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ENTERPRISE ARCHITECTURE MATURITY AND AI-DRIVEN AUTOMATION STRATEGIES FOR DIGITAL TRANSFORMATION IN INDIA'S OIL AND GAS INDUSTRY

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Abstract

Digital transformation in the oil and gas sector necessitates a solid architectural foundation with capacity for integrating and scaling new technologies like Artificial Intelligence (AI), cloud infrastructure, and data analytics. This research explored the principal contribution of Enterprise Architecture (EA) maturity in driving the adoption and scaling of an AI-driven automation strategy in India's energy sector. Utilizing a hybrid EA assessment scheme encompassing an integration of The Open Group Architecture Framework (TOGAF) with the India Enterprise Architecture (IndEA) blueprint proposed by the Ministry of Electronics and Information Technology (MeitY), four major companies were subjected to assessment: Oil and Natural Gas Corporation (ONGC), Indian Oil Corporation Limited (IOCL), Hindustan Petroleum Corporation Limited (HPCL), and Reliance Industries Limited; in the business, application, data, and technology architecture areas. A five-point scale was used, where Reliance scored the highest overall maturity (4.75) and HPCL the lowest (2.25). A strong positive correlation between EA maturity ($\rho = 0.88$) and scaled applications of AI like predictive maintenance, digital twinning modeling, intelligent document processing, and cognitive supply chain optimization was established in the case study outcome. Reliance Industries emerged as a business champion of digitization with transformative-level architecture, while public sector undertakings reflected mixed maturity levels, commonly limited by legacy infrastructure and siloed data environments.

***Index Terms*—** Enterprise Architecture Maturity, Artificial Intelligence, Oil and Gas Industry, Digital Transformation, Predictive Maintenance

I. INTRODUCTION

INDIA'S oil and gas sector is at the cusp of a great revolution brought about by the expanding energy security need, environmental demands for Sustainability, and operational agility [1,2]. As energy markets become increasingly unpredictable and ecological standards more demanding, the sector can no longer rely on traditional practices involving manual heavy interventions, siloed Information Infrastructure, and reactive maintenance practices [3,4]. For oil and gas businesses operating in India to be competitive and sustainable in a fast-changing world scenario, they cannot but accept digital transformation as a strategic necessity [5]. This transformation is not about adopting an individual technology but reimagining the overall organizational and technological basis underlying business operations [6,7]. At the center of this revolution lies the notion of Enterprise Architecture (EA); a disciplined method of

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holistically aligning an enterprise's business mission with its Information Technology (IT) infrastructure, data infrastructure, and application environment [8]. A mature EA forms a basis for holistically integrating new-age technologies like Artificial Intelligence (AI), Internet of Things (IoT), blockchain, and advanced analytics into enterprise business operations [9,10]. It injects consistency, interoperability, modularity, and governance across processes and allows companies to adapt more quickly and precisely in the context of changes in the market. Conversely, siloed or infantile architectures lead to disconnected systems, duplicative workflows, and poor insight into data with limited potential for digital resources to bring about real change [11,12].

In the context of India's oil and gas sector, which includes both large public sector undertakings and agile private enterprises, the level of EA maturity varies significantly [13-15]. Many organizations continue to operate legacy systems that inhibit digital innovation, while others are taking proactive steps to modernize their technology stack [16,17]. This uneven landscape has created a situation where some companies are rapidly advancing with AI-enabled operations such as predictive maintenance, digital twins, and autonomous monitoring. In contrast, others struggle to scale pilot projects beyond initial experimentation [18-20]. The ability to adopt and expand these technologies is increasingly tied to the structural readiness of the enterprise itself. Artificial Intelligence, in particular, is emerging as a key enabler of automation and efficiency across the energy value chain. From upstream exploration to downstream distribution, AI-driven strategies can optimize asset performance, enhance safety protocols, reduce downtime, and streamline supply chains [21,22]. However, the integration of AI requires not just access to algorithms or computing power, but also well-defined business processes, clean and accessible data, and interoperable applications, all of which depend on the strength of the underlying EA [23,24].

Furthermore, the transition toward digital operations is influenced by broader national and global trends, including sustainability targets, digital policy frameworks, and market pressures for greater transparency and accountability [25,26]. EA provides a mechanism through which organizations can align these external demands with internal capabilities, ensuring that technology investments translate into tangible outcomes [27]. A strong EA also enables cross-departmental collaboration, encourages data-driven decision-making, and enables continuous innovation [28,29]. At this dynamic juncture, gaining insight into the contribution of EA maturity becomes essential for steering digital transformation agendas, particularly in capital-intensive industries such as oil and gas [30,31]. An organization's architecture maturity dictates whether it can effectively incorporate current and future forms of intelligent automation into day-to-day business, react promptly to disruption driven by new business models or ecosystems, and scale innovations along its value chain efficiently [32,33]. For this reason, harmonizing AI adoption with architectural growth is not a purely technological choice but a strategic one with the potential to determine the future course of the entire industry over a defined timespan [34,35].

