

A multidimensional analysis of artificial intelligence perceptions as a tool for enhancing sustainable quality in petroleum operations: An analytical study in the East Baghdad oil field

Zainab Thaeer Tawfeeq Alharbi

Polytechnic College, Al-Furat Al-Awsat Technical University, Iraq
zainab.tawfiq.ikr@atu.edu.iq

Abstract

The study aimed to analyze the perceptions of oil sector workers about artificial intelligence and its use as a tool to enhance sustainable quality in oil operations. The study applied the quantitative approach. The study population consisted of the East Baghdad oil field. The study sample amounted to 200 individuals working in the maintenance and engineering departments and the safety and environment department. The data collection tool was a questionnaire in addition to personal interviews. 200 questionnaires were distributed to the study sample in the field, and 187 questionnaires were returned, representing 93% of the total. After conducting statistical processing of the study sample's opinions, the study revealed a set of results, the most important of which was that the application of artificial intelligence tools (such as predictive data analysis and predictive maintenance) contributed to increasing the efficiency of operations such as production and maintenance. It also enhanced the Safety and Environment Department's ability to monitor pollutants and reduce emissions using smart methods, in addition to encouraging employees to adopt more sustainable solutions, especially in planning and development. Based on the study results, recommendations were formulated, such as developing ongoing training programs for all departments on the use of artificial intelligence tools in quality and sustainability, improving communication systems, providing smart sensors, linking data between departments, and deploying artificial intelligence systems to monitor emissions and assess the environmental impact in real time.

Keywords: Sustainable, Quality Sustainability, Oil Company, East Baghdad Field.

1. Introduction

Artificial intelligence (AI) is a rapidly evolving technology that has been used for more than two decades across various industries. AI-based workflow capabilities have proven promising for various fields, including the oil and gas sector, including but not limited to optimizing development plans, detecting residual oil, detecting fractures, optimizing oil recovery, and dynamic forecasting of oil field production (Li, 2021). It is important to note that AI solutions are not universally applicable and cannot be easily purchased. Rather, they require customization to align with the specific business context and data of the organization (Sircar et al., 2021; Koroteev & Tekic, 2021). Therefore, it is essential for organizations to develop internal groups of data and AI professionals to effectively

integrate AI into their operations and offerings. The oil and gas industry (OGI) are expected to adopt a partially data-driven approach due to this emerging trend, with AI technology being integrated into various stages of the industry (Koroteev & Tekic, 2021). Smart drilling is one of its many applications in exploration and production, development, pipeline construction, and processing. Furthermore, the oil and gas industry have the potential to leverage AI to assess the potential implications of new projects or to examine the environmental risks associated with a new initiative before developing plans particularly in enhancing quality, sustainability, and operational efficiency. Through the integration of machine learning, computer vision, and big data analytics, AI technologies have improved the accuracy and responsiveness of industrial processes. In the oil and gas sector, the concept of “Oil and Gas 4.0” reflects a growing shift toward adopting Fourth Industrial Revolution technologies. This framework emphasizes leveraging AI, the Industrial Internet of Things (IIoT), and big data to increase value creation and optimize operations (Lu et al., 2019).

With technological developments worldwide, it has become imperative to preserve and protect the environment from environmental impacts by developing plans, mechanisms, and work procedures necessary to address the impacts of environmental aspects. These impacts pose a challenge to industrial organizations in how to transform these environmental aspects into opportunities to improve the environment and enhance their environmental reputation (Resen et al., 2023). Since oil and gas companies are much quicker to adopt new technologies than to experiment and change their business models, which contributes to more informed strategic decisions (Tekic & Koroteev, 2019), the primary goal of their AI (and other digitization efforts) is to improve efficiency and thus quality. In practical terms, this usually means accelerating operations, reducing risks, and improving development plans (Lu et al., 2019; Shafiee et al., 2019; Li et al., 2021).

This research is structured into four key sections, each tackling a distinct dimension of the study. The first section explores how artificial intelligence supports sustainable quality, particularly by examining recent technological innovations and their implications for oil companies. The second section outlines the adopted methodology, presenting the research problem identified within the target company and highlighting the significance of the study from both theoretical and practical standpoints. It also describes the process of designing and distributing the questionnaire, which was targeted at employees in the Maintenance and Engineering Department and the Environmental Safety Department to ensure varied insights. The third section presents the findings of the field survey along with an in-depth analysis that connects these results to broader theoretical and practical contexts. Finally, the fourth section concludes with key insights and recommendations intended to support institutional development and promote sustainable quality practices in the workplace.

