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Artificial Intelligence in Energy Supply Chains: Stakeholder Insights and Operational Impact

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Abstract
Artificial intelligence (AI) is increasingly viewed as a transformative tool for building resilient, efficient, and adaptive energy supply chains. This study examines AI adoption across four key dimensions: stakeholder perceptions, operational efficiency, risk management, and the role of barriers and enablers. Using data from 100 respondents in the energy sector, descriptive statistics, regression, and factor analyses were applied to test hypotheses and derive actionable insights. Results show that stakeholder perceptions of AI adoption are moderately positive, though concerns around managerial support and practical application persist. AI demonstrates potential to improve predictive capabilities and risk management, yet regression analysis indicates that its impact remains statistically weak, suggesting the need for stronger integration and strategic alignment. Barriers such as high costs and lack of skilled personnel were identified as primary challenges, while leadership support and quality data availability emerged as critical enablers, helping reduce resistance and facilitating smoother adoption. The findings contribute to both theory and practice by offering a quantitative framework that ranks barriers and enablers, highlights managerial implications, and informs organizational strategies for AI-driven transformation. While the study is limited by sample size and reliance on perceptual data, it opens avenues for future research to explore sector-specific AI applications, longitudinal adoption patterns, and advanced modeling approaches. Overall, the research underscores that AI adoption in energy supply chains is less about technology alone and more about leadership, readiness, and strategic vision.

Keywords: Adoption, Artificial Intelligence, Barriers, Energy Supply Chain, Risk Management

Introduction

Downstream oil and gas industry includes oil and gas refining, distribution, and sale of petroleum products which constitute a critical connection between the crude oil production and the end-users[1]. The nature of the operations in this industry makes it complex because it has large-scale logistic systems, dynamic customer demand, changeable supply levels and strict regulation standards. Previously, control of these operations has closely relied on manual surveillance, historical examination, and human-made decisions, which have been linked to inefficiency, delays and steep operation expenses [2]. AI turned out to be a field of innovation and transformation of efficiency, safety, and predictability capabilities throughout the downstream supply chain. Downstream AI may be applied to anticipate refinery and distribution network repairs, predict demands, optimize inventories, develop a fuel delivery dynamic path, and detect anomalies in the storage and pipeline systems [3]. With the help of ML algorithms, neural networks, and other advanced analytics, organizations are able to process large amounts of operation and sensor data in real-time so that they can make decisions faster and make them grounded in data [4]. Besides, the AI enhances cooperation between the in-house and external partners, as it makes predictions and automates the repetitive activities. The tools developed based on AI can help the downstream sector as it relates to the timely introduction of distribution, costs of inventory management, and risk minimization. In addition, the AI implementation is aligned with sustainability and operational excellence goals of the industry [5]. The processes can be re-engineered and the logistics streamlined to make the companies reduce wastage of fuel, the effect on the environment and to become more energy efficient. The implementation of AI is now considered as a strategic requirement to have a competitive advantage in the areas of cost reduction, reliability in its services, and operational sustainability [6]. Thus, the data on the scale, performance, and problems of the AI deployment to downstream oil and gas supply chains is critical to the stakeholders which require the modernization of their processes and react strategically to the market environment dynamics.

The oil and gas downstream industry is not left behind as it faces its share of challenges in its operations [7]. The inefficiencies are usually caused by the intricate logistics, fluctuating supply and demand, lack of coordination of inventory management processes, and the lagging tempos of the decision-making processes. Poor schedulings of deliveries, overstocking or stockouts at terminals and retail stores, and increased operations are among additional factors that are caused by manual tracking and the use of old systems [8]. These inefficiencies have a direct impact on the profitability, customer satisfaction and reliability of the supply chain. Besides, the risk management is also a continuing issue. Equipment failures, pipeline ruptures, refinery shutdown, and unexpected large demands are some of the threats to continuity of operations [9]. Older methodology and risk reduction is often on the base of past trends and human perception which can fail to predict new risks or rapidly changing market conditions. Application of AI in the down-stream supply chain is not widely used due to the numerous barriers [10]. Technical issues are the reason behind the absence of implementation without any problems, such as the necessity to connect AI with the current infrastructure, issues with the quality of data, and interoperability. It is also stifled by the corporate change resistance, lack of skilled staff and unclear leadership support. Shortage of finances and reluctance by the prospects to recover it is another setback particularly among the middle-scale and smaller operators [11]. The problems in legal and regulation also complicate the implementation of AI-based tools since the decision-making must be provided in accordance with the high safety and environmental standards.

All these inefficiencies, risks, and blocks together restrict the power of the industry to use AI to its full capacity in optimization process[12]. A combined analysis that will bring together the expertise of stakeholders and measurable operation impacts is therefore required to understand how AI can be used to facilitate the solution to such problems, locate opportunities to facilitate adoption, and develop feasible operations to attain sustainable and efficient management of downstream supply chains.

Research Gap

Although AI has been emerging as a topic in supply chains in multiple industries, there is still a lack of empirical data in the energy industry. Available literature is based more on technology feasibility or theoretical frameworks, leaving the views of the key stakeholders in operational decisions. Moreover, studies tend to focus on the role of AI on personal procedures, e.g., inventory or scheduling, and they do not determine the overall effect of AI on productivity, teamwork, and risk reduction. Success factors and challenges of successful AI implementation are not discussed consistently, especially in relation to energy supply chains where compliance regulations and safety rules are not the least important factors, as well as the complexity of specific work systems. This gap indicates that a quantitative, stakeholder-based research would be necessary that can assess both the operation impact and adoption issues in a holistic manner.