This study aims to examine the relationship between EA maturity and the adoption of AI-driven automation strategies within India's oil and gas industry. Focusing on major enterprises and evaluating EA maturity across business, application, data, and technology domains using a

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hybrid TOGAF and IndEA-based framework. It identifies key AI use cases and assesses how architectural readiness influences the scalability of intelligent automation. The scope extends to proposing a transformation roadmap aligned with national policy frameworks, offering practical insights for advancing digital maturity across both public and private sector energy enterprises.

This study contributes a sector-specific EA maturity model tailored to India's oil and gas industry, linking it to the scalability of AI-driven automation strategies. By evaluating four leading enterprises, it establishes a strong correlation between architectural maturity and successful AI adoption, particularly in core operational domains. The research offers a practical framework for diagnosing digital readiness, identifying high-impact use cases, and guiding strategic investments, thereby providing a replicable model for digital transformation in other asset-intensive sectors.

The remaining sections of this study are organized as follows: Section II reviews relevant literature on EA maturity models and AI-driven automation in the energy sector. Section III outlines the research methodology, including the hybrid EA assessment framework. Section IV presents the findings from the maturity evaluation and AI use case deployment across selected enterprises. Section V concludes the study with a summary of key contributions and suggests directions for future research.

II. Literature Review

This review of literature synthesizes recent research focused on evaluating enterprise architecture maturity models. Al-Hajri et al., (2025) [36] implemented a digital transformation strategy framework for the Oil and Gas (O&G) industry with a focus on Sustainability. This study looked at the challenges that oil and gas companies in Qatar and other hydrocarbon-dependent nations encounter when trying to embrace digital transformation. Critical obstacles to digital transformation were identified through a qualitative case study method, including semi-structured interviews with industry experts. These included organizational resistance to change, cybersecurity concerns, a shortage of skilled workers, and the complexities of incorporating new technologies with legacy systems. Similarly, Rudra et al., (2025) [37] proposed a unified framework for the O&G industry using AI and Big Data Analytics to improve the precision of price forecasts, introduce dynamic pricing, and maximize their marketing efforts. For accurate oil price prediction, the suggested framework used state-of-the-art machine learning methods, such as hybrid deep learning models and Long Short-Term Memory (LSTM) networks. By utilizing hybrid deep learning architectures, the AI models were able to reach a Mean Absolute Percentage Error (MAPE) of 8.7 percent, and experimental evaluations showed a 30% improvement over traditional techniques of forecasting. Furthermore, Al et al., (2025) [38] investigated the use of AI in the United Arab Emirates (UAE)'s oil and gas industry, with special attention to the difficulties encountered at the operational, project management, and executive levels. The research was carried out utilizing an interpretivist technique and consisted of three phases. The oil and gas industry in the UAE was surveyed using semi-structured interviews with operational engineers, project managers, and senior executives. Researchers utilized theme analysis to analyze the results after collecting enough data. Because AI is still in its infancy in this industry, the study found that a lessons-

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learned strategy was necessary. However, Judijanto et al., (2025) [39] analysed the qualitative literature on the topic of palm oil and the ways digital technologies and AI could revolutionize the industry. Using a thematic analysis, researchers were able to pinpoint the most significant ways in which AI and digital tools were changing the sector, with a focus on four main areas: supply chain traceability, precision agriculture, environmental monitoring, and labor productivity. The results showed that AI applications greatly improve yield optimization with advanced machine learning and remote sensing algorithms, supply chain transparency with blockchain and NLP, and environmental compliance with satellite monitoring and detection of emissions.

Khan et al., (2024) [40] analysed how the oil and gas industry's spare parts storage system incorporates Industry 4.0 technology like the Industrial Internet of Things (IIoT). Analysis of frequency and content served as the framework for the investigation. The objective was to provide a theoretical groundwork that might guide the industry in finding future solutions. A long list of advantages of implementation was compiled from the available literature. A strong preference for limited and controlled adoption of certain technologies was suggested by the list of difficulties, which was especially relevant to the oil and gas industry. The analysis suggested areas for future research and found gaps in existing literature. Likewise, Onyeme et al., (2023) [41] identified the industry's unique needs by conducting a thorough and methodical literature review. In order to help this industry successfully implement Industry 4.0, this study looked at the upstream O&G sector and found research gaps that need to be filled. According to the analysis of 19 chosen Industry 4.0 Maturity Models (MMs), the current MMs were not tailor-made for the oil and gas upstream sector. Moreover, AlNuaimi et al., (2020) [42] blended Green Business Process Management (GBPM) with the preexisting procedures of O&G firms. This study employed the analytical hierarchy approach and data derived from a survey of twelve strategy experts from four O&G businesses to rank the primary and secondary enablers behind GBPM. Results reveal that among the enablers, strategy and management were ranked highest, while governance was placed lowest. The most important strategy enabler was the ability to measure green metrics; the most important sub-enablers were changes to duties and engagement from management in the strategy formulation process.