2. Literature Review

2.1 Artificial Intelligence:

In recent years, artificial intelligence (AI) has gained significant attention across various fields. Much of the existing literature highlights the impressive capabilities and potential of AI technologies

(De Mattos et al., 2024; Zeadally et al., 2020; Ahmadi et al., 2016; Binu et al., 2021). However, relatively fewer studies have addressed the limitations and challenges associated with AI applications (Wirtz et al., 2020; Saghiri et al., 2022; Cheng et al., 2022). Among the concerns raised are issues related to data security (Hanif et al., 2018; Zeadally et al., 2020), algorithmic fairness (Bellamy et al., 2019; Pagano et al., 2023), safety and reliability (Varshney, 2016), ethical dilemmas (Smuha, 2019; Monteith et al., 2023), and the high energy demands of AI systems (Strubell et al., 2019; Mhlanga et al., 2023). These aspects highlight the need for a more balanced view that considers both the benefits and potential drawbacks of AI adoption. The widespread use of AI brings new challenges. There is confusion about what artificial intelligence (AI) is or what it encompasses, rooted in the collective inability to define it and develop a globally agreed-upon definition. The field lacks a clear definition (Monett and Lewis, 2018; Bhatnagar et al., 2018; Wang, 2019; Fogel, 2022). AI is defined based on its ability to simulate human intelligence, and the definition shifts to the ability of an information system to understand inputs and devise solutions to problems. More precisely, the system's focus is on performing tasks and solving problems (Wang, 2019).

Artificial intelligence (AI) is the study of the characteristics of human activities and the construction of a specific intelligent system to enable computers to complete tasks that were previously only capable of being performed by humans. It applies computer hardware and software to simulate the basic theories, methods, and techniques of human behavior. AI has been evolving for more than 60 years, becoming interdisciplinary and interdisciplinary between the natural sciences and the social sciences, and comprising diverse disciplines (Došilović, Brčić, & Hlupić, 2018; Mata et al., 2018; Murphy, 2012; Tan & Lim, 2018).

Contemporary artificial intelligence (AI) technologies have advanced toward greater levels of autonomy, encompassing areas such as robotics, autonomous vehicles, facial recognition, natural language processing, and intelligent virtual agents (Baird & Maruping, 2021). According to Balakrishnan et al. (2020), by 2020, over half of global firms had already adopted some form of these emerging technologies. The rapid expansion of AI applications continues to reshape various aspects of everyday life, with tangible impacts across sectors including healthcare, education, transportation, and personal safety (Rahwan et al., 2019; Stone et al., 2016). These developments suggest not only technological progress but also a growing reliance on AI-driven systems in both public and private domains.

2.2 Artificial Intelligence Applications in Oil Companies:

Lantham (2019) discussed the need for petroleum-related materials that are growing daily. Therefore, companies must take action to improve production, reduce costs, and address the environmental impacts of hydrocarbon production. These goals cannot be achieved using traditional methods of exploring, producing, and managing hydrocarbon resources. Therefore, it is necessary to provide newer technologies and reservoirs to explore hydrocarbons at greater depths and in more remote locations.

AI provides companies with unprecedented opportunities to design smart products, create new service offerings, and innovate new business models and organizational forms (Agrawal et al. 2019; Davenport et al. 2020; Townsend & Hunt 2019). However, AI is not a technological panacea.

The petroleum industry includes disciplines for oilfield exploration, reservoir engineering, drilling, and production engineering. Oil and gas are also a fuel source for other chemicals, including pharmaceuticals, solvents, fertilizers, pesticides, and plastics (Anderson, 2017). If fossil fuel prices continue to rise, fossil fuel companies will need to develop new technologies and enhance their operations to increase efficiency and build on their existing capabilities. Improving control over major oilfields requires rapid decision-making while taking into account ongoing challenges. A smart oilfield will achieve this by developing a comprehensive oilfield technology infrastructure, digitizing hardware systems, and establishing network-based knowledge exchange to optimize production (Temizel et al., 2019).

The influence of digital technologies on both business operations and societal structures has grown significantly in recent years. This ongoing evolution has led many scholars and practitioners to refer to digital transformation as the “Fourth Industrial Revolution.” This phase is marked by the integration of advanced technologies—such as artificial intelligence, robotics, and autonomous systems—that increasingly merge the physical, digital, and biological domains, reshaping how industries function and how individuals interact with technology. Artificial intelligence (AI) technologies are gaining significant attention due to their rapid response times and strong generalization capabilities (Evans, 2019). In exploration and production operations, massive amounts of data are generated across various daily processes. These databases can be used in data-driven methodologies and big data interpretation to achieve useful decision-making strategies. The benefit of using these models is to optimize and enhance hydrocarbon production (Hamzeh, 2016).

