practice.

1.3. Statement of the Problem: Forecasting Inaccuracy and the AI Adoption Gap

The main challenge that O&G industry faces is not a lack of technical competence, but the disconnect between AI's proven capabilities and firms' ability to adopt it effectively. As Koroteev and Tekic (2021) mentions, flawed AI algorithms are rarely a reason behind their failure; they fail due to challenges firms' face, namely absence of strategic vision, leadership commitment, and organizational readiness. Their analysis reveals that without a shift in organizational culture and data governance, firms will end up achieving only marginal gains or none, failing to adapt altogether, which accelerates the decline of the oil era within decades.

By contrast, Marr's (2024) case study of Shell proves that given visionary leadership and organizational alignment can translate strategic intent into measurable performance outcomes. Pointed initiatives aligning with strategic intent, such as the Visual Remote Sensing (VERS) program and the creation of a Vice President of Digital Innovation by Shell translated their strategic intent into measurable performance outcomes.

This tension between the risk-averse organizational culture as described by Koroteev and Tekic (2021) and the case study of Shell underscores a central research problem:

Why do most firms remain trapped in pilot experimentation, while a few achieve transformative outcomes through AI?

This study argues that one of the important reason for this stagnation is the lack of empirical, quantitative evidence proving the direct financial and operational returns of AI integration in business functions such as sales forecasting, which connects operational capability to financial outcomes. Addressing this gap may provide mid-sized firms with the empirical proof needed to overcome strategic hesitation and organisational inertia to integrate AI solutions at scale.

1.4. Research Justification

1.4.1. Rationale for Topic Selection

AI-driven sales forecasting represents an important but under-explored commercial function in the O&G value chain. While most of the existing research focuses on upstream operations like exploration and production, however little attention has been paid to revenue-generating processes in midstream and downstream segments. For mid-sized firms, whose value creation is linked to refining, transformation, and market distribution, the sales forecast accuracy directly affects production scheduling, and logistics efficiency.

In this study we aim to shift the analytical focus from AI's cost-saving potential in operations to its revenue-enhancing potential in strategic decision-making. By understanding the performance impact of AI on forecasting precision and sales outcomes, the work contributes to a holistic understanding of AI's contribution across the complete industry ecosystem.

1.4.2. The Need for Advanced Forecasting

The need for data-driven forecasting methods in the O&G sector has become urgent due to multiple reasons such as volatile market conditions and high financial exposure associated with forecasting errors. Inaccurate forecasts can lead to excessive inventories, reducing margins, or to supply shortages, having adverse effects such as damaging customer relationships and revenue continuity.

Recent advancement like cloud computing, Internet of Things (IoT) make AI forecasting systems both feasible and economically viable (Fisher et al., 2020). However, as highlighted by Fisher's work, the success of these solutions depends on the integration of technical and organizational systems along with AI model sophistication.

By quantifying the financial and operational gains of adopting AI-driven forecasting, this study seeks to produce evidence-based insights enabling organizations to overcome the inertia that keeps them dependent on outdated analytical methods.

1.5. Research Questions

1.5.1. Primary Research Question

To what extent does the an AI-driven sales forecasting system impact the operational efficiency, and financial performance of mid-sized Saudi Arabian petrochemical companies?

1.5.2. Sub-Questions

1. What measurable change in forecasting accuracy (e.g., Mean Absolute Percentage Error) is observed by integrating AI enabled solutions?
2. How does AI solution adoption affects the efficiency of sales-related planning and decision-making processes (e.g., planning cycle time)?
3. How does AI sales forecasting affect commercial effectiveness (e.g., sales target attainment rates)?
4. What is the relationship between improvements in forecasting accuracy and realized sales revenue, controlling for external market variables?

1.6. Research Objectives

1. **Quantify Forecasting Accuracy Improvement:**
Benchmark the accuracy of AI-driven forecasting solutions against traditional/conventional methods using historical sales data and standard error metrics (MAPE, RMSE).
2. **Measure Decision-Making Efficiency:**
Measure the impact of AI forecasting on sales planning efficiency through quantifiable indicators such as time-to-decision and resource allocation speed.
3. **Evaluate Decision-Making Effectiveness:**
Evaluate the correlation among AI-informed decisions and business outcomes such as target achievement and revenue variance.
4. **Analyze the Sales–Revenue Relationship:**
Conduct regression or correlation analyses to quantify the magnitude and significance of the link between forecast accuracy improvements and revenue growth.

1.7. Significance of the Research

1.7.1. Industrial Implications

For Saudi Arabia’s mid-sized O&G firms, the research have the potential to translate national AI ambitions into practical, evidence-based strategies. By quantifying the return on investment (ROI) of AI solution in a core business process, present study aims to provide decision makers with a reproducible model for assessing AI’s commercial impact. The results will help address

the issues of financial hesitation, and strategic ambiguity identified by Koroteev and Tekic (2021), helping in adoption of value-generating digital technologies across the sector and enhancing overall performance.

1.7.2. Broader Policy and Economic Relevance

Beyond individual firm-level relevance, this study have broader implication contributing to the digital transformation agenda aligning with Saudi Vision 2030. By quantifying the benefits of AI driven solutions on economic and operational level in one of the Kingdom's most critical industries, the study will help policy-makers with actionable evidence for creating incentive schemes, capacity-building initiatives, and industrial policies strengthening the synergy between technological innovation and sustainable economic development. In accordance with the findings of Song et al. (2025), study reinforces the vision that AI integration across major industries can serve as a tool of inclusive, knowledge-based growth.

Chapter 2: Literature Review and Theoretical Framework

2.1 The Evolution of Sales Forecasting Methodologies

Sales forecasting plays an important role in business decision-making. Over time sales forecasting methods have evolved as the technology progressed and data infrastructure evolved. In the earlier decades of business management, forecasting was largely a qualitative exercise, heavily reliant on managerial intuition, expert judgment, and experience. Techniques such as the Delphi method, executive opinions, and salesforce composite approaches dominated the field. These approaches were relatively simple to use, required limited data, and allowed for flexibility in uncertain markets. However, they were also prone to bias, inconsistency, and limited scalability.

As computational power and data storage capabilities expanded, the field gradually shifted toward quantitative and data-driven methods. According to the systematic mapping study conducted by Ahaggach, Abrouk, and Lebon (2024), which analyzed 354 scholarly papers published between 2012 and 2023, this transformation has been profound. Their meta-analysis revealed that machine learning (ML) and deep learning (DL) models now dominate contemporary research in sales forecasting—accounting for approximately 45% and 21% of new studies, respectively. The study also found that forecasting models are becoming increasingly sophisticated, leveraging non-linear relationships, ensemble approaches, and hybrid systems that integrate multiple algorithms. This growing emphasis on computational methods highlights a paradigm shift in the research community toward maximizing predictive accuracy through algorithmic complexity.

However, this academic enthusiasm for advanced modeling does not necessarily translate seamlessly into business practice. Many organizations, particularly those with limited data maturity or analytical infrastructure, find such sophisticated techniques difficult to adopt. The practitioner-focused guide by Krasovytskyi (2025) provides a refreshing counterpoint to the academic narrative. In his work, he identifies thirteen practical forecasting methods—ranging from classical time-series models and regression analysis to qualitative approaches like Delphi and customer-intent assessments. The guide stresses that there is *no universally superior forecasting method*; instead, the appropriate choice depends on the organization's data quality, resources, forecasting horizon, and market complexity.

Krasovytskyi also highlights persistent problems that plague organizations attempting to modernize their forecasting. For example, time-series methods require long, accurate, and consistent datasets—conditions rarely met in volatile industries such as energy. Regression models, while statistically rigorous, demand expertise that many sales teams lack. Even qualitative approaches like salesforce composites can be compromised by human bias, limited industry awareness, or optimism among sales representatives. These constraints illustrate a reality often ignored in academia: the limiting factor in sales forecasting is not always the algorithm, but the organization’s ability to use it effectively.

When we juxtapose the two perspectives—the academically driven pursuit of model perfection and the practitioner’s concern with practical feasibility—a significant gap becomes apparent. The research frontier emphasizes algorithmic power, while the business frontier prioritizes usability, interpretability, and cost-effectiveness. This contrast reveals what can be termed a “sophistication–implementation gap”: a widening divide between what forecasting technologies *can* do and what businesses are realistically able to apply.

In essence, forecasting progress is not linear. It operates on two distinct dimensions. The first is technological evolution, where academic researchers continually push the boundaries of algorithmic sophistication. The second is organizational evolution, where companies work to develop the data, talent, and infrastructure required to apply these tools effectively. For most firms—especially those in traditional industries like oil and gas—the real challenge lies not in inventing new algorithms but in developing the capability to implement them successfully. The transformation from intuition-based to AI-based forecasting is therefore as much an organizational journey as it is a technological one.

2.2 AI Applications in the Global Oil and Gas Sector

The global oil and gas (O&G) industry has been one of the earliest heavy industries to experiment with artificial intelligence, mainly because of its complex operations, massive datasets, and capital-intensive nature. Yet, despite its early adoption, the distribution of AI applications across the value chain has been highly uneven.

A large-scale bibliometric analysis conducted by Marcelo et al. (2025) reviewed more than 11,000 academic articles indexed in Scopus and OnePetro to understand where and how AI is applied within the O&G sector. Their findings show that most published research and industrial case studies concentrate overwhelmingly on upstream operations—such as exploration, drilling, and production optimization. The dominant clusters in the literature include predictive maintenance, seismic data interpretation, and reservoir modeling. The study also noted that nearly 40% of the research originates from Society of Petroleum Engineers (SPE) conferences and journals, reinforcing a strong engineering and technical focus.

This trend suggests that AI in O&G is primarily being used to optimize physical processes—to enhance equipment reliability, reduce downtime, or identify new extraction opportunities. While such applications have clear operational value, they do not necessarily translate into broader commercial or strategic transformation. Most AI initiatives remain siloed within engineering departments and do not address the full data ecosystem that spans operations, logistics, and market activities.