Elijah et al., (2021) [43] examined oil and gas (O&G) market volatility and the influence of COVID-19 on oil demand decline. To accomplish this, researchers first reviewed the I4.0 framework, and then they conducted a systematic literature assessment, covering articles from 2012 to 2021. A total of 223 papers were examined. Some parts of the upstream industry were already tested using I4.0 technology. The I4.0 technologies that were least investigated include Virtual Reality and additive manufacturing. Lastly, Zuliansyah et al., (2020) [44] provided an approach for estimating EA in the upstream petroleum sector. A Systematic Literature Review (SLR) in conjunction with structured interviews formed the basis of the methodology. Researchers used a modified System Usability Scale (SUS) that takes agility, durability, effectiveness, and efficiency into account when conducting interviews. It was determined from the evaluation findings that the EA implementation still did not meet the usability requirement. Because of this, companies should keep working to improve EA, which means picking and using small, particular components.

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Most existing studies on EA maturity and digital transformation in the oil and gas sector adopt fragmented approaches, relying heavily on either qualitative interviews or secondary data without integrating comprehensive enterprise-level analysis or aligning with national digital frameworks [36, 38, 41]. There is a noticeable absence of sector-specific maturity models that account for the structural and operational nuances of the oil and gas industry, particularly in the upstream segment [41, 44]. Research often highlights AI implementation but rarely examines the connection between AI adoption outcomes and the maturity of EA, which limits the ability to assess readiness for scaling intelligent solutions [37, 40]. Several studies overlook the critical role of interoperability and the challenges posed by legacy systems and siloed data infrastructures, which continue to hinder enterprise-wide digital integration [36, 43]. Moreover, key architectural dimensions such as modularity, data governance, and coherence across business, application, data, and technology layers are either underexplored or inconsistently evaluated [42, 44]. These limitations restrict the applicability of existing frameworks for guiding strategic digital transformation in complex, asset-intensive industries like oil and gas.

III. METHODOLOGY

This study adopts a qualitative, exploratory research design to examine the relationship between EA maturity and AI-driven automation strategies within the Indian oil and gas industry. The objective is to identify how varying levels of EA maturity influence the adoption, scalability, and integration of AI technologies across upstream, midstream, and downstream operations. The methodology employed in this study combines framework-based assessment, industry case analysis, and secondary data synthesis. The approach consists of three key phases:

Phase I: Enterprise Architecture Maturity Assessment

To evaluate the EA maturity levels of selected oil and gas enterprises in India, the study employs a hybrid maturity model integrating the principles of TOGAF and India's national framework, IndEA Framework, developed by the Ministry of Electronics and Information Technology. The maturity criteria are categorized into five progressive levels: Initial (Ad hoc), Developing (Defined), Established (Integrated), Advanced (Optimized), and Transformative (Innovative). Each level is assessed based on four architecture domains: Business, Application, Data, and Technology, aligned with capability dimensions such as interoperability, governance, modularity, data integration, and stakeholder alignment.

Enterprise case profiling was conducted for four major companies: ONGC, IOCL, HPCL, and Reliance Industries, drawing from their annual reports, digital strategy documents, public disclosures, and third-party industry analyses as shown in Table 1. Qualitative indicators of EA maturity, such as the presence of integrated operations centers, cloud migration progress, ERP standardization, and architecture governance mechanisms, were analyzed and benchmarked.

ENTERPRISE ARCHITECTURE MATURITY FRAMEWORK FOR OIL AND GAS SECTOR (ADAPTED FROM TOGAF AND INDEA)

Maturity Level	Business Archi	Application	Data Architecture	Technology Archi

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	tectu re	**Architec ture**		**tectu re**
Level 1: Initial	Ad hoc proce sses; no archit ecture vision	Fragment ed systems, lack of standards	Siloed datasets ; minima l data sharing	Legac y infras tructu re, poor scala bility
Level 2: Develo ping	Defin ed archit ecture goals; early align ment	Emerging integratio n; partial standardi zation	Data capture d in silos; manual extracti on	Introd uctio n of cloud or virtua lized syste ms
Level 3: Establis hed	Align ed busin ess– IT goals; gover nance in place	Standardi zed enterprise apps, modular systems	Centrali zed data wareho use; early governa nce practice s	Infras tructu re upgra des; cyber securi ty meas ures in place
Level 4: Advanc ed	Cross - functi onal coord inatio n; KPI-drive n	SOA/Mic roservice s; inter-app communi cation enabled	Real-time analytic s, mature metadat a strategy	Hybri d/mul ti-cloud adopt ion; auto matio n infras

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	design			tructure
Level 5: Transformative	Agile enterprise; architecture-led innovation	Dynamic application landscape; platform thinking	Self-optimizing data systems; AI-ready architecture	Fully digital, autonomous architecture; edge computing

Phase II: Identification of AI-Driven Automation Use Cases

To explore the role of AI in digital transformation, this study reviews automation initiatives undertaken by Indian oil and gas companies over the past five years. Use cases were identified from secondary data sources, including government white papers, corporate digital transformation strategies, vendor case studies (e.g., Infosys, TCS, Wipro), and energy sector reports published by consultancies like McKinsey and BCG. Particular emphasis was placed on applications involving:

- Predictive maintenance
- Intelligent document processing
- Digital twin modeling
- Cognitive supply chain optimization
- Autonomous drilling and safety monitoring

Each use case was mapped to the corresponding segment of the energy value chain (exploration, production, refining, distribution), and further cross-tabulated against the company's observed EA maturity level. This helped uncover patterns linking architectural readiness to automation depth and scalability.