It can help companies intelligently automate production and improve production efficiency (Arend, 2014), product quality, and other organizational activities (Pesämaa, 2017).

Particularly in addressing complex and data-intensive challenges. Techniques such as artificial neural networks (ANN) and fuzzy logic (FL) have been widely adopted in the literature to model reservoir behavior and optimize production strategies (Anifowose et al., 2017). As AI continues to expand its role in engineering disciplines, there is a growing recognition of the need for a structured framework that captures the breadth and depth of AI-related knowledge. Cuomo et al. (2022) propose a multidimensional framework encompassing four key domains, which together enable a more critical and responsible engagement with AI. This framework encourages not only technical understanding but also ethical and contextual awareness in the application of AI technologies.

The framework consists in detail of the following dimensions:

2.3 Dimensions of Artificial Intelligence:

- Knowledge Dimension: Includes an understanding of the basic concepts of artificial intelligence, with an emphasis on basic skills and attitudes that do not require prior

technological knowledge and Product description of artificial intelligence and voice recognition (Ng et al., 2021; Lee et al., 2025).

- **Operational Dimension:** This dimension centers on the practical implementation of AI concepts across various fields. It encourages the development of problem-solving skills using AI tools, along with designing algorithms and building simple applications to strengthen students' analytical and critical thinking abilities (Druga et al., 2019; Kim et al., 2021; Li et al., 2025).
- **Critical Dimension:** This aspect focuses on how AI can stimulate higher-order thinking by involving students in activities that demand creativity, cognitive engagement, and critical assessment. It also underlines the importance of fostering effective interaction with AI technologies and critically assessing their implications on society (Su et al., 2022; Wang & Wang, 2025).
- **Ethical Dimension:** This dimension addresses the importance of responsible and informed use of AI technologies. It draws attention to sensitive ethical concerns, such as delegating decision-making to machines in areas like recruitment or healthcare. Increasing attention is being paid to AI ethics, which encompasses principles like transparency, fairness, accountability, privacy, and security (Abulibdeh et al., 2024).

2.4 Sustainable Quality:

In today's dynamic business environment, companies are increasingly challenged by a complex set of contextual pressures, including fierce market competition, limited resource availability, rising consumer expectations, rapid technological advancement, climate-related concerns, and growing stakeholder demands. Addressing these challenges effectively requires a structured and forward-looking management approach—one that prioritizes the integration of economic, environmental, and social objectives within a long-term strategic framework. Several paths have been proposed for this purpose, namely the development of specific tools and models for sustainability management. It is essential to integrate sustainability at various management levels, such as the strategic and operational levels, while taking into account the current and future needs of stakeholders. Among a wide range of tools to support this goal, Quality Management Systems (QMS) have been identified as a path to integrating sustainable development principles (Ranängen & Zobel, 2014). Quality management systems have led to increased change and adaptation in organizations so that they can respond effectively to political, economic, and social changes. (Van Kemenade & Hardjono, 2019) Organizations expect to realize the value of the quality management system, hoping that its mechanisms (tools, practices, procedures, and processes) will effectively help them overcome current challenges, in which sustainable development is prominent.

Thus, this research supports the proposition that integrating sustainability into a quality management system can be a viable path to developing a sustainable quality management model. It has been advocated for integrating sustainability into a quality management system as a path to improving a company's performance, thereby increasing its competitive advantage by achieving its economic,

social, and environmental goals efficiently and effectively (Savino & Batbaatar, 2015; Bernardo et al., 2017; Fundin, 2018)

Sustainability efforts focus on product and process development, despite their proven potential and the emergence of minor developments in the early stages. However, there is less focus on environmental management (Tingström et al., 2016). Consequently, current quality management models do not aim to achieve optimal synergy between sustainability concepts and quality elements, despite their potential. Therefore, implementing these concepts requires a comprehensive approach and a general framework of interconnected elements that integrate quality management systems, energy management systems, and sustainability aspects under one umbrella. An integrated framework is essential. Therefore, developing an integrated quality management framework is justified to make the concept of "sustainable quality management" more feasible and research-effective.