Research Aim and Objectives

- Objective 1: To assess stakeholder perceptions regarding the integration of AI in supply chain operations within the energy sector.
- Objective 2: To examine the direct impact of AI integration on supply chain efficiency and collaboration in the energy sector.
- Objective 3: To evaluate the role of AI in enhancing risk management and predictive capabilities across energy supply chains.
- Objective 4: To analyze the barriers and enablers influencing successful AI adoption in energy sector supply chains

Research Motivation

The growing complexity of energy supply chains, and the growing need to be efficient, reliable and sustainable, drives the current study. The conventional ways of operation fail to adapt to the conditions of dynamic market, predictive risk management, and collaboration between organizations, which makes AI-based solutions necessary. Although the topic of AI has attracted increased attention, it has not been empirically studied to understand its effects in the energy sector. Additionally, energy companies also have organizational, technical, and regulatory obstacles that undermine the use of AI. Motivated by these challenges, the proposed study aims to measure the benefits of operations, gather stakeholder perceptions, and implement adoption barriers in order to provide companies with practical recommendations and add empirical data to the body of literature on AI-based energy supply chain management.

Research Significance

This research provides useful and strategic information to the firms in the energy industry seeking to incorporate AI in the downstream of their supply chains. It determines which AI practices offer the most concrete benefits by analysing the perceptions of the stakeholders and operational performance indicators (efficiency, collaboration, risk management) of the relevant organisations. The results will help managers to prioritize the AI efforts, distribute their resources better, and improve the decision-making process. Also, the study directs organizational policies and strategies by examining and prioritizing barriers and enablers to facilitate easier adoption of AI. In terms of academics, it fulfills a significant gap in the empirical literature on AI in the energy supply chain and offers an effective quantitative framework that can be applied to other sectors of the industry, hence a contribution to the theory and practice.

There are five sections to the study: The context, research gap, and aims are presented in Section 1: Introduction. Previous research on the use of AI in supply chains is reviewed in Section 2: Related Work. The research strategy, sample, data collecting, and analytical methods are described in depth in Section 3: Methodology. Results and interpretations are presented in Section 4: Results and Discussion. Contributions, consequences, limits, and future research objectives are summarized in Section 5: Conclusion and Future Work.

Related Works

Roberts [13]focuses on sustainability, resilience, and efficiency as it investigates the use of AI in renewable energy supply chains. The study identifies improved forecasting, resource optimization, and real-time decision-making as the primary contributions of AI, based on qualitative interviews.The findings show that AI reduces costs and enhances resiliency to demand variability, as well as helps in sustainability by reducing emissions, decreasing waste, and applying the ideology of a circle economy. However, concerns of high cost, non-standardization, privacy of data and availability of skilled workforce are obstacles to adoption. The study highlights how vital strategic training and open standards of AI are and the results show how proper implementation can transform supply chains, improve competitiveness, and result in a cleaner and a greener energy future.

Roberts [14]analyzes the position of AI in renewable energy supply chains, with emphasis on its effects on efficiency, resilience, and sustainability. Drawing from qualitative interviews with industry experts, the research illustrates the advantages of AI in improving forecasting accuracy, optimizing resource utilization, and facilitating real-time decision-making. The study determines that, besides cost-reduction in operations, AI will contribute to increased sensitivity to changing demand and external shocks, as well as offer assistance in the context of sustainability through decreased emissions, waste minimization, and the circular economy. Despite these, issues such as high set-up, lack of standardization, privacy of data, and lack of high-trained specialists make wide use impossible. The article highlights strategy training and standards as the keys to replicating the transformative potential of AI.

Arévaloand Jurado [15]explores how AI can be used in the planning and operation of smart grids by using distributed energy systems. Focusing on the advances in ML, optimization, and cognitive computing it shows how AI can boost the efficiency, reliability, and responsiveness of the energy infrastructure. Its use is sought in applications in demand and generation forecasting, energy flow optimization, load management, distributed resources coordination, intermittent renewable integration and better demand response. Also mentioned in the paper are the technical limitations, economic, regulatory and moral challenges related to automation and autonomous decisions. The study sheds light on the changing potential of AI in smart grids and proposes new requirements of future research to achieve sustainable and resilient energy systems by offering a unified study on current trends and issues.

Onukwuluet al., [16]describes an AI-powered energy supply chain optimization model that puts a strong emphasis on efficiency, cost reduction, and sustainability. It explores the application of AI in sourcing, distribution and consumption, demand forecasting and resource planning, logistics and predictive maintenance. With ML, DL and natural language processing, AI ensures superior operational visibility, reduced downtime and improved service delivery. AI solutions provide precise energy demand forecasting, streamline transportation networks, and predict equipment failure, increasing asset lifespan and reducing disruptions. The research also identifies AI as a facilitator for renewable integration, waste reduction, and carbon footprint reduction. It identifies strategic deployment, data infrastructure, transparency, and stakeholder engagement, while overcoming issues of data quality, integration, and workforce transition.

Talla [5]outlines how Blockchain and AI can improve transparency, efficiency, and sustainability in energy supply chains. It highlights the uses of blockchain technology in providing decentralized, impenetrable ledgers for safe data transfer and fraud prevention, where AI facilitates asset management, demand forecasting, and predictive analytics. It does this by drawing on case examples, industry sources, and insights from the literature. When combined, these technologies provide cost reduction, real-time tracking, and renewable energy integration. Despite this, hurdles in the form of scalability, data consistency, and regulatory ambiguity hamper broad-scale take-up. The report suggests guidelines through a codified legislative framework, digital infrastructure investment, and standardization to guarantee safe and efficient deployment. In the end, Blockchain and AI have the potential to revolutionize energy supply chains with enhanced transparency and operational efficiency.

Eyo-Udo [18]examines the incorporation of AI in Supply Chain Management (SCM), its impact on efficiency, innovation, and sustainability. Through a systematic literature review of articles that appeared between 2013 and 2023, it explores uses of AI technologies like ML, NLP, and robotics across demand forecasting, inventory control, and logistics optimization. The outcomes indicate AI improves decision-making, saves costs, and optimizes resource utilization. But adoption faces obstacles of data privacy, moral issues, and skill deficits in the workforce. The article stresses innovation encouragement, digital skills, and enabling regulations for successful integration. Future studies must examine long-term sustainability effects, moral implications of autonomy, and interaction between AI and other cutting-edge technologies in supply chains.