Phase III: Framework Integration and Analytical Synthesis

An integrative framework was developed to align EA maturity stages with AI adoption capability. The framework introduces a three-tiered transformation lens (Figure 1):

Foundation Layer – where fragmented architectures constrain AI deployment

Integration Layer – where modularized systems enable discrete AI use cases

Optimization Layer – where AI systems are enterprise-wide and interoperable

This model was then used to evaluate strategic gaps, identify priority enablers (e.g., cloud

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infrastructure, data governance, change management), and propose a roadmap for AI-centric digital transformation based on EA progression.

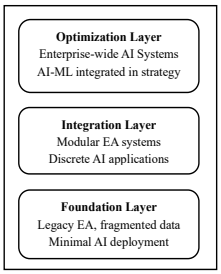

Fig. 1. AI-Driven Automation and EA Maturity Alignment Model

IV. RESULTS AND DISCUSSION

This section presents the findings of the research based on a structured assessment of EA maturity and the adoption of AI-driven automation strategies in selected Indian oil and gas enterprises. The results are organized into three key dimensions: (1) EA maturity levels across architecture domains, (2) deployment status of AI-based automation use cases, and (3) the correlation between EA maturity and digital transformation readiness.

A. Enterprise Architecture Maturity Analysis

The EA maturity of four major Indian oil and gas companies, namely ONGC, IOCL, HPCL, and Reliance Industries, as illustrated in Table 2, was evaluated using a hybrid model combining elements of TOGAF and the IndEA framework. Maturity was assessed across four architecture domains: Business, Application, Data, and Technology, using a five-point scale ranging from Level 1 (Initial) to Level 5 (Transformative).

TABLE I

ENTERPRISE ARCHITECTURE MATURITY SCORES BY COMPANY

Company	Business	Application	Data	Technology	Overall Score
ONGC	4	3	3	4	3.5
IOCL	4	4	3	3	3.5
HPCL	3	2	2	2	2.25
Reliance	5	5	4	5	4.75

Reliance Industries demonstrates the highest level of EA maturity (4.75), characterized by strong architectural governance, advanced modularization of enterprise applications, and robust infrastructure for AI and analytics. This is consistent with the company's significant investments in cloud-native platforms, AI data centers, and edge computing technologies. ONGC and IOCL exhibit moderate to advanced maturity (3.5), supported by their gradual migration to hybrid-cloud environments and structured enterprise systems such as ERP and SCADA integration. In contrast, HPCL ranks the lowest (2.25), with limited application standardization and lagging adoption of centralized data governance. Figure 2 visualizes the comparative maturity status of the four companies, highlighting the disparities in architectural

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readiness that influence digital enablement and AI scalability.

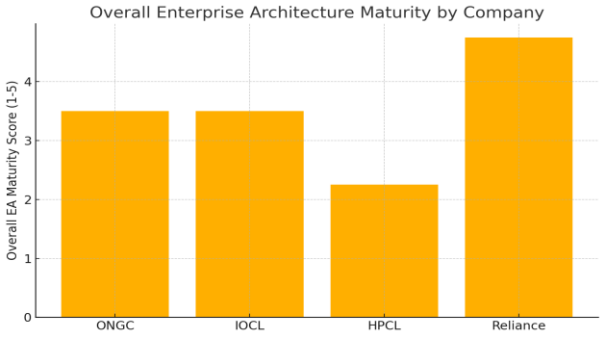

Fig. 2. Overall, EA Maturity Score by Companies

B. AI-Driven Automation Use Case Deployment

The second stage of analysis mapped current AI-based automation initiatives across the energy value chain (exploration, production, refining, logistics, and retail) for each company. As illustrated in Table 3, the presence and scale of implementation were examined across five key use cases: predictive maintenance, digital twins, intelligent document processing, cognitive supply chains, and autonomous systems.