2.5 Studied Dimensions of Sustainable Quality:

Silva et al. (2021: 2050) addresses the dimensions of sustainable quality as follows:

- Integration of quality and sustainability: The research indicates that integrating sustainability principles into quality management systems enhances organizations' ability to adapt to environmental, social, and economic challenges, leading to improved overall performance.
- Transformational leadership: The study highlights the importance of transformational leadership in promoting sustainable quality, as leaders demonstrate the ability to motivate and direct employees toward achieving quality and sustainability goals.
- Stakeholder focus: The study emphasizes the need to consider the needs and expectations of various stakeholders, including customers, society, and the environment, when developing and implementing sustainable quality management systems.
- Flexibility and adaptability: The results indicate that organizations that adopt sustainable quality management systems are better able to adapt to rapid changes in the external environment, enhancing their long-term sustainability.

3. Research Methodology

This part of the research discusses the methodology used to achieve the research objective. This includes the research design, type and sources of data, study population, sampling method, sample size determination, and methods of data collection and analysis.

3.1 Research Design and Data Collection:

In line with the subject of the study in an attempt to achieve its objectives, in order to achieve the desired results, the research will adopt the quantitative approach, as it is suitable for studying the reality of the East Baghdad oil field, and because this approach depends on (personal interviews -

observation method -questionnaire -in addition to field experience) which helps in evaluating the reality of field work and highlighting the perceptions of workers through answers, eye observations and related official documents, in addition to interweaving the analytical description approach in order to clarify the results of the questionnaire answers, arriving at determining the conclusions and giving appropriate recommendations and solutions with a tangible impact.

4. Result and Discussion

The study population consisted of the East Baghdad oil field, where the study sample amounted to 200 individuals working in the maintenance and engineering departments and the safety and environment department. The data collection tool was the questionnaire, in addition to personal interviews. 200 questionnaires were distributed to the study sample in the field, and 187 questionnaires were retrieved, representing a percentage of 93% valid for analysis.

4.1 Data Type and Source:

Quantitative data were collected to study the organization's AI capability. The study relied on primary data sources. Data were collected through structured survey-based questionnaires distributed to employees of the East Baghdad Oil Field, focusing on their perceptions of AI capabilities and their impact on sustainable quality.

The questionnaire contained two main variables (concepts): perceptions of AI and sustainable quality. The first variable, perceptions of AI, included four dimensions adapted from the study (Cuomo et al., 2022) and included twelve measurement items. The second variable, sustainable quality, was measured using four dimensions adapted from the study (Silva et al., 2021) and included eight measurement items. All items used a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). This method is common in experimental studies in the absence of objective measures (Robinson, 2014).

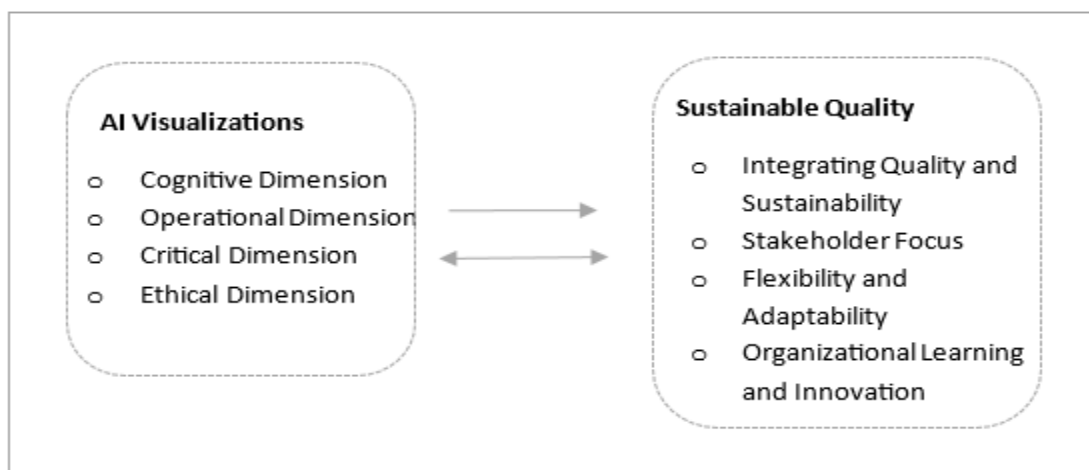


Fig. (1): Conceptual framework

4.2 Response Rate and Data Sorting Analysis:

Two hundred questionnaires were distributed to employees of the East Baghdad Oil Field to study the impact of AI perceptions on enhancing sustainable quality within the company. 187 responses were received (93 %), demonstrating a significant increase in the response rate. This indicates a high level of interest and willingness on the part of employees to provide feedback on the impact of AI on enhancing and sustaining quality. Furthermore, the high participation and response rate can be attributed to the importance of the study topic and its relevance to employees and the company.