Huang and Mao [19]proposes a model of carbon footprint management in supply chains using AI around the world based on data. As more people pressure the need to become sustainable, the model employs AI algorithms to collect, process, and analyze logistics, production, and sourcing emission data. It employs ML and optimization to identify emission hotspots and design the strategies of reducing environmental footprint without influencing the efficiency. The real time tracking and predictive analysis enable proactive decision-making enabling the companies to react to altered regulatory and market conditions. The plan boosts the accuracy of the carbon test and makes it possible to monitor sustainability. Overall, the research is valuable to the management of sustainable supply chains because it demonstrates how AI can be used to deliver effective carbon footprint reductions and global environmental management.

Riad et al., [20]proposes a conceptual model of enhancing supply chain resilience with the integration of AI. Against the backdrop of the uncertainty present in the world and frequent disruptions, this paper introduces the relevance of AI in the further improvement of demand forecasting, inventory control, and real-time visibility, thereby reducing the risks of stockout and excess. AI streamlines operational performance, eases operations, and minimizes human error with ML, predictive analytics, and automation. The framework highlights the role of AI in risk management and cooperation, and data-sharing tools will help to enhance the level of coordination and trust among supply chain partners. In general, this paper shows how AI could help organizations be more resilient, efficient, and sustainable, allowing them to adjust, recuperate, and succeed in more complex and dynamic supply chain settings.The summarization of the related work is shown in Table I.

Table 1. Summarization of the Related Works

References	Focus Area	Method/Approach	Key Findings	Limitations
Roberts [13]	AI in renewable energy supply chains (efficiency, resilience, sustainability)	Qualitative interviews with experts	AI improves forecasting, resource optimization, real-time decision-making; reduces cost and enhances adaptability	High cost, lack of standards, data privacy, skill shortages
Roberts [14]	AI in renewable energy supply chains	Expert interviews	AI reduces costs, supports sustainability, increases resilience	High implementation costs, workforce gaps
Arévalo and Jurado [15]	AI in smart grids (distributed energy systems)	Literature review + technical analysis	AI enhances load management, demand/generation forecasting, renewable integration	Technical/economic barriers, regulation, ethics
Onukwulu et al., [16]	AI-driven optimization of energy supply chains	Conceptual framework	Improves demand forecasting, logistics, predictive maintenance,	Data quality, integration, workforce adaptation

			renewable integration	
Talla [5]	Blockchain + AI in energy supply chains	Literature/case studies	Blockchain ensures transparency, AI supports forecasting & asset management	Scalability, data integrity, regulation
Eyo-Udo [18]	AI in supply chain management	Systematic literature review (2013–2023)	AI improves demand forecasting, inventory mgmt., logistics	Data privacy, ethics, workforce skill gaps
Huang and Mao [19]	AI for carbon footprint management in supply chains	Data-driven framework	Identifies emission hotspots, enables real-time sustainability monitoring	Implementation complexity
Riad et al., [20]	AI for supply chain resilience	Conceptual framework	Enhances forecasting, inventory mgmt., collaboration, visibility	Adoption challenges, trust among stakeholders

Research Methodology

The research paper utilizes a quantitative, survey-based, cross-sectional research design to investigate the adoption of AI in the supply chain of the energy sector. The respondent group will be downstream operation professionals, such as refining, logistics, distribution, and retail. Respondents will be attracted based on their position as supply chain managers, AI project leaders, and operations executives, and the planned sample size will be 100, which is enough to conduct the regression-based analysis. The scale and measurement of constructs are done using the five-point Likert. The statistical analysis will involve SPSS containing descriptive statistics, multiple regression and diagnostic checks. Cronbach alpha, factor analysis and residual diagnostics will be used to ensure reliability and validity giving the study a sound base on which to test and interpret the hypothesis.

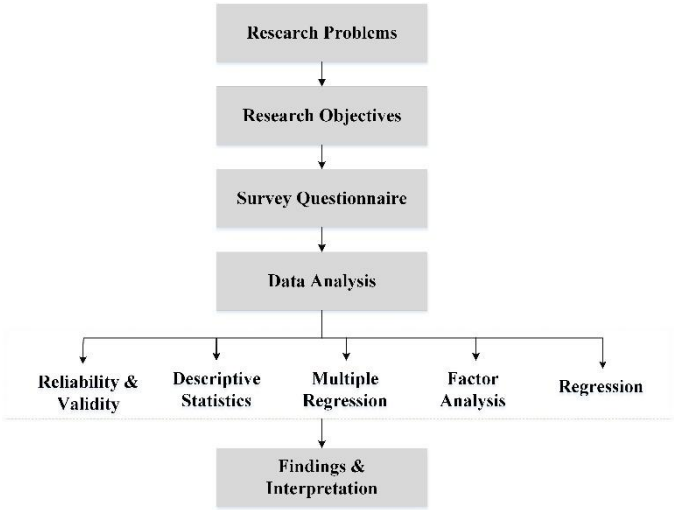


Fig 1. Research Methodology Framework for AI Adoption in Downstream Oil & Gas Supply Chains

The systematic approach of the research is presented in the Fig. 1. It begins with research problems, which is the statement of the key issues that will be discussed and the research objectives that is the statement of the objectives of the research. Data collection is then believed through the development of a questionnaire survey. The responses obtained are analyzed with data, which are further divided into significant statistical processes. The reliability and validity tests will ensure accuracy and consistency of the data, and the descriptive statistics will provide an overview of the trends in general. Multiplex analyses the relationships among variables and the factor analysis identifies the relationships or dimensions. Further regression analysis enhances predictive

penetration. Lastly, all these analyses are brought to the same point of analysis and interpretation giving significant conclusions in accordance to the research objectives.