AI AUTOMATION USE CASES BY COMPANY AND DEPLOYMENT STATUS

Company	**Predictive Maintenance**	**Digital Twin Ops**	**Cognitive SCM**	**Autonomous Drilling**	**Intelligent Document Processing**	**Scaled Use Cases**
ONGC	✓ Yes (offshore wells)	✓ KG Basin	Pilot Only	Pilot (AI modeling)	Not Deployed	3
IOCL	✓ Refineries	Not Deployed	✓ IBP in logistics	Not Deployed	✓ OCR in finance	3
HPCL	Pilot Stage	VR-based pilot	Not Deployed	Not Deployed	✓ RPA with NLP in procurement	1–2
Reliance	✓ Pan-refinery level	✓ Petrochemicals	✓ Fuel chain	✓ Drones + AI	✓ GenAI support	5

From Table 3, Reliance leads with the deployment of all five AI use cases, having scaled initiatives such as intelligent inspection drones, digital twins in the Jamnagar cracker complex, and AI-enhanced logistics optimization. IOCL and ONGC have adopted AI for key operational areas such as predictive maintenance and demand sensing, but remain at early or pilot stages for more advanced applications such as autonomous operations. HPCL, while making progress

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with RPA and intelligent document workflows, has yet to scale AI applications across core operational processes.

C. Relationship Between EA Maturity and AI Adoption

To assess whether EA maturity correlates with successful AI integration, the total number of scaled AI use cases was plotted in Figure 3 against each company's overall EA score. A Spearman rank correlation yielded a coefficient (ρ) of 0.88, indicating a strong positive relationship between EA maturity and AI adoption.

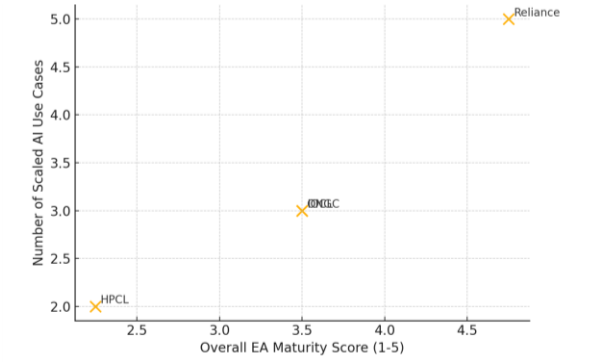

Fig. 3. Correlation between EA Maturity and AI Use Case Scaling

D. Sectoral Insights and Cross-Company Trends

Several broader patterns emerged from the cross-case analysis:

- **Digital leadership is architecture-dependent:** Companies that have achieved higher levels of architectural coherence and standardization are demonstrably better positioned to derive value from AI initiatives.

- **Use case concentration:** Predictive maintenance and document automation are the most widely adopted AI applications across the sample, suggesting they serve as entry points for digital transformation in the sector.

- **Data and application maturity as bottlenecks:** In most cases, limited progress in data architecture (e.g., lack of data lakes or real-time pipelines) and fragmented application environments were found to be the chief inhibitors to AI scalability.

- **Public vs. private sector divide:** Reliance's performance, compared to public sector undertakings like ONGC and HPCL, highlights how strategic investments in digital platforms, talent, and partnerships are reshaping the competitive dynamics in India's energy landscape.

The result section presents a comprehensive analysis of the digital maturity and AI automation landscape in India's oil and gas sector. The results substantiate the hypothesis that EA maturity serves as a critical enabler for scaling AI-driven strategies. The next section would further interpret these findings in the context of policy implications, organizational capabilities, and recommendations for driving enterprise-wide digital transformation.

E. Discussion

The findings of this study demonstrate that EA maturity plays a critical role in enabling the effective adoption and scaling of AI-driven automation in India's oil and gas industry. Firms

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with higher EA maturity levels, particularly in the application and data domains, showed significantly greater capacity to implement AI solutions across their operational value chains. Reliance Industries, with a transformative level of maturity, led in deploying AI use cases such as predictive maintenance, digital twins, autonomous inspections, and cognitive supply chains, reflecting a strong alignment between architecture and enterprise-wide digital strategy. In contrast, HPCL, with lower EA maturity, had limited AI adoption confined to back-office pilot projects due to fragmented systems and the absence of a unified data layer. ONGC and IOCL, with mid-level maturity, have initiated AI projects but face challenges in scaling due to infrastructural and integration constraints. A strong positive correlation ($\rho = 0.88$) was observed between EA maturity and the number of scaled AI use cases, confirming that architectural coherence, data readiness, and modularity are essential for digital transformation. The findings further highlight a widening gap in digital maturity between private and public enterprises, with public sector undertakings lagging in operationalizing EA frameworks despite national policy support. Based on the above findings, the following strategic and operational recommendations are proposed for advancing digital transformation through AI and EA in India's oil and gas sector:

- **Institutionalize Enterprise Architecture Governance**

Firms should establish dedicated EA governance bodies that are aligned with national frameworks like IndEA and international best practices (e.g., TOGAF, Zachman). These bodies must ensure periodic maturity assessments, cross-functional architectural reviews, and integration roadmaps that include data, application, and process layers.

- **Invest in Data Infrastructure and Interoperability**

A unified data architecture including enterprise data lakes, streaming platforms, and semantic metadata layers should be prioritized to facilitate real-time analytics, machine learning operations (MLOps), and intelligent automation. Open data standards and APIs should be adopted to ensure interoperability across departments and business units.