4.3 Personal Characteristics of the Sample:

Table (1) displays the personal characteristics of (187) individuals representing the research sample, distributed according to the following variables: gender, age, educational attainment, and years of service. This data provides precise statistical details that contribute to drawing a preliminary picture of the workforce composition at the oil site under study. This information serves as a preliminary reflection on understanding the characteristics of human resources in terms of age distribution, level of educational qualifications, and degree of practical experience. These are important indicators in interpreting the level of organizational performance and response in a complex and specialized operational environment such as an oil field.

Table (1): Personality trait (Source: Prepared by researchers based on SPSS V26 program outputs)

The feature	Category	repetition	percentage
gender	male	183	98%
	female	4	2%
	Total	187	100%
Age	25years and under	26	14%
	26-35	67	36%
	36-45	58	31%
	46-55	21	11%
	56 and over	15	8%
	Total	187	100%
Academic achievement	PhD	2	1%
	Master's	2	1%
	Higher Diploma	2	1%
	Bachelor's	136	73%
	Other	45	24%
	Total	187	100%
Years of service	5years and under	19	10%
	10-Jun	28	15%
	15-Nov	62	33%
	16-20	45	24%
	21-25	25	13%
	26and over	8	4%
	Total	187	100%

The following table (1) shows:

- Gender: The data indicate that males constitute the overwhelming majority of the study sample, with (183) individuals representing (98%), while females represent only (2%), with (4) individuals. This distribution is attributed to the masculine nature of the field operations sector in the oil industry, where jobs often require physical, technical, and field tasks, in which male participation is preferred due to the prevailing professional and cultural reality.
- Age Groups: The ages of workers were distributed as follows: 26-35 years old constituted the highest percentage (36%), followed by 36-45 years old (31%), 25 years and younger (14%), 46-55 years old (11%), and finally 56 years and older (8%). The distribution indicates that oil field workers are concentrated in the young and middle-aged age groups, which are most capable of working in difficult field conditions that require physical energy and continuous technical preparation. The low percentage of those over 55 suggests the existence of flexible management for gradual retirement or the redeployment of older personnel to non-field work.
- Academic achievement: Bachelor's degree holders represent the majority (73%), which is the expected percentage in oil fields that rely on specialized engineers and technicians. While the percentage of graduates (PhD, Master's, Higher Diploma) was very low (3%), the percentage of "other" (24%), which often includes technical or vocational degrees below university level. The oil field's reliance on bachelor's degree holders aligns with the need for technical professional expertise in mechanical engineering, chemistry, geology, and drilling techniques. The low percentage of graduate studies is logical in operational settings, where the need for high academic specialization is less than the need for applied competencies.
- Years of Service: The service category (11-15 years) represents the largest (33%), followed by (16-20 years) with (24%), then (6-10 years) with (15%). The categories with little experience (5 years or less) represent (10%), the category (21-25 years) represents (13%), and the category above (26 years) represents (4%). These data demonstrate that the vast majority of employees have accumulated professional experience in the oil sector ranging from 6 to 20 years, which enhances operational stability and quality of field performance. The low percentage of newly appointed cadres may indicate a lack of new appointments in recent years or the existence of strict hiring criteria that require practical experience.

a. Stability Test:

Cronbach's alpha was used to measure the internal consistency of the study instrument, ensuring the consistency of the items measuring each dimension of the research.

The value of this coefficient ranges from 0-1, with a value of 0.70 or higher being an acceptable indicator of the instrument's reliability.

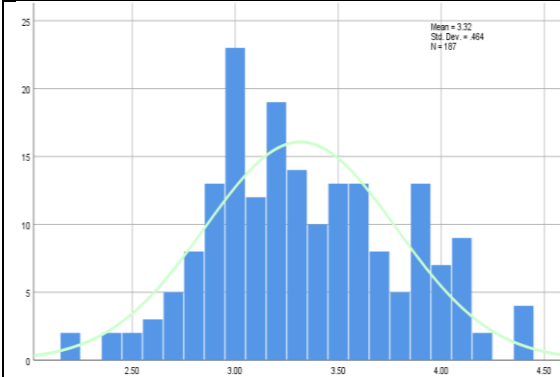
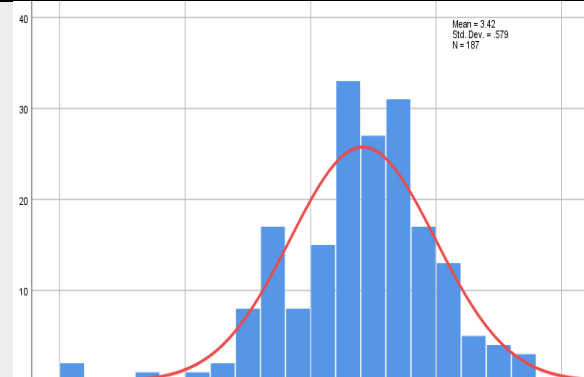
The results showed that all calculated values were within acceptable limits, indicating the high reliability of the measurement instrument.