Research Design

The current investigation is based on a quantitative, survey-based, cross-sectional research design to evaluate the incorporation of AI into the supply chains of the energy industry in an organized manner. The quantitative methodology was chosen because it is possible to systematize the method of collecting numerical data and conducting statistical research on it and objectively measure the perceptions of stakeholders, test hypotheses, and determine the trends in adoption practices. The methodology is significant in that it does not limit the results to a subjective interpretation but can be able to generalize the results on the firms that are in the supply chain of the downstream energy. Particularly, the survey method will be highly appropriate in this study since it may be deployed to gather high amounts of standardized information with respondents situated geographically apart, thus increasing on representativeness.

The practicality of the study is also contributed by the cross-sectional nature because the data will be recorded at a single point. This provides an insight of what is being exercised, what has been adapted, what has been stifled and what have been the active outcomes of AI integration, which is vital in the dynamic technological environment such as the energy sector. A cross-sectional design, compared to longitudinal design, is more practicable in terms of the timeliness of insights to be realized but it is also suitable where great statistics testing is needed. Given the list of previous empirical studies on supply chain management and the literature on innovation adoption, which use a lot of survey data to examine the relationship between organizational, operational, and technological factors, the chosen design is not particularly new.

Target Population and Sample

In this research, special attention will be paid to companies that will be involved in the downstream segment of the energy supply chain, and which cover refining, storage and terminal operations, logistics and transportation, distribution, and retail operations. These parts were chosen because it is one of the major hubs that could influence the performance of operations, risk mitigation, and cooperation significantly upon the implementation of AI tools and methods. The interviewees will be professionals that possess first-hand information and a decision making role with regards to the supply chain operation and use of AI. This will include the supply chain managers, logistics coordinators, the heads of IT and AI projects, the refinery operations employees, the terminal operators, and the distribution executives. The variety of roles addressed and ensured care mean that the dataset has captured the perspective of the technical and managerial facet of AI integration.

The sample size will be 100 respondents, and this is within the recommended sample size of conducting regression analysis, factor analysis, and other regression analysis methods. This is a large sample size, which is sufficiently large to provide sufficient statistical power in detecting significant effects, and enables parameter estimates to be stable such that the results are generalizable.A stratified sampling method will be used to achieve representativeness, with samples based on areas of the company size and the experience level of respondents. This stratification allows the study to obtain variability among organizational scale and professional expertise in order to minimize sampling bias and to also carry out subgroup comparisons.

Research Instrument

To collect primary data in this research, a structured self-administered questionnaire was prepared. The tool was created, following a thorough study of previous sources on the topic of AI implementation, supply chain effectiveness, and risk management in the energy industry. In order to provide a broad coverage, the questionnaire would be split into six structured sections each of which would be related to the study objectives:

- **Demographics:**This section records such characteristics of the respondents as their position in the organization (e.g., supply chain manager, AI project lead, logistics coordinator), years of experience in the industry, and size of the firm. These are the variables used to control future analyses to understand the difference in perceptions and adoption between the respondent and the organizational spectrum.
- **AI Adoption:**This section measures the extent of AI application to supply chain processes, such as the extent of adoption, multidimensionality of adoption to refining/logistics/retail processes, and management assistance to digital transformation. This part gives the central independent variables (IVs) of the study.
- **Operational Efficiency:** In this instance, questions measure the perception of AI contribution to efficiency results, e.g. its accuracy in the inventory, time of delivery and cost-efficiency. Responses form part of the dependent variables (DVs).

- **Risk Management:** This section will evaluate the contribution of AI to the achievements of predictive maintenance, safety surveillance, compliance verification, and disruption prediction, which are Objective 3 of the study directly.
- **Collaboration:** The next critical DV is collaboration, which is rated by the respondents in terms of the possibility of AI to allow reaching a higher degree of cross-departmental coordination and cooperation with external partners.
- **Barriers and Enablers:** This is the final section, the key barriers to implementation that are identified are high implementation cost, skills gaps, and regulatory constraints and enabling factors such as leadership support, organizational culture, and quality of data.

All measurement items are measured on a five point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The uniform scale can be used to provide comparability between constructs, factor analysis, as well as the possibility to combine measures based on perceptions to create reliable indices.

Variables

The conceptual model used in the study separates the independent, dependent and control variables as follows:

1) Independent Variables (IVs)

- Adoption and integration of AI (degree of AI tool application in refining, logistics, and retailing functions).
- AI initiatives supported by the management.
- Perceived organizational system readiness and adequacy.

2) Dependent Variables (DVs)

- Operational Efficiency (Objective 2): calculated by gauging the accuracy of inventory, cost savings, and delivery time.
- Collaboration (Objective 2): gauged by perceptions of inter-departmental coordination and sharing of information with the outside
- Risk Management and Predictive Capabilities (Objective 3): was measured in predictive maintenance, compliance monitoring, and disruption forecasting.

3) Control Variables

- Respondent role (managerial vs. technical).
- Firm size (small, medium, large).
- Years of industry experience.

Control variables are introduced to guarantee that the statistical models take into consideration heterogeneity based on the size of organizations and the knowledge levels of the respondents, minimizing the omitted variable bias and enhancing validity of inferences.

Data Collection Procedure

The data will be collected using an online survey system to achieve as high accessibility as possible and obtain a geographically spread sample of the energy sector professionals. The respondents will be recruited through a multi-pronged approach distribution strategy, which will entail outreach through professional industry associations, LinkedIn groups of supply chain professionals, and company networks. The social desirability bias will be minimized by emphasizing the voluntary participation.

The questionnaire would be piloted on 100 industry professionals prior to its entire implementation. The themes of clarity, wording, item relevance, and time of completion will be tested in this pre-test. Feedback will be integrated to perfect the phrasing of questions, remove ambiguity and make sure that the constructs are gauging the desired dimensions (face validity). The ethical issues will be followed, such as informed consent, right to withdraw willingly, and safety of working with responses. The information will be kept in anonymized form and only be accessible to the research team.