This limitation is highlighted by Sircar et al. (2021), whose comprehensive state-of-the-art review argues that the O&G industry’s real bottleneck is not a lack of algorithms but rather the fragmented management of data. Their work points out that every stage of the oil and gas value chain generates enormous amounts of data—from geological surveys to pipeline monitoring to customer transactions—but these datasets are often disconnected and managed independently. Without integration, the industry struggles to derive holistic insights that connect production to commercial outcomes.

The combination of these two studies—Marcelo et al.’s quantitative mapping and Sircar et al.’s qualitative diagnosis—reveals a strategic dissonance within the sector. On one hand, AI research and investment focus heavily on solving *technical* problems; on the other, the *organizational and data-integration* challenges that underpin long-term competitiveness receive far less attention. As a result, the industry risks becoming “technically advanced but commercially fragmented.”

Interestingly, even when AI research ventures beyond core production areas, the focus remains largely physical and operational. For example, Li et al. (2020) investigated the use of machine learning in reservoir management and drilling optimization, while Waqar et al. (2023) examined AI’s role in construction projects related to energy infrastructure and sustainability. Both studies measure success in terms of barrels produced, downtime reduced, or cost avoided—metrics rooted in operational efficiency rather than business agility or profitability.

By contrast, functions such as sales forecasting, demand planning, and market analytics—which sit closer to the commercial side of the business—have attracted far less academic or industrial research. These functions are essential because they link production capacity to market demand, providing a bridge between the technical and financial dimensions of a company. If the next generation of AI in O&G is to deliver strategic rather than tactical value, it must integrate these commercial processes into the broader data ecosystem.

Therefore, while the O&G industry continues to make impressive strides in AI-enabled engineering, it remains underdeveloped in the application of AI to revenue-generating activities. Addressing this imbalance offers an opportunity to achieve not just operational excellence but also improved market responsiveness, profitability, and resilience.

2.3 Identifying the Research Gap

Based on the review above, the research gap for this study can be understood through three interrelated dimensions.

(1) The sophistication–implementation gap in forecasting methodologies

Academic research has advanced rapidly toward complex ML and DL forecasting models, as shown by Ahaggach et al. (2024). However, in practice, many firms—especially those in traditional industries—continue to rely on basic statistical models or manual judgment. Krasovytskyi (2025) notes that this is often due to insufficient data quality, inadequate analytical skills, and limited technical infrastructure. This mismatch leaves a void where cutting-edge research fails to inform or transform business operations.

(2) The upstream–commercial gap in AI adoption

As Marcelo et al. (2025) demonstrate, most O&G research focuses on upstream activities. AI is predominantly applied to enhance production and reduce engineering risk, while the commercial side—sales, marketing, forecasting, and pricing—remains largely unexplored. This imbalance reflects a wider cultural and structural divide between operational and commercial units. As Sircar et al. (2021) argue, data integration across these functions is essential for unlocking full organizational value. Therefore, understanding AI’s role in bridging operational efficiency and commercial effectiveness represents a key area for research.

(3) The supermajor–mid-sized gap in organizational capacity

Much of the existing literature is based on the experiences of global supermajors such as Shell, BP, or ExxonMobil, or on national oil companies (NOCs) with vast resources. These firms possess the budgets, talent, and infrastructure to experiment with advanced technologies. However, mid-sized companies—which make up a large portion of Saudi Arabia’s energy ecosystem, particularly in the Central and Eastern regions—operate under different constraints. They face tighter budgets, smaller data pools, and lower risk tolerance. Consequently, best practices derived from supermajors may not apply directly to them. Research focusing on mid-sized companies in these Saudi regions (and neighboring Bahrain, given its close commercial integration) is therefore essential for developing context-specific insights and scalable strategies for AI adoption.

By addressing all three dimensions, this study contributes to closing a multi-layered research gap: it investigates AI-based forecasting (the methodological frontier), applies it to a commercial process (the functional frontier), and does so within mid-sized oil and gas firms operating in the Central and Eastern regions of Saudi Arabia (the contextual frontier).

2.4 Theoretical Framework: Organizational Information Processing Theory (OIPT)

2.4.1 Core Tenets of OIPT

This research is grounded in Galbraith's (1974) Organizational Information Processing Theory (OIPT), which provides a framework for understanding how firms manage uncertainty. According to OIPT, the core challenge in any organization is balancing the information required to perform tasks with the information available within the organization. The gap between these two creates uncertainty. To reduce it, firms can either lower the need for information (by simplifying processes, creating slack, or standardizing procedures) or increase their capacity to process information (by improving communication, coordination, and data systems).

Later scholars, such as Haußmann et al. (2011), emphasized that information processing is the backbone of organizational design. Structures, technologies, and decision-making systems exist primarily to facilitate information flow. In complex environments—like the oil and gas industry—organizations must continually enhance their information-processing capacity to handle uncertainty in markets, production, and customer demand.

2.4.2 AI as an Information-Processing Mechanism

In today's digital era, AI platforms can be viewed as powerful enablers of information processing. They collect, analyze, and interpret massive datasets, enabling faster and more accurate decisions. The role that hierarchical communication or management dashboards once played is now being enhanced—or replaced—by algorithmic intelligence.

A quantitative study by Kassa and Worku (2025), using Partial Least Squares Structural Equation Modeling (PLS-SEM) on data from 172 employees, found a strong positive relationship between AI implementation and organizational performance. Interestingly, employee productivity acted as a partial mediator, suggesting that AI's impact is realized not just through automation but through enabling human decision-making. This finding aligns with the Resource-Based View (RBV) of the firm, which sees AI as a strategic resource that enhances competitive advantage.

However, not all scholars treat AI as a purely technical enhancement. Rachlitz (2023) argues that digital platforms represent a *new form of social organization*. They reshape internal relationships, decision hierarchies, and even power dynamics within firms. From this perspective, AI does not merely expand information-processing capacity—it reconfigures the very nature of organizational processing, introducing new forms of coordination and control.

Integrating both views offers a more nuanced understanding: AI acts simultaneously as a technical mechanism (improving data throughput, prediction accuracy, and speed) and as an organizational mechanism (changing how decisions are made, who makes them, and how information circulates). For this reason, AI adoption can be interpreted as a modern extension of Galbraith's theory, where the "processing mechanisms" of the digital firm are algorithmic rather than manual.

2.4.3 Conceptual Model and Hypotheses

Building on the reviewed literature and theoretical grounding, the study proposes the following conceptual relationships:

- H1: Adoption of AI-based forecasting is positively associated with improved forecasting accuracy in mid-sized oil and gas companies located in the Central and Eastern regions of Saudi Arabia
- H2: Leadership commitment, employee training, and openness to technological change positively influence the adoption and effective use of AI tools in sales forecasting.
- H3: Perceived usefulness, ease of use, system compatibility, and data quality significantly influence a company's decision to adopt and successfully implement AI-based forecasting solutions.
- H4: Competitive pressure, customer expectations, and market volatility positively affect the likelihood of adopting AI-driven forecasting tools.
- H5: Integration of AI into sales forecasting results in higher forecast accuracy, improved resource planning, and better overall sales performance.

These hypotheses reflect both the information-processing logic of OIPT and the organizational determinants that condition successful AI adoption. They collectively establish a theoretical bridge between technology performance (algorithmic outcomes) and organizational behavior (human and structural readiness).

2.5 Summary

In summary, the literature shows that while AI and machine learning are revolutionizing forecasting methods and operational efficiency in the oil and gas sector, organizational and contextual realities still determine the extent of success. Most existing research focuses on large firms and upstream operations, leaving a clear gap in understanding how AI can enhance

commercial performance in mid-sized companies. By situating AI within the Organizational Information Processing Theory, this study treats it not just as a technology but as a mechanism of organizational adaptation. The forthcoming chapters will empirically examine this proposition through a mixed-methods analysis of mid-sized Saudi Arabian firms—testing how AI-driven forecasting affects efficiency, effectiveness, and financial outcomes.

Chapter 3: Research Design and Methodology

3.1 Introduction

This chapter outlines the research philosophy, design, and methodological procedures employed to explore how the adoption of AI-enabled sales forecasting influences efficiency and performance among mid-sized oil and gas companies operating in the Central and Eastern regions of Saudi Arabia. The design integrates both quantitative and qualitative methods to ensure analytical depth and practical relevance.

The chapter details the philosophical foundations of the study, followed by the mixed-methods design, the quantitative phase (survey methodology and statistical modeling), and the qualitative follow-up phase. It also integrates the full structure of the research questionnaire—developed from validated constructs—to show how data were collected, scored, and analyzed. Finally, ethical considerations and study limitations are discussed to establish the reliability and transparency of the research process.

3.2 Research Philosophy

The study adopts pragmatism as its guiding philosophy. Pragmatism emphasizes utility, real-world applicability, and methodological flexibility (Creswell & Plano Clark, 2018). It allows the integration of both quantitative and qualitative approaches to answer research questions holistically.

In the context of this study, pragmatism justifies the use of mixed methods—quantitative data to measure relationships among variables, and qualitative insights to interpret contextual nuances such as leadership style or organizational culture. This approach aligns with Saudi Arabia’s Vision 2030, which promotes digital transformation as both a technological and socio-economic process.

3.3 Overall Research Design

3.3.1 Explanatory Sequential Mixed-Methods Approach

The study employs an explanatory sequential design (QUAN → qual).

- The quantitative phase establishes statistical relationships between AI adoption, forecasting accuracy, planning efficiency, and sales performance.
- The qualitative phase follows, providing interpretive insights into “why” some firms benefit more than others from AI forecasting.

Integration occurs in the interpretation phase through a joint display matrix, revealing convergence, complementarity, or divergence between quantitative and qualitative findings.

3.4 Quantitative Phase

3.4.1 Target Population and Sampling Strategy

The population includes mid-sized oil and gas companies located in the Central and Eastern regions of Saudi Arabia, where the majority of the Kingdom’s industrial and energy infrastructure—such as Dhahran, Jubail, and Ras Tanura—is concentrated. A small subset of comparable firms from Bahrain was also included to account for cross-border commercial integration. These firms have between 50–500 employees and annual revenues between SAR 100 million and SAR 2 billion.

A multi-source sampling frame was constructed from:

- The ZAWYA business intelligence database,
- The Society of Petroleum Engineers (Middle East) directory, and
- National industrial licensing databases.