Table (2): Stability values (Source: Prepared by the researchers based on the outputs of the SPSS V26 program)

Variables and scale	Number of paragraphs	Reliability value (Cronbach's Alpha)
artificial intelligence	12	0.871
Sustainable Quality	8	0.794
Total scale	20	0.903

Table (2) shows that the reliability value for the artificial intelligence axis reached (0.871), which is a high value and indicates strong internal consistency between the items of this axis, which enhances the validity of the tool in measuring the attitudes and opinions of employees regarding the uses of artificial intelligence in oil operations. This high value is attributed to the integration between the sub-dimensions (cognitive, operational, critical, ethical), which form a homogeneous unit of analysis that reflects the integrated understanding of the respondents. As for the sustainable quality axis, its reliability coefficient reached (0.794), which is also a good value and falls within the scientifically acceptable level, indicating a reasonable degree of interconnection between the axis items. It is noted that the diversity of dimensions in this axis (such as quality integration, focus on stakeholders, flexibility and learning) has produced an appropriate degree of coherence given the diversity of items. While the overall scale of the questionnaire, which includes all items (20 items), recorded a high reliability coefficient of (0.903), which reflects a high degree of overall reliability of the tool, and confirms that the questionnaire as a whole can be relied upon in studying the relationship between artificial intelligence and sustainable quality in the oil work environment.

Table (3): Test of normal distribution of research variables (Source: Prepared by the researchers based on the outputs of the SPSS V26 program)

Kolmogorov-Smirnov normal distribution test			
	Test statistic	Degree of freedom df	Test significance Sig.
artificial intelligence	.082	187	.064
Sustainable Quality	.076	187	.071
Figure (2) shows the data for the variable Sustainable Quality.		Figure (3) Gradient of AI variable data	
			

4.4 Descriptive Analysis of Questionnaire Variables:

This section aims to analyze the questionnaire's paragraphs and dimensions using descriptive statistics (arithmetic mean, standard deviation, coefficient of variation), as shown in Table (3). The analysis covers the dimensions of artificial intelligence and sustainable quality variables, to diagnose their level of availability and the degree of variation in sample responses. This helps understand general trends without delving into the interpretation of current values.

Table (4): Descriptive analysis of the questionnaire (Source: Prepared by the researchers based on the outputs of the SPSS V26 program)

Paragraphs, Variables, And Dimensions	Arithmetic Mean	Standard Deviation	Coefficient Of Variation
Q1	3.829	1.023	26.71%
Q2	3.551	1.068	30.09%
Q3	3.225	0.875	27.15%
Cognitive dimension (X1)	3.535	0.750	21.21%
Q4	2.947	0.860	29.18%
Q5	3.898	0.965	24.74%
Q6	3.845	0.952	24.75%
Operational dimension (X2)	3.563	0.590	16.55%
Q7	3.733	0.941	25.20%
Q8	3.241	0.951	29.34%
Q9	3.417	0.966	28.26%
Critical Dimension (X3)	3.463	0.731	21.11%
Q10	2.856	0.959	33.59%
Q11	3.449	1.043	30.23%
Q12	3.273	1.080	33.01%
Moral Dimension (X4)	3.193	0.785	24.59%
Q13	3.465	0.929	26.81%
Q14	2.957	0.955	32.30%
Integration of Quality and Sustainability (Y1)	3.211	0.643	20.02%
Q15	3.444	0.990	28.74%
Q16	2.936	0.993	33.81%
Stakeholder Focus (Y2)	3.190	0.755	23.67%
Q17	3.829	0.838	21.88%
Q18	2.984	0.779	26.12%
Flexibility and Adaptability (Y3)	3.406	0.612	17.96%
Q19	3.219	1.005	31.23%
Q20	3.556	0.899	25.27%
Organizational Learning and Innovation (Y4)	3.388	0.757	22.35%
Artificial Intelligence (X)	3.416	0.579	16.96%
Sustainable Quality (Y)	3.316	0.464	14.00%

The cognitive dimension (X1) showed an arithmetic mean of 3.535, as shown in Table (5), indicating a high awareness among individuals of the importance of knowledge related to artificial intelligence. This is offset by a standard deviation of 0.750, reflecting moderate dispersion of opinions, and a coefficient of variation of 21.21%, demonstrating acceptable stability in estimates. These results reflect that individuals possess a clear cognitive awareness of the impact of artificial intelligence technologies and are keeping up with developments in this field. They also indicate the presence of a good information environment within the company that enhances understanding. However, the variance in responses may indicate a disparity in access to knowledge or a difference in technical backgrounds, which requires systematically promoting a culture of technical learning to raise the level to a very high level.