- **Scale Modular Applications and Cloud-Native Platforms**

Legacy systems must be progressively replaced or integrated with microservices-based applications that are cloud-native and DevOps-enabled. These architectural changes reduce technical debt and create the agility required to embed AI into operational workflows such as predictive maintenance, supply chain optimization, and intelligent exploration.

- **Build AI Centers of Excellence (CoEs)**

Organizations should invest in internal AI/ML centers of excellence tasked with driving cross-functional AI strategies, talent development, model governance, and solution scaling. CoEs can also serve as intermediaries between business units and IT, ensuring that AI initiatives align with both enterprise goals and architectural feasibility.

- **Leverage Public-Private Collaboration**

Public sector undertakings can accelerate their digital transformation by forming partnerships with private technology providers, research institutions, and innovation hubs. This collaborative model can foster technology transfer, co-creation of use cases, and pilot-to-

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production support for AI applications.

- **Enhance Regulatory Alignment and Policy Adoption**

The Ministry of Petroleum and Natural Gas (MoPNG) and MeitY should work collaboratively to enforce the IndEA framework across all major PSUs, ensuring that EA principles are embedded within digital strategy blueprints and capital expenditure plans.

- **Measure ROI and Transformation KPIs**

Firms must go beyond technological deployment and track transformation outcomes through KPIs such as AI-driven downtime reduction, logistics efficiency, energy consumption optimization, and enhanced EBITDA contributions. A balanced scorecard for digital transformation should be integrated into corporate performance dashboards.

V. Conclusion and Future Scope

The Indian oil and gas industry is undergoing a significant transformation driven by rising energy demands, environmental imperatives, and rapid advancements in digital technologies such as artificial intelligence (AI), cloud computing, and data analytics. However, fragmented legacy systems and inconsistent enterprise architecture (EA) continue to hinder the sector's ability to scale digital innovation. Addressing this gap, the present study investigates the relationship between EA maturity and the successful adoption of AI-driven automation strategies in India's oil and gas sector by assessing how varying levels of EA maturity influence AI integration across operational domains and proposing a strategic transformation roadmap. Using a hybrid maturity assessment framework that combines TOGAF and India's IndEA model, the EA maturity of four key enterprises: ONGC, IOCL, HPCL, and Reliance Industries; was evaluated across business, application, data, and technology domains. A five-point scale was used, where Reliance scored the highest overall maturity (4.75) and HPCL the lowest (2.25). A strong positive correlation ($\rho = 0.88$) was found between EA maturity and the number of scaled AI use cases, demonstrating that higher architectural maturity enables more effective deployment of AI in areas such as predictive maintenance, digital twins, and autonomous operations, underscoring the importance of modular applications, unified data governance, and interoperable systems. While the framework offers practical insights and a replicable maturity model, future research should explore longitudinal impacts, stakeholder perspectives, AI model performance data, and cost-benefit analyses to deepen understanding and guide both industry and policy-level decision-making. This study primarily utilizes secondary qualitative data and is therefore limited by the availability and granularity of publicly reported digital metrics. While the findings offer insight into broad industry trends, firm-specific nuances might be underrepresented in the absence of direct interviews or proprietary system audits.

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REFERENCES

[1] E. Alagoz and Y. Alghawi, "The energy transition: Navigating the shift towards renewables in the oil and gas industry," Journal of Energy and Natural Resources, vol. 12, no. 2, pp. 21–24, 2023. doi: 10.11648/j.jenr.20231202.12

[2] A. Safari, N. Das, O. Langhelle, J. Roy, and M. Assadi, "Natural gas: A transition fuel for sustainable energy system transformation?" Energy Science & Engineering, vol. 7, no. 4, pp. 1075–1094, 2019. https://doi.org/10.1002/ese3.380

[3] N. H. Dawda, "Energy Transition in India's Transport Sector: Current Policies, Key Challenges, and Potential Pathways," Key Challenges, and Potential Pathways, Dec. 2024. https://dx.doi.org/10.2139/ssrn.5080787

[4] N. K. Jain, A. Panda, and P. Choudhary, "Institutional pressures and circular economy performance: The role of environmental management system and organizational flexibility in oil and gas sector," Business Strategy and the Environment, vol. 29, no. 8, pp. 3509–3525, 2020. https://doi.org/10.1002/bse.2593

[5] K. J. Meitei, "Oil resource and its geopolitics in India," Ph.D. dissertation, Amity Univ., 2025.

[6] T. Mitrova and Y. Melnikov, "Energy transition in Russia," Energy Transitions, vol. 3, no. 1, pp. 73–80, 2019. https://doi.org/10.1007/s41825-019-00016-8

[7] International Energy Agency, India Energy Outlook 2023. [Online]. Available: https://www.iea.org/reports/india-energy-outlook-2023

[8] S. S. Narayana, "Synergizing edge computing and cloud integration for enhanced efficiency in the oil and gas industry," J. Comput. Eng. Technol., vol. 15, pp. 63–71, 2024.