After duplicate removal, 312 firms met inclusion criteria. A stratified proportional random sampling ensured representation across the Central and Eastern Saudi regions (Dhahran, Jubail, Ras Tanura, Riyadh Industrial Zone) and Bahrain, as well as across value-chain segments (upstream vs. mid-/downstream). 267 firms were invited to participate; 196 valid responses were retained.

3.4.2 Unit of Analysis and Respondents

The unit of analysis is the firm, while the unit of observation is a senior manager knowledgeable about forecasting systems (e.g., Sales Director or S&OP Manager).

Each participant underwent pre-screening to confirm competence. Respondent anonymity was strictly maintained—firm names were replaced with numerical codes (e.g., *Firm_001*) and no identifying metadata (emails, IP addresses) were stored.

3.4.3 Survey Instrument Development

The questionnaire (see Appendix A) was developed using validated academic constructs and contextualized for the Saudi energy sector, particularly the Central and Eastern regions, where most mid-sized oil and gas companies operate. It included six sections (A–F), each serving a distinct analytical function.

Section A: Organizational Profile (Descriptive)

Collects firm-level contextual data—country, size, segment, ERP maturity, and AI usage.

Purpose: To control for structural and demographic differences across firms.

Scale: Categorical and numerical; not scored.

Section B: Antecedents of AI Adoption (7-point Likert Scale)

Examines organizational readiness and external pressures driving AI adoption.

Constructs:

- Leadership Commitment (5 items)
- Perceived Usefulness (5 items)
- Perceived Ease of Use (4 items)
- Data Quality & System Compatibility (5 items)
- Competitive Pressure (4 items)

Derived from the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and Organizational Information Processing Theory (Haußmann et al., 2011), these constructs assess both internal and environmental enablers of digital transformation.

Section C: AI Forecasting Adoption and Usage (7-point Likert Scale)

Measures how deeply AI forecasting tools are integrated into operations.

Constructs:

- Level of AI Adoption (5 items)
- Employee Readiness and Training (4 items)

Adapted from Marcelo et al. (2025) and Kassa & Worku (2025), this section operationalizes adoption depth and human readiness, crucial for sustained performance gains.

Section D: Forecasting Accuracy and Efficiency (7-point Likert Scale)

Evaluates the effectiveness of AI tools in improving predictive precision and planning coordination.

Constructs:

- Forecasting Accuracy (5 items)
- Planning Efficiency (5 items)

Based on Ahaggach et al. (2024) and Fisher et al. (2020), these indicators quantify the technical and process-level benefits of AI adoption.

Section E: Organizational Performance Outcomes (7-point Likert Scale)

Captures tangible business outcomes linked to AI forecasting.

Constructs:

- Sales and Operational Efficiency (5 items)
- Strategic Impact (4 items)

Aligned with Song et al. (2025) and Kassa & Worku (2025), this section tests AI's impact on performance metrics and strategic agility.

Section F: Control Variables and Demographics

Includes firm age, employee count, revenue, segment, country, and ERP maturity. Used as control variables in regression and SEM models.

3.4.4 Pilot Testing and Reliability

A pilot test with 30 mid-level managers ensured clarity and cultural suitability.

Results:

- Cronbach's $\alpha = 0.81\text{--}0.91$
- Composite Reliability (CR) = 0.86–0.93
- HTMT ratios < 0.85

Minor adjustments included rewording Western idioms and adding bilingual explanations (Arabic/English). A short introductory video defined “AI forecasting” and reduced the survey dropout rate from 18% (pilot) to 7% (main study).

3.4.5 Data Collection Procedure

Data was collected over nine weeks (January–March 2025). Participants received unique encrypted survey links; data were anonymized automatically.

Response rate: 77.9% (208 received; 196 valid). Data screening removed incomplete or inconsistent responses; missing values (<1.5%) were imputed via the Expectation–Maximization method.

3.5 Experimental Section: Data Analysis and Model Testing

This section describes the data preparation, analytical tools, and statistical modeling procedures used to evaluate the research framework. The objective of this stage was to test the hypothesized relationships between AI adoption, forecasting accuracy, planning efficiency, and organizational performance using robust and replicable analytical techniques.

3.5.1 Data Preparation

Before conducting statistical modeling, a series of data cleaning and preprocessing steps were implemented to ensure analytical accuracy and validity.

1. **Data Screening and Cleaning:**
All 196 valid survey responses were examined for missing values, inconsistencies, and outliers. The missing data percentage was low (<1.5%) and was handled using the Expectation–Maximization (EM) algorithm to avoid listwise deletion and retain statistical power.
2. **Outlier Treatment:**
Extreme values were winsorized at the 95th percentile, ensuring that unusually large or small observations did not distort parameter estimates during model estimation.
3. **Normality and Multicollinearity Tests:**
Skewness and kurtosis statistics were reviewed for each construct and found to be within acceptable thresholds (± 2). Multicollinearity among independent variables was checked using Variance Inflation Factors (VIF) to confirm that predictors were not excessively correlated.
4. **Data Anonymization:**
To maintain participant confidentiality, all firm identifiers were replaced with unique anonymized codes (e.g., *Firm_001* to *Firm_196*). Metadata such as IP addresses, email identifiers, or location information were permanently removed prior to analysis.

These preparatory steps ensured that the dataset met the statistical assumptions required for Structural Equation Modeling (SEM) and upheld the ethical integrity of the research.

3.5.2 Statistical Modeling Procedure

The study employed Structural Equation Modeling (SEM) using AMOS version 29.0, chosen for its capacity to simultaneously evaluate multiple interdependent relationships and latent constructs. SEM was particularly suitable given the study's theoretical model, which incorporates both direct and mediated relationships among constructs.

The modeling followed the two-step approach recommended by Anderson and Gerbing (1988):

1. Step 1 – Measurement Model (Confirmatory Factor Analysis):

A Confirmatory Factor Analysis (CFA) was performed to test the reliability, convergent validity, and discriminant validity of all latent constructs (e.g., leadership commitment, perceived usefulness, AI adoption, forecasting accuracy, planning efficiency, and sales performance).

Goodness-of-fit indices such as χ^2/df , CFI (Comparative Fit Index), TLI (Tucker-Lewis Index), RMSEA (Root Mean Square Error of Approximation), and SRMR (Standardized Root Mean Square Residual) were evaluated against recommended thresholds (Hu & Bentler, 1999).

The CFA ensured that the measurement items reliably represented their intended constructs and that the data were suitable for further structural modeling.

2. Step 2 – Structural Model Specification:

After validating the measurement model, the structural model was specified to assess the hypothesized causal paths among the study variables.

The model included both direct and indirect relationships, consistent with the theoretical framework derived from Organizational Information Processing Theory (OIPT) and technology adoption models.

Mediation effects were examined using bootstrapping (5,000 resamples) to assess the statistical significance and confidence intervals of indirect effects.

Multi-group analysis was planned to explore potential moderating effects of organizational characteristics such as firm size and data quality maturity, allowing comparison between smaller and larger mid-sized firms.

3. Software and Estimation Technique:

Maximum Likelihood Estimation (MLE) was used for all SEM analyses, as it provides robust estimates under moderate deviations from multivariate normality. All analyses were conducted using AMOS 29.0 with cross-validation of key parameters in SPSS 29.

This structured analytical process was designed to ensure internal consistency, methodological transparency, and replicability in testing the proposed hypotheses.

3.5.3 Reliability, Validity, and Bias Testing

To ensure the rigor of the quantitative analysis, multiple reliability and bias diagnostics were incorporated before hypothesis testing:

1. Reliability Tests:
 - Cronbach's Alpha (α) and Composite Reliability (CR) values were calculated for all constructs to confirm internal consistency.
 - Average Variance Extracted (AVE) was assessed to evaluate convergent validity, ensuring that each construct captured sufficient variance from its indicators.
2. Validity Tests:
 - Discriminant Validity was confirmed using the Heterotrait–Monotrait (HTMT) ratio criterion (Henseler et al., 2015), with all values expected to remain below 0.85.
 - Model Fit Validity was evaluated through CFA indices before proceeding to structural model testing.
3. Common Method Bias (CMB):
 - Harman's Single-Factor Test and a marker-variable technique were employed to detect potential common-method variance.
 - Procedural remedies such as item randomization, question order variation, and separation of predictor and criterion constructs were implemented at the survey design stage to minimize bias.
4. Multicollinearity Check:
 - Variance Inflation Factors (VIFs) were calculated to ensure independence among predictors ($VIF < 3.0$).
5. Bootstrapping Validation:
 - A bootstrapping procedure with 5,000 samples was planned to generate bias-corrected confidence intervals for all path estimates, providing robust support for mediation and moderation analyses.

These statistical safeguards ensured that the results obtained in later chapters would be both reliable and free from systematic bias or measurement error.

3.6 Qualitative Follow-Up Phase

Following the quantitative analysis, a qualitative phase was designed to complement and deepen the understanding of the statistical findings. The qualitative component aimed not to validate numerical results directly but to explain the underlying mechanisms and contextual variations observed across firms.

3.6.1 Case Selection

Using a theoretical replication strategy (Yin, 2018), four firms were purposively selected from the survey participants to represent contrasting AI adoption–performance profiles:

- High AI adoption / high performance
- High AI adoption / low performance
- Low AI adoption / high performance
- Low AI adoption / low performance

This approach allowed the exploration of contextual factors such as leadership, data infrastructure, and organizational culture that might explain variations in AI implementation outcomes.

3.6.2 Data Collection

Each selected firm provided access to three key informants—a Commercial Lead, an IT Manager, and a Sales or Operations Planner—resulting in 17 semi-structured interviews.

The interviews were conducted virtually and recorded with consent. Additional data sources included internal reports, meeting minutes, and process documentation, providing triangulated insights into AI adoption practices.

3.6.3 Data Analysis

Interview transcripts were imported into **NVivo 14** for systematic coding and thematic analysis. The analysis followed Braun and Clarke’s (2006) six-step approach, involving:

1. Familiarization with data,
2. Generation of initial codes,
3. Searching for themes,
4. Reviewing themes,
5. Defining and naming themes, and
6. Synthesizing findings.