The operational dimension (X2) recorded an arithmetic mean of (3.563), as shown in Table (5), indicating a high level of awareness of the effectiveness of artificial intelligence in improving operational efficiency. This was accompanied by a standard deviation of (0.590), reflecting a low degree of dispersion, and a coefficient of variation of (16.55%), indicating a significant degree of homogeneity in opinions. These results demonstrate that the company actually relies on artificial intelligence to improve performance quality and reduce breakdowns and downtime. Furthermore, employees clearly understand the temporal and technical impact of these technologies, indicating advanced operational readiness and a high ability to leverage artificial intelligence in resource and operations management.

Meanwhile, the critical dimension (X3) achieved an arithmetic mean of (3.463) (see Table (5), reflecting a high degree of adoption of critical thinking when using artificial intelligence. This was offset by a standard deviation of (0.731), representing moderate variance, and a coefficient of variation of (21.11%), reflecting a good degree of consistency. This indicates a management orientation focused on using evidence and data to judge the effectiveness of technologies, and an awareness of the importance of distinguishing between the true value of technologies and temporary market trends. This is an important indicator of advanced strategic thinking and an environment that supports the objective evaluation of digital transformation technologies.

The ethical dimension (X4) reached an arithmetic mean of 3.193, as shown in Table (5), indicating a moderate level of ethical commitment in the use of AI technologies. A standard deviation of 0.785 reflects medium to high dispersion, and a coefficient of variation of 24.59% indicates a significant disparity in opinions. This dimension demonstrates the presence of partial ethical endeavors within the company, such as balancing efficiency and values, and training employees on ethical principles. However, the average level and disparity of opinions indicate a weakness in the institutional ethical framework, which requires management to deepen ethical awareness and formally incorporate it into operational and educational policies.

The quality and sustainability integration dimension (Y1) came with an arithmetic mean of (3.211), see Table (5), reflecting a moderate awareness of the relationship between quality practices and sustainability principles, with a standard deviation of (0.643) showing limited variance, and a

coefficient of variation of (20.02%) indicating acceptable stability in responses. This shows that the company has started taking practical steps towards integrating quality objectives with environmental and social responsibility, through employee support and sustainable initiatives. However, institutional awareness still needs to be strengthened through clear integration programs between quality and environmental management to enhance implementation to a high level.

The stakeholder focus dimension (Y2), as shown in Table (5), showed an arithmetic mean (3.190), indicating a moderate level of interaction with stakeholders. This is offset by a standard deviation (0.755), indicating moderate variance, and a coefficient of variation (23.67%), reflecting variance in organizational vision. This indicates that communication with stakeholders, such as suppliers and the local community, is partially present, but at an incomplete level. This requires the company to strengthen partnership channels and effectively open up to the external business environment within a comprehensive strategy to ensure alignment of interests and enhance the quality of corporate relationships.

The flexibility and adaptability dimension (Y3), as shown in Table (5), achieved an arithmetic mean (3.406), reflecting a high awareness of the importance of organizational flexibility. A standard deviation (0.612), demonstrating relative stability, and a coefficient of variation (17.96%), indicating a high degree of homogeneity in perceptions. This indicates that the company possesses a good ability to adapt to artificial intelligence technologies and provides a flexible training environment that facilitates the assimilation of technological changes. This reflects an active organizational response and a rapidly evolving environment when it comes to technological updates.

The Organizational Learning and Innovation (Y4) dimension reached an arithmetic mean of 3.388, indicating a moderate level of management support for organizational learning. A standard deviation of 0.757 indicates moderate variance, and a coefficient of variation of 22.35% reflects acceptable consistency. This reflects a management orientation that supports skill development and innovation through training and motivation, enhancing the company's ability to integrate modern technologies into operations and reduce environmental risks. However, there is still a need for more comprehensive programs to establish a culture of innovation as a component of corporate sustainability.

The artificial intelligence variable (X), as shown in Table (5), recorded an arithmetic mean of (3.416), reflecting a high awareness of the importance of artificial intelligence. A standard deviation of (0.579), reflecting strong stability, and a coefficient of variation of (16.96%), indicating significant homogeneity in understanding. This indicates that artificial intelligence represents a strategic pillar in the workplace, where management and employees are aware of its diverse dimensions and roles, enhancing opportunities to maximize its capabilities at all operational and analytical levels.