[9] K. R. Pothala, "Exploring reasons for digitalization not percolating into the power sector to the extent expected in India and suggesting a framework to expedite the same," Digital Repository of Theses - SSBM Geneva, 2024. https://doi.org/10.32629/jai.v7i4.1145

[10] A. H. Ikevuje, J. M. Kwakye, D. E. Ekechukwu, O. B. Ogundipe, and A. E. Esiri, "Negative crude oil prices: Supply chain disruptions and strategic lessons," Open Access Research Journal of Multidisciplinary Studies, vol. 8, no. 01, pp. 85–93, 2024. https://doi.org/10.53022/oarjms.2024.8.1.0050

[11] R. H. Wiser, A. D. Mills, J. Seel, T. Levin, and A. Botterud, "Impacts of variable renewable energy on bulk power system assets, pricing, and costs," 2017.

[12] J. Baffes and P. Nagle, Commodity Markets: Evolution, Challenges, and Policies. Washington, DC: World Bank Publications, 2022.

[13] A. N. Dugbartey, "Systemic financial risks in an era of geopolitical tensions, climate change, and technological disruptions: Predictive analytics, stress testing and crisis

Received: August 08, 2025

Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

response strategies," International Journal of Science and Research Archive, vol. 14, no. 02, pp. 1428–1448, 2025. https://doi.org/10.30574/ijsra.2025.14.2.0563

[14] P. F. Borowski, "Digitization, digital twins, blockchain, and industry 4.0 as elements of management process in enterprises in the energy sector," Energies, vol. 14, no. 7, p. 1885, 2021. https://doi.org/10.3390/en14071885

[15] I.H. Alsulaity, "Business model transformation in oil and gas industry in UAE: the influence of AI," Ph.D. dissertation, Univ. of Gloucestershire, 2024. https://doi.org/10.46289/SUAN4610

[16] A. Al-Hajri, G. M. Abdella, H. Al-Yafei, S. Aseel, and A. M. Hamouda, "A systematic literature review of the digital transformation in the Arabian Gulf's oil and gas sector," Sustainability, vol. 16, no. 15, p. 6601, 2024. https://doi.org/10.3390/su16156601

[17] S. E. Salim, "Impact of AI on future workforce: A study on oil & gas sector," Digital Repository of Theses - SSBM Geneva, 2025.

[18] S. A. Kalleparambil, S. Mekala, A. Ibrahim, and M. M. Granata, "Maximizing efficiency: Centralized project material management for owner operators in oil and gas," in Abu Dhabi Int. Petrol. Exhib. Conf., Abu Dhabi, 2024, p. D031S082R007. SPE. https://doi.org/10.2118/222760-MS

[19] U. Şener, "Development of a maturity index for digital transformation in organizations," Ph.D. dissertation, Middle East Technical University, Turkey, 2024.

[20] A. Enemosah, "Intelligent decision support systems for oil and gas control rooms using real-time AI inference," International Journal of Engineering Technology Research & Management, vol. 5, no. 12, pp. 236–244, 2021.

[21] R. Junin, A. Agi, and M. Y. Abdulfatah, "A survey on industry 4.0 for the oil and gas industry: Upstream sector."

[22] H. Y. Omar, D. M. Abdulqader, R. M. Abdullah, H. R. Ismael, Z. N. Rashid, and T. M. G. Sami, "A review on upshots of cloud computing and web technology on the future green transformation: AI, IoT, and secure enterprise systems in fostering sustainable work practices," Journal of Information Technology and Informatics, vol. 3.

[23] F. U. Ojika, O. Owobu, O. A. Abieba, O. J. Esan, A. I. Daraojimba, and B. C. Ubamadu, "A conceptual framework for AI-driven digital transformation: Leveraging NLP and machine learning for enhanced data flow in retail operations," IRE Journals, vol. 4, no. 9, 2021.

[24] K. M. Hanga and Y. Kovalchuk, "Machine learning and multi-agent systems in oil and gas industry applications: A survey," Computer Science Review, vol. 34, p. 100191, 2019. https://doi.org/10.1016/j.cosrev.2019.08.002

[25] F. F. Yusifov, "Digital technologies in the oil and gas industry: Technology selection, advantages and risks," 2024. http://dx.doi.org/10.5510/OGP20250201078

[26] S. E. Salim, "Impact of AI on Future Workforce: A Study on Oil & Gas Sector," Digital Repository of Theses–SSBM Geneva, 2025.