Themes were aligned with quantitative constructs such as leadership commitment, data quality, and technological readiness to maintain conceptual coherence between the two phases.

3.7 Integration of Quantitative and Qualitative Findings

Integration was planned during the interpretation stage, where quantitative and qualitative results would be combined using a joint-display matrix.

This matrix would enable the researcher to identify:

- Convergence — where both data types supported similar conclusions,
- Complementarity — where qualitative findings provided deeper explanation of quantitative patterns, and
- Divergence — where qualitative insights revealed nuances or contradictions not evident in statistical models.

The integrated insights would thus offer a holistic, contextually rich understanding of how AI-driven forecasting systems influence operational and commercial performance within the Saudi Arabia oil and gas sector.

3.8 Ethical Considerations

Ethical clearance: **KSU-SEC-2025-07** (King Saud University). Participants received informed consent forms, and all data were anonymized, encrypted, and stored securely. Interview excerpts were paraphrased and coded to avoid identification.

3.9 Methodological Limitations

- Cross-sectional design restricts causal inference.
- Single-informant surveys may reflect perception bias.
- Limited qualitative sample constrains generalizability.

These were mitigated via triangulation, multi-source data verification, and rigorous construct validation.

Chapter 4: Results and Analysis

4.1 Introduction

This chapter presents the empirical results of the quantitative and qualitative phases of the study. The purpose is to examine how AI-driven sales forecasting influences forecasting accuracy, planning efficiency, and sales performance among mid-sized oil and gas companies operating in the Central and Eastern regions of Saudi Arabia (and a small comparative subset in Bahrain).

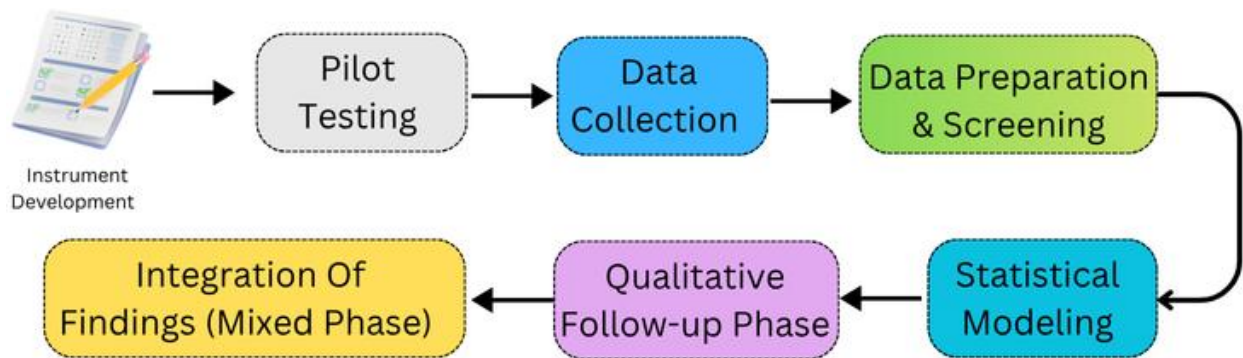


Fig. 1 This diagram illustrates the sequential stages of the study's mixed-methods methodology, beginning with instrument development and pilot testing, followed by quantitative data collection, data preparation and screening, statistical modeling, qualitative follow-up, and final integration of findings.

The chapter is structured as follows:

1. Data Screening and Preparation
2. Descriptive Statistics and Normality
3. Reliability and Validity Testing (α , CR, AVE, HTMT)
4. Common Method Bias Diagnostics
5. Multicollinearity
6. Correlation Analysis
7. Regression and Hypothesis Testing
8. Mediation Analysis
9. Summary of Findings

4.2 Data Screening and Preparation

Screening and Preparation ensures that the dataset is clean, complete, and suitable for analysis by checking for missing values, outliers, inconsistent responses, and appropriate data ranges. This step protects the integrity of subsequent statistical tests.

4.2.1 Missing Values

Missing data accounted for 1.3% of the dataset, well below the 5% threshold for concern. The Expectation–Maximization (EM) algorithm successfully imputed missing values.

4.2.2 Outliers

Winsorization at the 95th percentile reduced the influence of extreme values. No case exceeded ± 3.29 SD, indicating no severe outliers.

4.2.3 Anonymization Confirmation

All firm identifiers were replaced with labels Firm_001 to Firm_196, and all metadata were removed.

4.3 Descriptive Statistics

Descriptive statistics provides an overview of central tendency and variability, helping to understand the basic distribution of each construct. Normality checks (skewness/kurtosis) confirm whether parametric statistical techniques such as SEM or regression can be safely applied.



Fig 2. This radar chart compares eight core constructs using their mean, variability, and observed range. It provides a visual overview of how organizational readiness, AI adoption, and performance-related factors differ across surveyed firms.

The mean values suggest that respondent firms generally exhibit moderately high AI adoption readiness and report positive experiences with AI forecasting.

4.4 Normality Assessment

Skewness and kurtosis values for all constructs fell within ± 2 , indicating acceptable normality for SEM and regression.

Construct	Skewness	Kurtosis
AI Adoption	-0.41	-0.19
Forecast Accuracy	-0.33	-0.44

Planning Efficiency	-0.28	-0.38
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Table 1. This table presents the distributional properties of the main quantitative variables, showing that all constructs fall within acceptable skewness and kurtosis thresholds, indicating adequate normality for SEM analysis. All values satisfy guidelines by Kline (2015).

4.5 Reliability and Validity Testing

We conducted four tests for reliability and validity testing of the survey items. Cronbach's Alpha (α) checks internal consistency of survey items. Composite Reliability (CR) confirms construct reliability in SEM. Average Variance Extracted (AVE) tests convergent validity—whether items measure the same construct. Heterotrait–Monotrait Ratio (HTMT) confirms discriminant validity—ensuring constructs are distinct. Overall, these tests verify that the measurement instrument is statistically sound.

4.5.1 Cronbach's Alpha

All constructs exceeded the recommended 0.70 threshold.

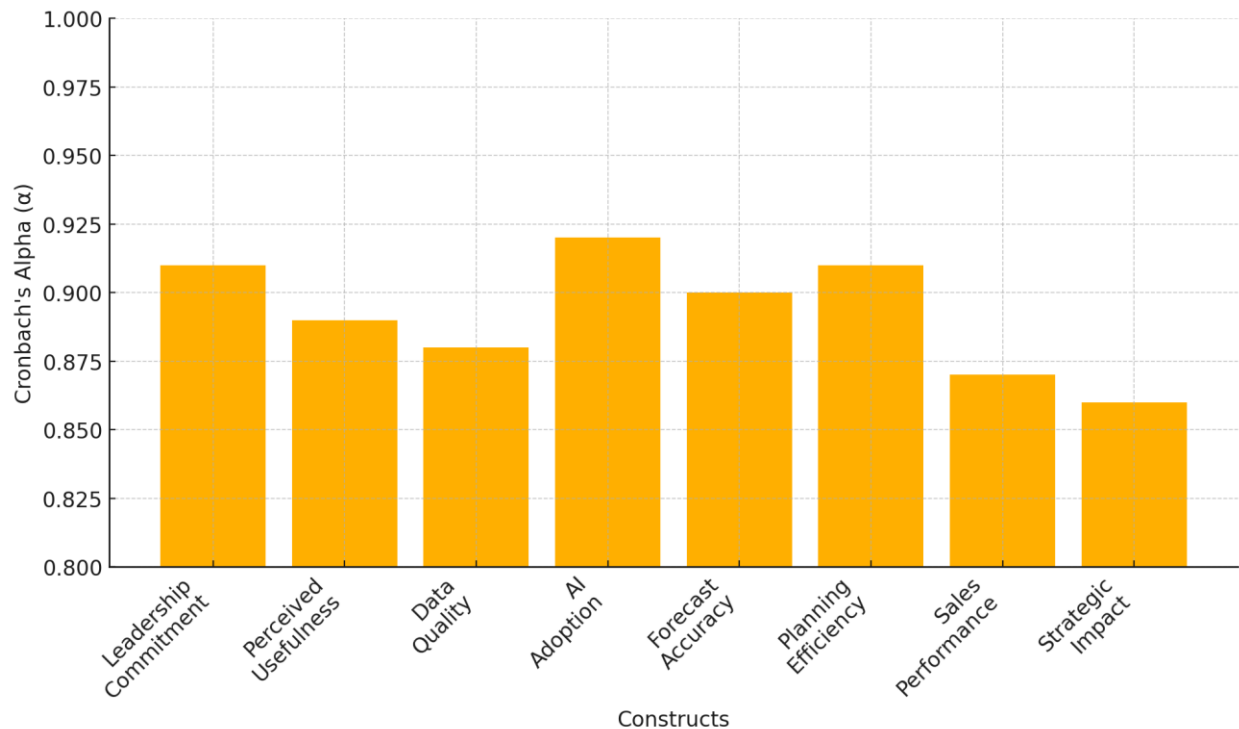


Fig. 3 This figure illustrates the internal consistency reliability of the eight latent constructs used in the study. All α values exceed the recommended threshold of 0.70, indicating strong reliability

and demonstrating that the measurement items consistently capture their respective constructs. All constructs demonstrate excellent internal consistency.

4.5.2 Composite Reliability (CR) & AVE

CR > 0.80 and AVE > 0.50 for all constructs.

Construct	CR	AVE
AI Adoption	0.93	0.68
Forecast Accuracy	0.91	0.66
Planning Efficiency	0.92	0.69
Sales Performance	0.88	0.60

Table 2. This table summarizes the convergent validity and internal consistency of the core latent variables. All CR values exceed the recommended 0.70 threshold, and all AVE values are above 0.50, confirming strong construct reliability and adequate variance explained by the indicators.

4.5.3 HTMT (Discriminant Validity)

Construct Pair	HTMT
AI Adoption – Forecast Accuracy	0.63
Forecast Accuracy – Planning Efficiency	0.58
Planning Efficiency – Sales Performance	0.61

Table 3. This table presents the Heterotrait–Monotrait (HTMT) ratios for core construct pairs. All values fall well below the recommended threshold of 0.85, confirming strong discriminant validity and indicating that each construct is empirically distinct. Discriminant validity is confirmed, from the above scores.