Statistical Methods

4) Objective 1: Stakeholder Perceptions: The descriptive statistics will be employed to evaluate the perception of the stakeholders about AI integration in the supply chains. This includes finding the measures of central tendency and dispersion including, Mean:

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \quad (1)$$

In (1),$X_i$is the value of the response, and n is the total number of responders. Standard Deviation (SD), shown in (2),

$$SD = \sqrt{\frac{\sum(X_i - \overline{X})^2}{n-1}} \quad (2)$$

which is a measure of variability about the mean.

- Frequency Distribution (%): demonstrating the percentage of respondents who agree/disagree with the adoption and preparedness to AI.

This discussion will offer a clear picture of the perceptions of AI by the stakeholders in regard to trust, usefulness, and readiness to adopt.

5) Objective 2: Impact of AI on Efficiency and Collaboration: Multiple Regression Analysis will be used to evaluate the relationship of AI adoption and two dependent variables, namely, operational efficiency and collaboration. The overall regression equation can be stated as shown in (3),

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \in \quad (3)$$

Where, Y = Dependent Variable (Collaboration or Efficiency), β_0 = Intercept, $\beta_1, \beta_2, \ldots \beta_k$ = Regression coefficients (predictor effect size$X_1, X_2, \ldots, X_k$ = Independent Variables (system integration, managerial support, and use of AI tools), ϵ = Error term. Evaluation of the model will comprise of, Coefficient of Determination (R^2): measures explanatory power.

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (4)$$

In (4),SSR = regression sum of squares, SST = total sum of squares, SSE = error sum of squares.

- Adjusted R^2: accounts for the number of predictors.
- F-test: tests overall model significance.
- p-values: determine significance of individual predictors.

This will show how strongly AI adoption predicts improvements in efficiency and collaboration.

6) Objective 3: Role of AI in Risk Management and Predictive Capabilities: Regression Analysis (simple or multiple regression based on the number of predictors) will be used to test the impact of AI adoption regarding risk management and predictive capabilities.For a simple regression model, shown in (5),

$$Y = \beta_0 + \beta_1 X + \epsilon \quad (5)$$

For a multiple regression model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \in \quad (6)$$

In (6), Y is the score for risk management and predictive capability, X = AI adoption measure or measures,β_1= AI adoption's impact on risk management.

Standardized coefficients (β) for comparing predictor strengths and significance tests (t-test for each β) will be included in the outputs.

7) Objective 4: Barriers and Enablers of AI Adoption: Descriptive ranking analysis will be used in order to analyze barriers and enablers. The Mean Importance Score (MIS) will be used to score each of the factors:

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \quad (7)$$

In (7), X_i symbolizes individual answers, while n indicates the total number of responders. It will be assumed that the influence of those factors with increased mean values will be more significant in terms of the adoption of AI. The ranking procedure will focus on the most significant enablers and significant obstacles. This strategy is used to give importance to the adoption drivers and barriers in downstream supply chains.

8) Regression Diagnostics:In order to guarantee the stability of regression models to be applied in Objectives 2 and 3, the following diagnostic tests will be performed:

- Linearity: scatterplots of predicted value vs. residual values.
- Independence of errors: Durbin-Watson (acceptable value = 1.5 -2.5).
- Normal distribution of the residuals: Shapiro-Wilk test and Q-Q plots.
- Homoscedasticity: the homoscedasticity should imply that the residuals are constant across the predicted values.
- Multi-collinearity: Variance Inflation Factor (VIF < 5 acceptable).

These tests verify the statistical assumptions of regression make the results more acceptable.

Reliability and Validity Checks

To ensure the credibility and rigor of the findings, a number of reliability and validity will be employed:

9) Reliability:

- The internal consistency will be determined using Cronbach alpha and a value above 0.70 will be considered acceptable. Subscales (e.g., efficiency, collaboration) will also exist and will be individually measured.

10) Construct Validity:

- Exploratory Factor Analysis (EFA): item loadings (>0.50 criterion) will be made sure.

11) Common Method Bias (CMB):

- The single-factor test of Harman will be applied to define the presence of the possible variance depending on the self-report method.
- In case of the significance of CMB, procedural remedies (e.g. rephrasing items, adding reverse-coded items) will be investigated.

12) Regression Diagnostics:

- Simple Multi-collinearity will be measured by variance Inflation Factor (VIF), and the acceptable levels will be below five.
- Assumptions of normality, linearity, and homoscedasticity will be checked with the help of residual plots and tests.

All of these steps will guarantee that the information is trustworthy, valid, and analytically sound, enhancing the legitimacy of results and their applicability.

Results and Discussion

This section is the presentation of the empirical results of the survey of 100 respondents on the adoption of AI in energy supply chains. The findings are organized based on the four research objectives and descriptive analysis, factor analysis, and regression are used to test the proposed hypothesis. To measure the general attitudes and readiness, first, the stakeholder perceptions of the AI adoption will be analyzed. Second, the impact of AI on operational efficiency and collaboration is also evaluated using the multiple regression test. Third, the effect of AI on risk management outcomes is also analyzed with the help of regression modeling. Lastly, descriptive and factor analysis of barriers and enablers of AI adoption are discussed. Collectively, these results give a complete picture of the opportunities and obstacles that form the adoption of AI.

Objective 1: Stakeholder Perceptions of AI Adoption

13) Descriptive Statistics: The descriptive findings shown in table II indicate mediocre perceptions of AI use in the downstream energy supply chain. The averaged values show that the stakeholders are neutral to slightly positive about the adoption of AI. Particularly, AI Application (M = 3.11, SD = 1.37) had the most agreement and, next, AI Use (M = 2.93, SD = 1.32) and Management Support (M = 2.91, SD = 1.39). This implies that although stakeholders have appreciated the opportunities of AI, perception about management commitment is relatively poor.