Received: August 08, 2025

Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[27] S. Purohit, S. Purohit, and A. K. Jain, "Transforming Indian Petro Retail: Enhancing Customer Experience through IoT and AI Solutions," Scientific Research, New Technologies and Applications, vol. 10, pp. 61–74, 2024. https://doi.org/10.9734/bpi/srnta/v10/3554

[28] A. P. Anyebe, O. K. K. Yeboah, O. I. Bakinson, T. Y. Adeyinka, and F. C. Okafor, "Optimizing Carbon Capture Efficiency through AI-Driven Process Automation for Enhancing Predictive Maintenance and CO2 Sequestration in Oil and Gas Facilities," American Journal of Environment and Climate, vol. 3, no. 3, pp. 44–58, 2024. https://doi.org/10.54536/ajec.v3i3.3766

[29] A. B. Amale, I. K. Kantharaj, B. M. Ashok, A. Amudha, L. Bareja, and P. M. Raut, "Integrating Real-Time Automation and Big Data Analytics in the Oil and Gas Industry," in Proc. 15th Int. Conf. on Computing Communication and Networking Technologies (ICCCNT), 2024, pp. 1–6. https://doi.org/10.1109/ICCCNT61001.2024.10723854

[30] A. Aldoseri, K. N. Al-Khalifa, and A. M. Hamouda, "AI-powered innovation in digital transformation: Key pillars and industry impact," Sustainability, vol. 16, no. 5, p. 1790, 2024. https://doi.org/10.3390/su16051790

[31] S. Purohit and A. K. Jain, "Technological transition from analog to internet of things (IoT) on Indian petro-retail's customer service," Indian Journal of Science and Technology, vol. 13, no. 42, pp. 4364–4368, 2020. https://doi.org/10.17485/IJST/v13i42.1964

[32] S. Purohit and A. K. Jain, "Technological Transition to the Internet of Things (IoT) in the Indian Oil & Gas Business and Economy," https://doi.org/10.5281/zenodo.8370605

[33] F. SoleimaniRoozbahani, R. ShojaeiBarjouei, and S. N. Hojjati, "Identifying an appropriate model for information systems integration in the oil and gas industry," Int. J. of Advanced Networking and Applications, vol. 10, no. 1, pp. 3687–3691, 2018.

[34] P. S. Aithal and V. V. Prabhu, "New Job Opportunities due to Integration of AI-driven GPTs across Four Industry Sectors—A Futuristic Analysis," Poornaprajna Int. J. of Emerging Technologies (PIJET), vol. 1, no. 1, pp. 63–89, 2024. https://doi.org/10.5281/zenodo.13839921

[35] M. Zakizadeh and M. Zand, A Comprehensive Guide to Digital Transformation in the Oil & Gas Industries.

[36] A. Al-Hajri, A. M. Hamouda, and G. M. Abdella, "Sustainability-Based Strategic Framework for Digital Transformation in the Oil and Gas Industry," IEEE Access, 2025. https://doi.org/10.1109/ACCESS.2025.3548960

[37] A. Rudra, M. S. Karumuri, and M. Agrawal, "AI-Driven Big Data Analytics for Strategic Marketing and Price Optimization in the Oil and Gas Industry," DOI: 10.51542/ijscia.v6i3.10

Received: August 08, 2025

Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[38] I. Al Sulaity, D. Yourston, O. Khassawneh, and T. K. Darwish, "Driving digital transformation in the oil and gas sector: unlocking AI's potential in the UAE," Int. J. of Organizational Analysis, 2025. https://doi.org/10.1108/IJOA-01-2025-5145

[39] L. Judijanto, "Exploring the Potentials of Artificial Intelligence and Digital Technologies in Transforming the Palm Oil Industry: A Review," Journal of Information, Technology and Policy, pp. 1–13, 2025. https://doi.org/10.62836/jitp.2025.431

[40] N. Khan, W. D. Solvang, and H. Yu, "Industrial internet of things (IIoT) and other industry 4.0 Technologies in Spare Parts Warehousing in the oil and gas industry: a systematic literature review," Logistics, vol. 8, no. 1, p. 16, 2024. https://doi.org/10.3390/logistics8010016

[41] C. Onyeme and K. Liyanage, "A systematic review of Industry 4.0 maturity models: applicability in the O&G upstream industry," World Journal of Engineering, vol. 20, no. 6, pp. 1160–1173, 2023. https://doi.org/10.1108/WJE-12-2021-0689

[42] B. K. AlNuaimi, M. Al Mazrouei, and F. Jabeen, "Enablers of green business process management in the oil and gas sector," Int. J. of Productivity and Performance Management, vol. 69, no. 8, pp. 1671–1694, 2020. https://doi.org/10.1108/IJPPM-11-2019-0524

[43] O. Elijah, P. A. Ling, S. K. A. Rahim, T. K. Geok, A. Arsad, E. A. Kadir, M. Abdurrahman, R. Junin, A. Agi, and M. Y. Abdulfatah, "A survey on industry 4.0 for the oil and gas industry: Upstream sector," IEEE Access, vol. 9, pp. 144438–144468, 2021. https://doi.org/10.1109/ACCESS.2021.3121302

[44] M. Zuliansyah, M. I. Desa, and S. Ahmad, "Method for Estimating the Performance of Enterprise Architecture Implementation in an Upstream Petroleum Industry," DOI:10.35940/ijrte.E6441.038620

Received: August 08, 2025