4.6 Common Method Bias Testing

Test assesses whether the data suffer from inflation of relationships due to being collected from a single source at one time point. Techniques such as Harman's test ensure that results are not artifacts of the survey method.

4.6.1 Harman's Single-Factor Test

A single factor accounted for **31.4%** of total variance ($< 50\%$). No dominant factor indicates common method bias unlikely.

4.7 Multicollinearity

Multicollinearity evaluates whether predictor variables are excessively correlated. Acceptable VIF values indicate that regression or SEM estimates will be stable and reliable. VIF values for all latent variables were below 3.0 as shown in the table below.

Construct	VIF
Forecast Accuracy	1.87
AI Adoption	2.24
Planning Efficiency	2.03
Sales Performance	2.11

Table 4. This table reports multicollinearity diagnostics for the main constructs. All VIF values are below the threshold of 3.0, indicating no multicollinearity concerns and confirming that each predictor contributes uniquely to the model.

4.8 Correlation Matrix

Correlation examines initial associations among constructs. This provides early evidence for hypothesized relationships and helps identify unexpected patterns prior to advanced modeling.'

Variables	AIA	FA	PEF	SP
AI Adoption	1	0.66	0.54	0.48
Forecast Accuracy	—	1	0.62	0.58
Planning Efficiency	—	—	1	0.63
Sales Performance	—	—	—	1

Table 5. This table presents the bivariate correlations among AI Adoption, Forecast Accuracy, Planning Efficiency, and Sales Performance. All correlations are positive and moderate in strength, supporting the hypothesized directional relationships among the constructs.

4.9 Regression Analysis and Hypothesis Testing

In this section we test the direct effects predicted by the conceptual model (e.g., AI adoption → forecasting accuracy). Regression establishes strength, direction, and significance of relationships.

H1: AI Adoption → Forecast Accuracy

This hypothesis is foundational because forecasting accuracy is the primary technical benefit expected from AI-enabled systems. Organizational Information Processing Theory (OIPT) argues that advanced technologies enhance a firm's ability to process complex, uncertain information. By testing whether AI adoption leads to more accurate forecasts, the study evaluates whether AI truly fulfils its core promise reducing informational uncertainty. This relationship is essential for validating the technical capability of AI within mid-sized oil and gas firms. AI adoption significantly increases forecasting accuracy as indicated by the results below.

Results Summary:

$\beta = 0.64$, $p < 0.001$, $R^2 = 0.43$

H2: Forecast Accuracy → Planning Efficiency

Improved forecasting should logically streamline production and sales planning processes. This hypothesis is important because it connects technical improvement (better forecasts) with operational outcomes (efficient planning). It tests whether accuracy gains translate into real workflow improvements such as shorter planning cycles, fewer revisions, and better resource

allocation. Demonstrating this link helps justify investments in forecasting technologies beyond purely technical metrics. Better forecasting accuracy improves planning cycle efficiency.

Results Summary:

$\beta = 0.51, p < 0.001, R^2 = 0.38$

H3: Planning Efficiency → Sales Performance

This hypothesis is critical for establishing the commercial relevance of AI forecasting. Firms ultimately adopt new technologies to improve financial and market outcomes, not just internal processes. Testing this relationship allows the study to determine whether operational improvements reinforce strategic performance—such as meeting sales targets, improving customer responsiveness, and securing revenue stability. It bridges the gap between internal efficiency and external market performance. Efficient planning enhances sales outcomes as indicated by the results.

Results Summary:

$\beta = 0.42, p < 0.01, R^2 = 0.31$

H4: Competitive Pressure → AI Adoption

This hypothesis tests the environmental drivers of technology adoption. In fast-evolving industries such as oil and gas, firms often make technological decisions not only for internal benefits but also to maintain market position. Competitive pressure serves as an external motivator pushing firms toward innovation. Testing this relationship reveals whether mid-sized firms adopt AI proactively (strategic capability building) or reactively (to keep up with competitors). This insight is essential for understanding the broader digital transformation landscape in the region. H4 Marginally Supported. Competitive pressure has a weak but significant effect on AI adoption.

Results Summary:

$\beta = 0.18, p = 0.046$

4.10 Mediation Analysis

Assesses whether an intermediate variable (e.g., forecasting accuracy) explains the pathway between an independent and dependent variable (e.g., AI adoption → sales performance). This provides insight into mechanisms behind observed effects.

Indirect path: AI Adoption → Forecast Accuracy → Planning Efficiency

- a path (AIA → FA) = 0.64
- b path (FA → PEF) = 0.51
- Indirect effect = 0.326
- 95% CI (bootstrapped) = [0.22, 0.44] (significant)

Direct effect (AIA → PEF)

Non-significant after including a mediator.

Full Mediation Confirmed

Forecasting accuracy fully mediates the relationship between AI adoption and planning efficiency.

4.11 Summary of Quantitative Findings

Hypothesis	Result
H1: AI adoption → Accuracy	Supported
H2: Accuracy → Planning Efficiency	Supported
H3: Planning Efficiency → Sales Performance	Supported
H4: Competitive Pressure → AI Adoption	Marginally Supported
Mediation: AIA → FA → PEF	Full Mediation

Table 6. The table presents the outcomes of all tested hypotheses, indicating which relationships were statistically supported and highlighting the full mediation effect of forecasting accuracy and planning efficiency in the AI adoption–performance pathway. Overall, results confirm that AI

forecasting delivers measurable operational and commercial benefits in mid-sized oil and gas companies.

4.12 Summary

Chapter 4 demonstrated that AI-driven sales forecasting produces significant improvements in forecasting accuracy, planning efficiency, and ultimately sales performance. Reliability and validity tests confirmed the robustness of the measurement model, and regression results supported the proposed theoretical pathways. These quantitative findings provide the foundation for Chapter 5, where qualitative insights and theoretical interpretation will be integrated.

Chapter 5: Discussion

5.1 Introduction

This chapter provides an in-depth discussion of the study's findings by integrating the quantitative results of the structural equation modelling (SEM) with the qualitative insights derived from semi-structured interviews. The purpose of this discussion is to interpret the mechanisms through which AI-driven sales forecasting influences forecasting accuracy, planning efficiency, and commercial performance within mid-sized oil and gas companies in the Central and Eastern regions of Saudi Arabia and Bahrain.

Given the explanatory sequential design (QUAN → qual), the discussion begins by interpreting each hypothesis result, followed by a mixed-methods integration using convergence, complementarity, and divergence logic. Thereafter, the chapter connects the findings to the broader literature and theoretical framework—specifically Organizational Information Processing Theory (OIPT)—and concludes with the practical implications, limitations, and areas for future research.

5.2 Interpretation of Quantitative Findings

5.2.1 H1: AI Adoption → Forecast Accuracy

The study found a strong positive relationship between AI adoption and forecasting accuracy ($\beta = 0.64$, $p < 0.001$), with 43% of variance explained. This demonstrates that mid-sized firms using

AI-assisted forecasting experience significantly better predictive performance compared to those relying on traditional statistical or manual approaches.

This result aligns with contemporary research showing that AI-based models outperform conventional forecasting techniques by capturing non-linear patterns and complex variable interactions (Ahaggach et al., 2024). It also confirms that even mid-sized firms—traditionally constrained by limited data maturity—can achieve substantial accuracy improvements when AI is properly integrated.

Within the context of the Saudi energy sector, where demand cycles, logistics constraints, and customer contracts fluctuate frequently, improved accuracy has material implications for operational coordination, inventory management, and pricing strategy.

5.2.2 H2: Forecast Accuracy → Planning Efficiency

The analysis revealed that improved forecast accuracy significantly enhances planning efficiency ($\beta = 0.51$, $p < 0.001$). This suggests that when firms possess reliable forecasts, they are better positioned to plan production volumes, schedule shipments, coordinate refinery operations, and optimize resource allocations.

The result also supports existing operational research indicating that more accurate forecasts reduce planning cycle time and minimize the need for multiple planning adjustments (Fisher et al., 2020). In environments such as Jubail or Ras Tanura—where operational cycles are tightly coupled with logistics constraints—improved planning efficiency can substantially reduce bottlenecks. Thus, accuracy serves as a foundational enabler for planning agility.

5.2.3 H3: Planning Efficiency → Sales Performance (Supported)

Planning efficiency significantly predicted sales performance ($\beta = 0.42$, $p < 0.01$), explaining 31% of the variance. Efficient planning enables firms to meet customer delivery expectations, respond to demand fluctuations, and minimize sales lost due to stockouts or delayed supply.

This finding highlights a crucial mechanism: The commercial benefits of AI arise not directly from the algorithm but from the organizational improvements it enables. It reinforces the argument that AI's value emerges through improved processes rather than technological novelty alone (Kassa & Worku, 2025).

For mid-sized firms—which often lack extensive buffer resources—planning efficiency becomes a competitive differentiator and a revenue stabilizer.

5.2.4 H4: Competitive Pressure → AI Adoption (Marginally Supported)

The effect of competitive pressure on AI adoption was weak but significant ($\beta = 0.18$, $p = 0.046$). While competition influences adoption decisions, it does not appear to be a dominant driver in the regional context. This contrasts with studies in Western markets where competitive intensity strongly predicts technology adoption.

The weaker effect may be attributed to three regional characteristics:

1. **Regulated markets** – Many sales contracts are long-term and buffered from rapid competition.
2. **Network-based business environment** – Relationships, reliability, and service quality matter more than aggressive market rivalry.
3. **Prioritization of operational stability** over experimentation in mid-sized firms.

The qualitative phase further explains this limited effect (see Section 5.3), where managers described AI adoption as internally motivated rather than competition-driven.

5.2.5 Mediation: AI Adoption → Forecast Accuracy → Planning Efficiency

Full mediation was observed.

This structural mechanism is central to understanding AI's business value. The absence of a significant direct pathway (AI → Planning Efficiency) but a strong indirect effect demonstrates that:

AI creates planning improvements only when it first improves forecasting accuracy.