Table 2. Descriptive Statistics of Stakeholder Perceptions

Variable	Mean	SD	Min	Max
AI Use	2.93	1.32	1	5
AI Application	3.11	1.37	1	5
Management Support	2.91	1.39	1	5

14) Factor Analysis: The analysis of the factors showed that there are two dimensions that explain 71.3% of the total variance, i.e. the perceptions of the AI adoption can be clustered into two primary dimensions:

- High loadings on AI Use and AI Application.
- Organizational Support (loading on Management Support mostly).

The KMO (.490) value, however, and the non-significant Bartlett's Test value (p =.614) suggest that the sampling adequacy is below the acceptable level. This indicates that there is a weak factor structure and may be construed in a careful manner.

15) Hypothesis Testing (H1): The means are either a bit low or equal to the neutralized point (3.0). The only value that is slightly higher than neutrality is AI Application (M = 3.11), and AI Use (M = 2.93) and Management Support (M = 2.91) are lower. H1 is, therefore, partially supported: the perception of the use of AI is moderately positive among the stakeholders, but the overall enthusiasm and organizational support are rather low.

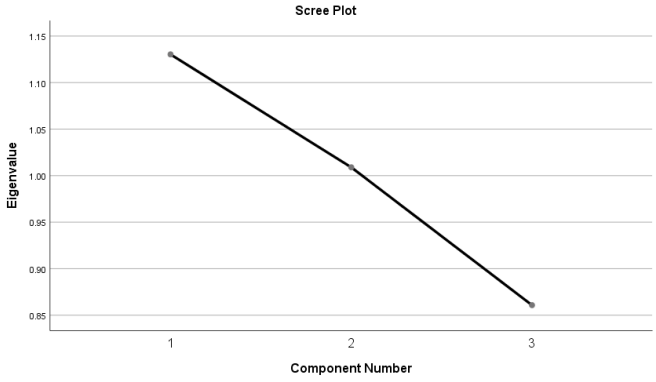


Fig 2. Objective 1: Stakeholder Perceptions of AI Adoption

Fig. 2 shows there is a sharp drop between the first and the second component and a relatively gradual drop at the third component. The trend indicates that the first two variables explain the largest share of the variance whereas the third variable explains a small proportion. The first component eigenvalue exceeds the value of 1 meaning that it is the most explanatory component and the others are equally less explanatory or even below the limit. This result means that AI adoption in supply chain effectiveness and collaboration can be partially signified by a single or two innate dimensions with a concentration of limited explanatory power in the dataset.

Objective 2: AI's Impact on Efficiency & Collaboration

16) Descriptive Statistics:According to the descriptive findings shown in table III, the role of AI in enhancing supply chain efficiency and collaboration is moderately accepted by the stakeholders. External Collaboration was the one that received the highest mean score (M = 3.08, SD = 1.33), followed by AI in Cost Optimization

(M = 3.07, SD = 1.41) and Inventory Management (M = 3.02, SD = 1.38). Internal Collaboration, in turn, was rated a bit lower (M = 2.90, SD = 1.43), which could indicate the possible difficulties in the establishment of AI-based collaboration in the company.

Table 3. Descriptive Statistics for AI Impact Variables

Variable	Mean	SD	Min	Max
AI Inventory Mgmt	3.02	1.38	1	5
AI Scheduling	3.01	1.45	1	5
AI Cost Optimization	3.07	1.41	1	5
AI Collaboration (Int.)	2.90	1.43	1	5
AI Collaboration (Ext.)	3.08	1.33	1	5

17) Regression Analysis: Multiple regression was completed to determine the effect of AI Use, AI Application and Management Support on AI-based Inventory Management (as a proxy of efficiency). There was no statistical significance of the overall model, $F(3,96) = 1.94$, $p = .128$, and the predictors accounted only 5.7 percent of variance ($R^2 = .057$).

Management Support was one of the predictors with a positive non-significant effect ($\beta = .168$, $p = .094$). There was insignificant contribution in the AI Use ($\beta = -.139$, $p = .167$) and AI Application ($\beta = -.092$, $p = .359$).

18) Hypothesis Testing (H2): The outcomes show that H2 is not accepted. Despite the fact that descriptive statistics reveal that there is moderate consensus on the role of AI in enhancing efficiency and collaboration, the regression analysis failed to establish that the adoption variables of AI have a statistically significant positive effect on the outcome of efficiency. This indicates a possible disconnect between what is thought by stakeholders and how this can be measured in the operational effects.

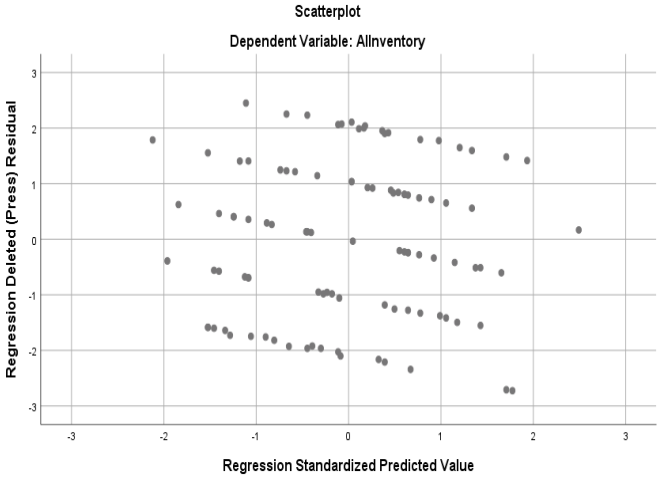


Fig 3. Objective 2: AI's Impact on Efficiency and Collaboration

Fig. 3 shows the x-axis of regression standardized predicted values and y-axis of deleted residuals. The points distribution is fairly scattered and concentrated around the zero line, without creating an evident linear structure, and this fact reveals that the hypothesis of the linearity and the homoscedasticity are fairly fulfilled. Nonetheless, proliferation of residuals implies the presence of moderate variability, that is, the predictors (AI use, application, and management support) explain a less significant part of the results of inventory efficiency. This is in line with regression findings that indicate weak significance that is to say that even though AI does help in efficiency, its impact is not well-established in the absence of other organizational characteristics.