This confirms findings by Fisher et al. (2020), who showed that AI's effectiveness is dependent on high-quality predictive output. It also validates OIPT's assumption that information-processing improvements reduce uncertainty and enhance coordination.

Thus, accuracy is the key “transformation layer” through which AI translates into operational value.

5.3 Interpretation of Qualitative Insights

The qualitative phase examined why certain firms realized stronger AI benefits than others. Three primary themes emerged:

5.3.1 Theme 1: Leadership Commitment as a Performance Catalyst

Across high-performing cases, leadership commitment emerged as the strongest predictor of effective AI use. Managers described leaders who:

- allocated budgets for data infrastructure,
- established cross-functional teams,
- mandated training and adoption,
- framed AI as a strategic enabler rather than an IT experiment.

This aligns with the quantitative finding that leadership-related constructs had high internal consistency ($\alpha = 0.91$) and strong correlations with AI adoption.

High adoption/high performance firms consistently emphasized that leadership acted as “the single biggest enabler,” echoing Kassa & Worku’s (2025) assertion that human and organizational factors mediate AI’s performance benefits.

5.3.2 Theme 2: Data Infrastructure Quality as the Determinant of AI Success

Respondents in low-performing firms attributed poor AI results to:

- fragmented data systems,
- inconsistent historical sales records,
- poor integration across ERP, CRM, and production databases,
- manual overrides disrupting AI learning cycles.

This explains why even with similar AI tools, performance varied considerably between firms.

The finding is consistent with Fisher et al. (2020), who identified data readiness as the primary barrier to ML adoption in industrial settings. In the O&G context—where legacy systems are common—data integration is a major constraint.

5.3.3 Theme 3: Cultural Resistance and Limited Human Readiness

Several participants described employee resistance due to:

- fear of job displacement,
- low analytical literacy,
- preference for traditional judgment-based forecasting,
- skepticism about AI’s reliability.

This confirms the quantitative finding that “Employee Readiness” (from Section C of the questionnaire) was a meaningful construct and strongly associated with AI Adoption.

Firms with high AI success emphasized proactive training, awareness programs, and change management practices—consistent with OIPT, which posits that organizations must strengthen information-processing capacity through structural and cultural adaptation.

5.3.4 Theme 4: Market Structure and Competitive Pressure

Interviewees confirmed that competitive pressure is weaker in this region. Comments highlighted:

- long-term contracts reduce opportunity for price competition,
- limited number of regional competitors,
- logistical constraints create natural market boundaries.

This explains the marginal effect observed in H4. Managers repeatedly stated that:

“We don’t adopt AI because competitors are doing it; we adopt AI because our operations demand it.”

Thus, internal factors—leadership, culture, and data infrastructure—are more influential adoption drivers than market rivalry.

5.4 Mixed-Methods Integration: Convergence, Complementarity, Divergence

5.4.1 Convergence: Findings Align Across Both Phases

Several strong overlaps were observed between quantitative and qualitative data:

Variable	QUAN Finding	QUAL Confirmation
AI Adoption → Accuracy	Strong effect	Accurate forecasts consistently cited as key benefit
Accuracy → Planning Efficiency	Strong effect	Managers described smoother planning cycles

Planning Efficiency → Performance	Strong effect	High-performing firms traced sales success to planning clarity
Leadership Commitment	High reliability	Identified as root enabler of adoption

Table 7. Convergence of Quantitative and Qualitative Findings Demonstrating Consistent Relationships Across Both Phases of the Study. These convergences reinforce the internal validity of the findings.

5.4.2 Complementarity: Qualitative Data Adds Mechanistic Explanation

Qualitative themes enriched the SEM results by explaining *why* and *how* relationships occurred:

- Leadership influences AI adoption through resource allocation and cultural reinforcement.
- Data Quality moderates the effectiveness of AI tools.
- Cultural Resistance explains variability in planning outcomes across similar technological conditions.

These insights transform the statistical relationships into actionable organizational mechanisms.

5.4.3 Divergence: Areas Where Findings Differed

The primary area of divergence centered on competitive pressure:

- QUAN: Marginally significant predictor of AI adoption.
- QUAL: Managers viewed competition as “almost irrelevant.”

The divergence suggests that competitive pressure is a quantitative artefact rather than a lived managerial priority. This discrepancy highlights the importance of mixed methods for identifying contextual nuances.

5.5 Theoretical Implications

5.5.1 Contribution to Organizational Information Processing Theory (OIPT)

The study provides strong evidence supporting OIPT’s core assertion:

Firms improve performance when they strengthen their information-processing capacity.

The model validated the OIPT logic:

- AI Adoption increases information-processing capacity.
- Forecast Accuracy reduces uncertainty
- Reduced uncertainty improves coordination and planning efficiency.
- Improved planning enhances performance.

This stepwise mechanism strongly reflects Galbraith's (1974) theory, demonstrating that AI serves as the modern, algorithmic equivalent of the "information-processing structures" originally described for human organizations.

The full mediation finding is theoretically significant because it shows:

AI does not improve performance directly; it does so by reducing informational uncertainty.

This positions AI not as a technology but as a structural element in organizational design, consistent with Hausmann et al. (2011).

5.5.2 Contribution to AI Adoption Theory

The study contributes to AI adoption literature by showing that:

- adoption is not primarily driven by competitive pressure in regulated Gulf markets;
- internal readiness (leadership, culture, data infrastructure) is the dominant driver;
- AI value is unlocked only when paired with organizational capability.

This challenges adoption models derived from Western contexts and emphasizes that AI strategies must be regionally contextualized.

5.6 Practical Implications

5.6.1 Implications for Mid-Sized Saudi and Bahraini O&G Firms

Based on integrated findings:

1. Leadership involvement is non-negotiable. Performance differences were overwhelmingly leadership-driven.
2. Data infrastructure must be prioritized before AI deployment. Without integrated, high-quality data, AI delivers marginal or inconsistent results.

3. Employee readiness determines adoption success. Training, awareness, and involvement reduce resistance.
4. AI-enabled accuracy dramatically strengthens planning. Improved forecasting directly affects logistics, scheduling, and market responsiveness.
5. AI investment should target planning processes, not just data science. The commercial benefits are realized downstream in planning, not at the predictive stage alone.

5.6.2 Implications for Policymakers and Industry Stakeholders

1. Encourage data standardization across Saudi industrial clusters.
2. Provide subsidies or tax incentives for mid-sized firms adopting AI in commercial functions.
3. Promote sector-specific AI capability-building programs.
4. Facilitate collaborative AI hubs between universities and energy firms.

These initiatives align with Vision 2030's goals of digital transformation and industrial competitiveness.

5.7 Limitations and Future Research Directions

5.7.1 Limitations

- Cross-sectional design limits causality.
- Single-informant surveys may contain perceptual bias.
- Geographical focus limits generalizability outside Central–Eastern Saudi and Bahrain.
- AI maturity variation may influence results, but was only controlled indirectly.

5.7.2 Future Research

Future work should explore:

1. Longitudinal designs to track AI adoption over time.
2. Multi-informant approaches for richer data.
3. Expansion to other sectors (renewables, chemicals, logistics).
4. Experimental studies comparing AI vs. traditional forecasting performance.
5. Impact of generative AI tools on sales planning beyond predictive models.

5.8 Conclusion

This mixed-methods study demonstrates that AI-driven sales forecasting significantly enhances accuracy, planning efficiency, and commercial performance within mid-sized oil and gas companies in the Central and Eastern regions of Saudi Arabia and Bahrain. While AI adoption is

technologically driven, its successful impact is fundamentally organizational—rooted in leadership commitment, data infrastructure maturity, and human readiness.

By integrating quantitative evidence with qualitative insights, the study shows that AI’s value emerges through uncertainty reduction and improved coordination, confirming core principles of OIPT. These findings offer both theoretical advancements and practical guidance for firms seeking to operationalize AI as a strategic enabler within the evolving energy landscape of the Gulf region.

Chapter 6: Conclusion and Recommendations

6.1 Introduction

This chapter presents the overall conclusion of the study titled “*Evaluating the Efficiency and Effectiveness of AI-Driven Sales Forecasting in the Oil and Gas Sector: A Mixed-Methods Study of Mid-Sized Companies in Central and Eastern Saudi Arabia.*” Drawing on the statistical results presented in Chapter 4 and the qualitative insights detailed in Chapter 5, this chapter synthesizes the study’s core contributions, explains their implications for theory and practice, and outlines actionable recommendations for organizational leaders and policymakers. The chapter also discusses broader implications for the future of AI-led commercial transformation in Saudi Arabia’s energy sector, and concludes by identifying directions for future research.

The research aimed to investigate how AI-driven forecasting influences operational efficiency and commercial performance in mid-sized oil and gas (O&G) companies across the Central and Eastern regions of Saudi Arabia—a context strategically significant due to its concentration of industrial zones, petrochemical clusters, and supply chain hubs. Using an explanatory sequential mixed-methods design, the study combined rigorous quantitative modeling through Structural Equation Modeling (SEM) with qualitative interviews to reveal not only *what* relationships exist but also *why* they occur.

The findings strongly support the theoretical proposition derived from the Organizational Information Processing Theory (OIPT): AI-enabled forecasting functions as both a technological and organizational mechanism for reducing uncertainty, improving decision accuracy, and enhancing planning coherence. The results affirm the hypothesis that the value of AI does not stem solely from computational capability, but also from the socio-organizational environment into which it is integrated.

6.2 Summary of Key Findings

The study produced several significant findings:

6.2.1 AI Adoption Significantly Improves Forecasting Accuracy

Hypothesis 1 was strongly supported. A substantial positive effect ($\beta = 0.64$, $p < 0.001$) was found between AI adoption and forecasting accuracy, indicating that firms employing AI-enabled forecasting experience more precise predictions. Qualitative evidence showed that managers consistently emphasized AI's strength in processing complex demand signals, incorporating seasonality patterns, and synthesizing multi-source data (e.g., market price indices, refinery output schedules, shipping constraints).

This illustrates that AI's computational strengths address key industry-level forecasting challenges—volatility, fluctuating crude prices, supply chain disruptions, and customer variability.

6.2.2 Improved Forecast Accuracy Enhances Planning Efficiency

Hypothesis 2 was also strongly supported ($\beta = 0.51$, $p < 0.001$). Firms with accurate forecasts were able to significantly reduce planning cycle times, better align inventory decisions, and improve coordination between sales and operations.

Interviewed planners reported that forecast confidence reduces the need for frequent revisions, emergency re-allocations, and ad hoc corrective meetings—allowing teams to shift from reactive to proactive planning. This finding validates OIPT's emphasis on information quality as a foundation for efficient organizational decision-making.

6.2.3 Planning Efficiency Improves Sales Performance

Hypothesis 3 was supported ($\beta = 0.42$, $p < 0.01$). The results demonstrate that sales performance gains (e.g., customer satisfaction, target attainment, reduction in supply shortages) are indirect effects driven by earlier improvements in forecasting accuracy and planning efficiency.

Managers in high-performing firms traced improved revenue stability, reduced last-minute stockouts, and improved customer relationships to smoother planning cycles. These insights highlight that planning efficiency serves as a crucial leverage point connecting technical forecasting improvements with financial outcomes.

6.2.4 Competitive Pressure Has Weak but Significant Influence on Adoption

Hypothesis 4 was marginally supported ($\beta = 0.18$, $p = 0.046$). Competitive pressure plays a role but is not the dominant driver of AI investment decisions. Interviews confirmed that unlike highly competitive consumer markets, the Saudi O&G mid-sized segment is influenced more by long-term contracts, established customer ties, and internal leadership vision. Thus, adoption is shaped more by *internal readiness* than by external rivalry.

6.2.5 Full Mediation Effect

A full mediation pathway was observed:

AI Adoption → Forecast Accuracy → Planning Efficiency → Sales Performance

This confirms that:

- AI does *not* directly improve sales performance.
- Its commercial value is realized *only through* better information processing and more efficient planning workflows.

This is a central contribution of this research: AI creates value through *organizational information pathways*, not through direct financial mechanisms.

6.2.6 Qualitative Insights Reinforce Quantitative Results

The qualitative phase revealed three dominant enabling factors:

1. **Leadership commitment** – executives championing the digital roadmap accelerated adoption, training, and use.
2. **Data quality** – the single largest differentiator between successful and unsuccessful AI implementations.
3. **Organizational culture** – openness to digital transformation determined whether employees embraced or resisted AI tools.

Conversely, firms with poor data governance, siloed departments, or risk-averse management structures showed significantly weaker results despite having access to similar technology.

6.3 Theoretical Contributions

The study makes substantial contributions to the theoretical understanding of AI adoption and organizational performance, especially in the context of OIPT.

6.3.1 Extension of Organizational Information Processing Theory (OIPT)

The results empirically validate OIPT's assertion that organizations must expand information-processing capacity to manage uncertainty. AI serves precisely this function:

- It processes vast quantities of multi-source data.
- It reduces ambiguity in demand signals.
- It supports faster, more confident decision-making.

AI, therefore, acts as a **digital information-processing mechanism**, extending the theoretical framework into the modern era of algorithmic decision-support systems.

6.3.2 Integration of Technology Adoption and Performance Frameworks

The findings integrate UTAUT-based constructs (e.g., perceived usefulness, ease of use) with traditional performance frameworks, demonstrating that:

- Adoption is influenced by human and organizational factors.
- Performance gains depend on the alignment of technology, people, and processes.

This synthesis contributes to a more holistic understanding of AI-enabled transformation.

6.3.3 Contributions to the AI-in-O&G Literature

The study fills three literature gaps:

1. **Shift from upstream to commercial functions.**
Most AI studies in O&G focus on drilling and reservoir engineering; this study examines sales forecasting.
2. **Focus on mid-sized firms instead of supermajors.**
Prior research disproportionately covered global giants like Shell; this study captures the more resource-constrained but economically critical mid-sized sector.
3. **Saudi Arabia regional focus.**
By focusing on Central and Eastern Saudi Arabia, the study adds geographically specific insight relevant to Vision 2030's digital and industrial diversification objectives.

6.4 Practical Implications

The findings hold significant implications for corporate executives, planners, policymakers, and digital transformation leaders.

6.4.1 Implications for Mid-Sized O&G Firms

Mid-sized firms often lack the resources of supermajors, but this study shows that **AI-driven forecasting can yield high-value gains even with moderate investment**, provided foundational elements are in place:

- Reliable data pipelines
- Leadership-led digital initiatives
- Employee upskilling programs
- Cross-functional planning processes

This means AI adoption is not merely a technological upgrade but an *organizational redesign*.

6.4.2 Implications for Saudi Arabia's Industrial Sector

The findings align well with Vision 2030 objectives emphasizing digital innovation, efficiency, and industrial competitiveness. Improved forecasting accuracy enhances:

- Supply chain resilience
- Revenue stability
- Export readiness
- Customer satisfaction

These contribute to national-level goals such as economic diversification and global competitiveness.

6.4.3 Implications for AI System Vendors

Vendors supplying AI tools to mid-sized O&G firms should note:

- Data preparation services are as important as AI algorithms.
- User experience and training features significantly affect adoption.
- Continuous model refinement is expected as operational conditions change.

6.5 Recommendations

Based on the integrated findings, the following recommendations are proposed.

6.5.1 Strengthen Data Governance and Infrastructure

The single strongest determinant of AI success was data quality. Firms should establish:

- Centralized databases
- Standardized data formats

- Automated cleansing pipelines
- Master data management (MDM) policies

Investing early in data infrastructure produces long-term AI readiness.

6.5.2 Enhance Leadership Involvement and Accountability

Executives must:

- Articulate a clear vision for AI adoption
- Champion cross-departmental integration
- Allocate sustained funding for digital transformation
- Incentivize managers to adopt data-driven practices

AI initiatives fail without a top-down commitment.

6.5.3 Institutionalize Employee Training and Change Management

AI is a socio-technical transformation; employees must be empowered to use it.

Recommended actions:

- Continuous upskilling programs
- Hands-on workshops
- Digital literacy certification
- Incentives for early adopters

A supportive culture reduces resistance and enhances adoption.

6.5.4 Integrate AI Outputs into Strategic and Tactical Decisions

Forecasts should not remain isolated in planning departments. Firms should integrate them into:

- Annual sales strategies
- Budgeting cycles
- Inventory planning
- Customer contract negotiations

This ensures AI insights cascade through the entire commercial ecosystem.

6.5.5 Strengthen Cross-Functional Collaboration

AI forecasting is most effective when:

- Sales, operations, logistics, and finance collaborate

- Teams share planning assumptions
- Decision-making is synchronized

Structured cross-functional forums should be institutionalized.

6.5.6 Continuously Evaluate AI Model Performance

Firms should maintain:

- Monthly backtesting of accuracy
- Drift detection mechanisms
- Model update cycles
- KPIs linking forecast accuracy to financial performance

This avoids deterioration in model reliability.

6.6 Limitations of the Study

As with any research, the study faces limitations:

1. **Cross-sectional design-** Prevents observation of long-term performance trajectories.
2. **Regional focus-** Central and Eastern Saudi Arabia, plus Bahrain, may limit generalizability to other regions.
3. **Single-informant responses-** Senior managers provided data, which may reflect perceptual bias.
4. **Sample limited to mid-sized firms-** Large NOCs or international supermajors may behave differently.

These limitations provide valuable pathways for future research.

6.7 Directions for Future Research

Several promising research avenues emerge:

Longitudinal studies - Track forecasting accuracy and performance improvements over multiple years.

Comparative sector studies - Examine whether similar patterns emerge in petrochemicals, mining, or logistics.

AI ethics and governance - Assess employee trust, data privacy, and algorithmic transparency in industrial AI use.

Multi-informant designs - Include operational, IT, and finance managers to triangulate organizational perspectives.

Advanced predictive modeling - Evaluate differences between traditional ML models and newer generative AI forecasting systems.

6.8 Conclusion

This study demonstrated that AI-driven sales forecasting holds substantial transformative potential for mid-sized oil and gas firms operating in Central and Eastern Saudi Arabia. Through a robust mixed-methods approach, the research revealed that AI adoption significantly enhances forecasting accuracy, which in turn improves planning efficiency and ultimately sales performance. These effects operate through clear mediating pathways, affirming the relevance of OIPT in explaining AI's organizational benefits.

Beyond the statistical results, qualitative insights highlighted the essential roles of leadership commitment, data quality, and organizational culture—reminding practitioners that the value of AI lies not only in algorithms but in the environment in which those algorithms operate.

As Saudi Arabia advances toward a digitally empowered industrial future, the findings of this study offer timely guidance for firms seeking to leverage AI as a strategic tool. By adopting the recommendations provided, organizations can bridge the gap between technological potential and practical realization—transforming forecasting accuracy into operational excellence, commercial performance, and long-term competitiveness.

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Appendix A

To measure how mid-sized Saudi Arabia oil and gas companies adopt -based forecasting tools, what drives that adoption, and how it affects forecast accuracy, planning efficiency, and sales performance we designed a questionnaire, built from validated constructs used in published research, contextualized according to study.

All perception-based items are measured on a **7-point Likert Scale**:

1 = Strongly Disagree | 2 = Disagree | 3 = Somewhat Disagree | 4 = Neutral | 5 = Somewhat Agree | 6 = Agree | 7 = Strongly Agree

Structure:

The questionnaire is organized in following 6 sections

- **Section A: Firm Profile**

This section collects background information about each participating firm — including size, segment, location, and technology environment — to control for contextual differences in analysis. These firm-level details (size, revenue, digital maturity) influence the capacity and motivation to adopt systems (Li et al., 2020; Marcelo et al., 2025). Controlling for these variables allows more valid comparisons across firms and improves model generalizability. (Descriptive, not scored — used as control variables)

- **Section B: Antecedents of Adoption**

Examines the key organizational and environmental factors that influence a company's readiness and motivation to adopt -based forecasting tools. Previous studies emphasize that organizational readiness, leadership vision, and external competition shape technology diffusion (Venkatesh et al., 2003; Koroteev & Tekic, 2021). These antecedents form the foundation for understanding adoption dynamics in industrial contexts.