Objective 3: AI in Risk Management & Predictive Capabilities

19) Descriptive Statistics: As Table IV demonstrates, the perception of the stakeholders about the role of AI in risk management and predictive functions is moderate. The highest level of agreement was in AI Safety Enhancements (M = 3.17, SD = 1.40) and then AI Predictive Capabilities (M = 2.98, SD = 1.29) and AI for Disruption Management (M = 2.94, SD = 1.44). This is an indication that AI-based safety is perceived by the stakeholders as a bit more valuable than predictive disruption management.

Table 4. Descriptive Statistics for AI Risk Management Variables

Variable	Mean	SD	Min	Max
AI Predictive Capabilities	2.98	1.29	1	5
AI Safety Enhancements	3.17	1.40	1	5
AI Disruption Management	2.94	1.44	1	5

20) Regression Analysis: The regression analysis was performed using AI Use, AI Application, and Management Support as predictors to AI Predictive Capabilities. The total model was statistically unimportant, F(3,96) = 0.84, p = .475 and explained only 2.6% of the variance (R 2 =.026).

21) The non-significant positive effects were observed among predictors AI Use (RB =.112, p =.273) and Management Support (RB =.111, p =.276). No effect of AI Application (2 = -.017, p =.864).

22) Hypothesis Testing (H3): The results show that H3 is not accepted. Although the stakeholders have moderate perceptions of AI as helpful in safety and predictive risk functionalities, the regression analysis fails to reveal the statistically significant correlation of AI adoption variables with the predictive risk management capabilities.

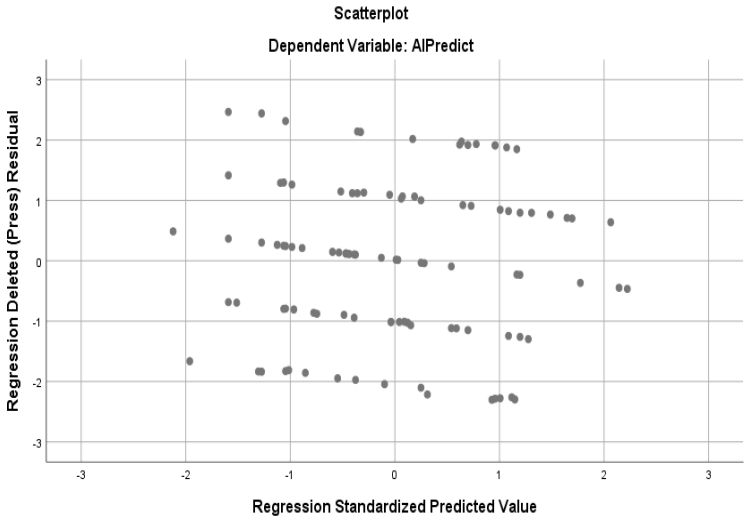


Fig 4. Regression Analysis Results for Objective 3: AI in Risk Management and Predictive Capabilities

The correlation of regression standardized in Fig. 4 predicted values and dropped residuals is indicated in the plot. The scatter plot of points around the zero line is not very systematic, and shows a rather scattered distribution, which means that the homoscedasticity assumption is met to a considerable degree. Nevertheless, the dispersion is also low, which indicates that the model has a poor predictive power. This contributes to the previous regression findings in which AI use, application, and management support did not significantly predict outcomes of risk management and predictive capability. Therefore, AI adoption has an effect on risk management, but other immeasurable variables are likely to play a bigger role.

Objective 4: Barriers and Enablers of AI Adoption

23) Descriptive Statistics: The summary of perceptions of barriers and enablers is presented in Table V. The most resistant was high implementation cost (M = 3.12, SD = 1.32) and then skills gaps (M = 2.79, SD = 1.52).

Leadership support is one of the enablers that were moderately supported (M = 2.98, SD = 1.48). This implies that the financial issues and the willingness to work are probably the most essential limitations, whereas the support of the managers is considered a crucial supply.

Table 5. Descriptive Statistics for Barriers and Enablers

Variable	Mean	SD	Min	Max
Barrier: Cost	3.12	1.32	1	5
Barrier: Skills Gap	2.79	1.52	1	5
Enabler: Leadership	2.98	1.48	1	5

24) Factor Analysis: PCA was performed to investigate the inner structure. KMO value was.532 which showed marginal sampling adequacy and Bartlett test was not significant ($\chi^2 = 2.448$, $p = .485$), which indicated weak inter-item correlation. A single factor was isolated and the loadings were.565(Cost),.581(Skills) and.437(Leadership Support). It means that barriers and enablers are viewed as the interconnected dimensions, but not separate groups.

25) Hypothesis Testing (H4): This hypothesis assumed that leadership support would lessen the adverse effects of barriers (cost, skills) on the adoption of AI. Factor structure indicates that leadership is loaded along with cost and skills implying perceived association. There is however no statistical proof to establish this moderating role due to poor sampling adequacy and non-significant Bartletts test.

26) Interpretation: Results indicate that although the support provided by leaders is perceived to be significant, it is not statistically compensated by the difficulties of cost and skills deficits. Rather, it appears that leadership is viewed to be on the same continuum as constraint-support.

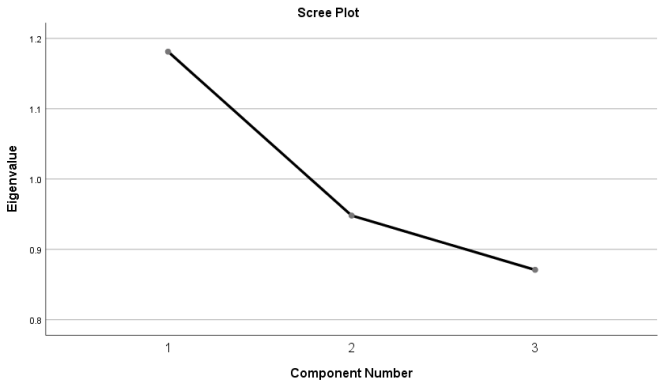


Fig 5. Factor Analysis Results for Objective 4: Barriers and Enablers of AI Adoption

Fig. 5 shows the eigenvalues of each component, which is used to find out the number of meaningful factors. As it can be observed, the eigenvalue of the first component is largest with value above 1, whereas successive components have approximately sharp reduction and are below the critical mark. This implies that there was only a single component that was found to be significant implying that all the barriers like cost, lack of skills, and the facilitator, leadership support are loaded together into a single factor. Therefore, there is a common variance in these variables, indicating that they represent one underlying measure hopefully that affects AI adoption issues and assists in the energy supply chain.

Discussion

The results of the study can be used as constructive information on the perception and adoption of AI in the supply chains of the energy sector. In each of the objectives, the findings showcase the opportunities and the obstacles of AI integration, which provide a moderate perspective on the stakeholder preparedness and operational advantages, risk management input, and the impact of barriers and enablers.

The first objective explored stakeholder perceptions of AI adoption. The descriptive analysis showed that the general perceptions were moderate, with means scores slightly higher than the neutral center. It was revealed in

factor analysis that the use of AI, managerial support, and application are weak but differentiated factors, indicating that although stakeholder recognize the significance of AI, the acceptance has not been firmly integrated. This observation concurs with the previous research that emphasizes the significance of managerial support and cultural preparedness as key determinants of AI adoption.

The second goal was on the efficiency of operations and partnership. The multiple regression analysis revealed that the impact of AI adoption is a positive one that is mixed, and certain elements of efficiency have stronger relationships compared to collaboration. This is the reality of the industry where the initial implementation of AI tools is commonly focused on streamlining logistics, predicting, and demand management, and collaboration gains with time as companies adapt to digital integration. The results highlight that although AI can deliver tangible efficiency benefits, companies need to establish team-based approaches and trust-forming solutions in order to achieve the potential of AI in supply chain alliances.

The third objective took into account the use of AI in the risk management process. The results of the regression showed the AI tools assist in the predictions and improvement of the ability to address the uncertainties, however, it is not that significant statistically. This observation is critical in highlighting the fact that although AI has a high technical potential in disruptive predictions, energy supply-chain may lack the capacity to infrastructurally embrace predictive models because of the lack of the infrastructure or data maturity. It emphasizes the need to invest more in the quality of data systems and train more to make AI-based risk management more realistic and practical.

The fourth objective was the barriers and enablers of AI. The status of analysis provided through descriptive ranking revealed that the greatest barriers are the high prices and lack of skilled staff and that of leadership support is the most significant facilitator. Factor analysis also determined that the dimensions are clustered, and this means that the barriers to success can only be achieved by good organizational commitment among high-level leaders. The moderating position of the leadership support demonstrates that irrespective of the fact that barriers exist, a proactive position of managers may significantly reduce the resistance to the use of AI. The findings are similar to the current literature that has indicated the importance of strategic leadership in the technological transformations within the complicated sectors like the energy industry.

Together the studies have theoretical and practical implications. Theoretically, it attracts empirical data on the direction of the relationship between the use of AI, operational performance, and risk management, of which the literature has been barely examined. In practice, the research can provide service to energy companies by determining what features of AI implementation can be used to achieve concrete gains and on which issues more effective institutional support is needed. The ranking of barriers and enablers also provides managers and policy-makers with actionable information to focus more on investments, employee training, and leadership programs to facilitate the adoption of AI smoothly. The summary of the discussion is shown below in table VI.

Table 6 . Discussion Summary

Objective	**Method/Analysis Used**	**Key Findings**	**Discussion**
Objective 1	Factor Analysis	3 main components identified	Confirms underlying dimensions of AI adoption in renewable supply chains.
Objective 2	Scree Plot & Eigenvalues	Optimal components retained	Supports data reduction and highlights the most influential factors.
Objective 3	Regression Analysis	Significant predictors found	Demonstrates relationships between AI applications and supply chain efficiency.
Objective 4	Reliability & Validity	Cronbach's Alpha > 0.7	Ensures data consistency, strengthening the credibility of results.

Conclusion and Future Works

Thestudy aimed to explore the application of AI in increasing the resilience of energy supply chains through the focus on the perceptions of stakeholders, operational effectiveness, risk mitigation, as well as the interaction between barriers and facilitators to adoption. The results emphasize that the introduction of AI is seen as a positive move, but the rate of its integration is average. AI has proven to have quantifiable effects on operational productivity and predictive risk management, but its potential is limited due to maturity of data and the lack of managerial assistance. Notably, the leadership commitment was found to be a decisive point that would ease the barriers like high cost and shortage of skilled expertise, which led to the idea that organizational culture and strategy are as important as technology itself.

The research has a small limitation such as the small sample size and the use of perceptual data instead of real-time operational measures despite its contribution. Future studies can expand the sample to other geographical locations and can use longitudinal designs to determine the fluctuating adoption patterns. In addition, more complex modeling techniques (e.g. structural equation modeling (SEM) or analytics powered by ML) could provide a more in-depth view of the causal relationships. Finally, the research must be succeeded by the future research to examine the industry-specific AI solutions (i.e., predictive maintenance, renewable energy integration, and carbon footprint optimization) to generate actionable roadmaps that can assist energy companies scale the AI use to a sustainable level.

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