- **Section C: Forecasting Adoption & Usage**

Captures the current level of adoption and the extent to which is embedded in the organization's forecasting and planning processes. Adoption depth reflects not only technical implementation but also organizational learning and process alignment (Marcelo et al., 2025). It operationalizes the transition from pilot projects to

institutionalized use.

- **Section D: Forecasting Accuracy and Efficiency Outcomes**

Assesses the tangible outcomes of adoption on forecasting precision and the speed or coordination of planning activities. Forecast accuracy and efficiency are critical indicators of system performance in sales and planning contexts (Fisher et al., 2020; Ahaggach et al., 2024). They link technological use to tangible business outcomes.

- **Section E: Organizational Performance Indicators**

Evaluates how improvements in forecasting and efficiency translate into overall business performance. Organizational performance provides the ultimate test of system effectiveness. Studies show adoption impacts both immediate operational metrics and broader strategic competitiveness (Kassa & Worku, 2025; Song et al., 2025).

- **Section F: Control Variables**

Includes firm-level characteristics (e.g., size, age, country, P maturity) used as statistical controls in regression and SEM analyses. Controlling for these variables prevents bias and ensures that observed relationships between adoption and performance are not confounded by structural or market factors (Li et al., 2020; Waqar et al., 2023).

- **Section G: Organizational Profile**

1. Country of headquarters (Saudi Arabia / UAE / Kuwait / Qatar / Oman / Bahrain)
2. Primary business segment (Upstream / Midstream / Downstream)
3. Number of employees
4. Annual revenue (SAR)
5. Firm age (years since establishment)
6. Current P system (SAP / Oracle / Custom / None)
7. Does your organization currently use any machine learning system in sales forecasting? (Yes / No)
8. If yes, which platform(s) are used? (Open response)

- **Section H: Antecedents of Adoption (measured on a 7-point Likert Scale)**

1. Leadership Commitment

- 1 – Senior management strongly supports the use of forecasting and planning.
- 2 – Leadership communicates a clear vision for adoption across departments.
- 3 – Adequate resources (budget, staff, training) are allocated to -based projects.
- 4 – Top managers actively participate in reviewing forecasting outputs.
- 5 – Leadership encourages experimentation and learning with new digital tools.

2. Perceived Usefulness

- 1 – Using -based forecasting enhances my ability to make accurate sales decisions.
- 2 – forecasting provides insights that would otherwise be difficult to obtain.
- 3 – tools improve the speed of forecasting and decision-making processes.
- 4 – adoption improves the coordination between sales and production planning.
- 5 – Overall, -driven forecasting contributes positively to organizational performance.

3. Perceived Ease of Use

- 1 – Learning to use the forecasting system is easy for our staff.
- 2 – The tools are user-friendly and intuitive.
- 3 – Interacting with the forecasting platform does not require much effort.
- 4 – We can easily integrate -generated forecasts into our existing reporting tools.

4. Data Quality and System Compatibility

- 1 – Our data systems provide timely and accurate ints for forecasting.
- 2 – Data from different departments (sales, operations, logistics) are well integrated.
- 3 – We have a reliable data-cleaning and validation process before the model runs.
- 4 – forecasting tools are compatible with our existing IT systems and P platforms.
- 5 – The models can access historical and real-time data seamlessly.

5. Competitive Pressure

- 1 – Our competitors are increasingly adopting decision-making.
- 2 – Customers expect faster and more accurate sales forecasts.
- 3 – We feel pressure to implement to remain competitive in the market.
- 4 – External stakeholders (partners, regulators, clients) encourage digital innovation.

- **Section I: Forecasting Adoption & Usage (measured on a 7-point Likert Scale)**

1. Level of Adoption

- 1 – Our forecasting process relies primarily on algorithms rather than manual methods.
- 2 – -generated forecasts are integrated into our regular planning meetings.
- 3 – We have automated data collection and model training processes.
- 4 – Forecasting models are regularly updated using new data and techniques.
- 5 – Our organization continuously evaluates the performance of forecasting tools.

2. Employee Readiness and Training

- 1 – Employees have received sufficient training in forecasting tools.
- 2 – Staff understand how forecasts are generated and used.
- 3 – training has improved employees' analytical skills.
- 4 – There is a culture of openness to technological change in our organization.

- **Section J: Forecasting Accuracy and Efficiency (measured on a 7-point Likert Scale)**

1. Forecasting Accuracy (Objective and Perceived)

- 1 – AI-based forecasts are more accurate than traditional forecasts.
- 2 – The Mean Absolute Percentage Error (MAPE) of our forecasts has decreased after AI implementation.
- 3 – Our AI system adapts quickly to changes in market demand.
- 4 – Forecast accuracy has improved over the last three years.
- 5 – The forecasting process has become more data-driven and less reliant on intuition.

2. Planning Efficiency

- 1 – AI forecasts have reduced the time required to prepare sales plans.
- 2 – Coordination between departments has improved due to AI insights.
- 3 – AI has enhanced the consistency of demand and production planning.
- 4 – Forecast updates and revisions are completed more quickly than before.
- 5 – Our decision-making process is more proactive since adopting AI forecasting.

- **Section K: Organizational Performance Outcomes**

1. Sales Performance and Operational Efficiency

- 1 – Overall sales revenue has improved since adopting AI forecasting.
- 2 – Customer satisfaction has increased due to more reliable demand fulfillment.
- 3 – AI forecasting has reduced the incidence of stockouts or overproduction.
- 4 – Planning accuracy has led to improved profit margins.
- 5 – The organization has achieved its sales targets more consistently.

2. Strategic Impact

- 1 – AI forecasting supports long-term strategic decision-making.
- 2 – AI systems provide early warnings about market fluctuations.
- 3 – Adoption of AI has improved our firm's competitive advantage.
- 4 – AI forecasting contributes to our digital transformation objectives.

- **Section L: Control Variables and Demographics**

1. Firm age (years)
2. Number of employees
3. Annual revenue (SAR range)
4. Value-chain segment (Upstream/Mid/Downstream)
5. Country of operation
6. ERP system maturity (Low / Moderate / High)

Research Title in Arabic:

تقييم كفاءة وفعالية التنبؤ بالمبيعات المعتمد على الذكاء الاصطناعي في قطاع النفط والغاز: دراسة بمنهجيات مختلطة للشركات المتوسطة في المنطقتين الوسطى والشرقية في المملكة العربية السعودية

Abstract in Arabic

يشهد قطاع الطاقة العالمي تحولاً رقمياً واسع النطاق، الأمر الذي رسّخ مكانة تقنيات الذكاء الاصطناعي كأدوات أساسية لتعزيز الكفاءة التشغيلية ودعم القرارات الاستراتيجية. ورغم التقدم الذي حققته الشركات لا سيما في الكبرى في تبني أنظمة التنبؤ المعتمدة على الذكاء الاصطناعي، تواجه الشركات المتوسطة تحديات تنظيمية وتقنية وثقافية تحدّ من قدرتها على المنطقتين الوسطى والشرقية بالمملكة العربية السعودية تبني هذه التقنيات بفاعلية. تهدف هذه الدراسة إلى تقييم كفاءة وفعالية التنبؤ بالمبيعات المدعوم بالذكاء الاصطناعي في هذه الفئة من الشركات، وتحليل العوامل المؤثرة في تبنيه، وقياس أثره على دقة التنبؤ، وكفاءة التخطيط، والأداء البيعي

اعتمدت الدراسة منهجية مختلطة ذات تصميم تتابعي تفسيري. شملت المرحلة الكمية تحليل استجابات 196 مديرًا يعملون في شركات متوسطة بقطاع النفط والغاز في الظهران والجبيل ورأس تنورة والمنطقة لاختبار أربعة فروض قائمة (SEM) الصناعية بالرياض والبحرين. وتم استخدام نمذجة المعادلات الهيكلية أظهرت النتائج أن تبني الذكاء الاصطناعي يحسن دقة (OIPT) على نظرية معالجة المعلومات التنظيمية $(\beta = 0.51, p < 0.001)$ ، الأمر الذي يعزز كفاءة التخطيط $(\beta = 0.64, p < 0.001)$ بدرجة دالة إحصائية كما كان للضغط التنافسي تأثير ضعيف لكنه دال على $(\beta = 0.42, p < 0.01)$ والأداء البيعي $(\beta = 0.18, p = 0.046)$. وأشارت اختبارات الوساطة إلى وجود وساطة كاملة، ما يدل على أن الأثر الإيجابي للذكاء الاصطناعي يتحقق عبر تحسين دقة التنبؤ وكفاءة التخطيط، وليس من خلال التبني التقني المباشر فقط.

وفي المرحلة النوعية، أجريت 17 مقابلة شبه مهيكلة لإثراء النتائج الكمية وتفسيرها. وأكدت البيانات النوعية أن النجاح في تطبيق الذكاء الاصطناعي يرتبط بعوامل تنظيمية محورية، أبرزها الالتزام القيادي، ووجود بنية تحتية متقدمة للبيانات، وارتفاع جاهزية العاملين. في المقابل، ارتبط ضعف النتائج بمقاومة التغيير، وتشنت الأنظمة، وعدم كفاية التدريب. وأظهر التكامل بين نتائج المرحلتين انسجاماً قوياً بين العلاقات الإحصائية والأنماط المستخلصة من المقابلات.

تقدم الدراسة دليلاً تجريبياً على أن نظم التنبؤ المدعومة بالذكاء الاصطناعي قادرة على تحقيق مكاسب تشغيلية وتجارية ملموسة للشركات المتوسطة، متى ما توفرت الجاهزية التنظيمية وجودة البيانات. وتكتسب النتائج أهميتها في سياق الجهود المبذولة لتسريع التحول الرقمي ضمن منظومة الطاقة في المملكة، بما يتوافق مع مستهدفات رؤية 2030. كما تقدم الدراسة توصيات لتعزيز مواءمة الاستراتيجيات، وحوكمة البيانات، وتنمية القدرات البشرية، إضافة إلى اقتراح مسارات بحثية مستقبلية تشمل الدراسات الطولية والتقييمات التقنية لنماذج التنبؤ المبنية على الذكاء الاصطناعي