The sustainable quality variable (Y), as shown in Table (5), recorded an arithmetic mean of (3.316), indicating a moderate level of adoption of sustainable quality concepts within the organization. This

indicates a partial and varying awareness of the importance of balancing economic performance with environmental and social responsibilities. The standard deviation was very low (0.464), indicating that the variance of opinions among sample members was limited, meaning that the majority were relatively consistent in their assessment of this dimension. Meanwhile, the coefficient of variation (14.00%) reflected a very high degree of consistency in participants' responses, a positive indicator of the clarity of the collective understanding of this concept within the organization. Although the results demonstrate clarity and consistency in managerial perceptions of sustainable quality, the moderate level of the arithmetic mean indicates that sustainable quality practices have not yet reached the stage of full implementation or institutionalization. This reflects the existence of preliminary or partial efforts in this area, such as establishing mechanisms to link quality and the environment or encouraging specific sustainability initiatives, but these efforts lack comprehensiveness or depth in planning and implementation.

4.5 Hypothesis Testing:

Hypothesis testing is used to examine relationships between variables in quantitative research.

Pearson's correlation coefficient measures the strength and direction of the linear relationship between two quantitative variables, while linear regression is used to determine the effect of an independent variable on a dependent variable and construct a model that explains the relationship between them. Both methods help support or reject hypotheses based on a specific statistical significance (usually 0.05).

H1: There is no correlation between the artificial intelligence variable and the sustainable quality variable at significance (0.05).

1. Pearson's correlation coefficient results showed a moderate positive relationship between the cognitive dimension of AI and sustainable quality. The correlation value reached 0.342 at a significance level of 0.05, indicating that individuals' awareness of AI technologies and their adherence to their developments contributes moderately to enhancing sustainability practices within the organization. However, this relationship also points to the need to enhance technical education and awareness to ensure that knowledge is reflected in environmental and social performance.
2. The relationship between the operational dimension and sustainable quality showed a correlation value of 0.420 at a significance level of 0.05, which represents a moderate to strong positive relationship. This indicates that the use of AI to improve operational efficiency and reduce breakdowns plays an important role in supporting sustainable quality practices. This reflects the organization's ability to effectively integrate operational technology into its environmental and social approach.
3. The critical dimension of AI showed a relatively strong positive relationship with sustainable quality, with a correlation coefficient of 0.470 at a significance level of 0.05. This indicates that critical thinking in evaluating the effectiveness of AI technologies and distinguishing between

true values and temporary trends enhances smart and sustainable decision-making and highlights an organization's maturity in using evidence and data to support the shift toward more sustainable practices.

4. The ethical dimension of AI showed the strongest correlation with sustainable quality, with a Pearson value of 0.564 at a significance level of 0.05. This indicates a very strong positive relationship and confirms that an organization's commitment to ethical principles in the use of AI—such as respecting privacy, training employees on responsible use, and balancing efficiency and values—is a critical component of building a sustainable and resilient corporate culture.

Based on the results of the Pearson correlation coefficient, strong and statistically significant direct relationships exist between all dimensions of AI (cognitive, operational, critical, ethical) and the dependent variable, sustainable quality. All significance values (Sig.) were below the approved level (0.05), which means rejecting the null hypothesis stating there is no relationship and accepting the alternative hypothesis: "There is a statistically significant correlation between AI and sustainable quality at a significance level of (0.05)." These results indicate that AI applications within organizations—especially when taking into account the ethical dimension and critical thinking—effectively contribute to supporting sustainable quality practices and enhance the organizational orientation toward balancing operational efficiency with environmental and social responsibility.

Table (6): Correlations between variables (Source: Prepared by the researchers based on the outputs of the AMOS V24 program)

Paths of association between variables			Pearson's correlation coefficient	Standard Error	Test significance (Sig.)
Sustainable Quality	↔	Cognitive Dimension	0.342	0.072	0.05
Sustainable Quality	↔	Operational Dimension	0.42	0.072	0.05
Sustainable Quality	↔	Critical Dimension	0.47	0.06	0.05
Sustainable Quality	↔	Ethical Dimension	0.564	0.049	0.05

Figure (4) shows the presence of direct and statistically significant correlations between the dimensions of artificial intelligence and sustainable quality, where the ethical dimension shows the strongest influence, followed by the monetary and then the operational, while the cognitive dimension had the least influence in supporting institutional orientations towards sustainability.

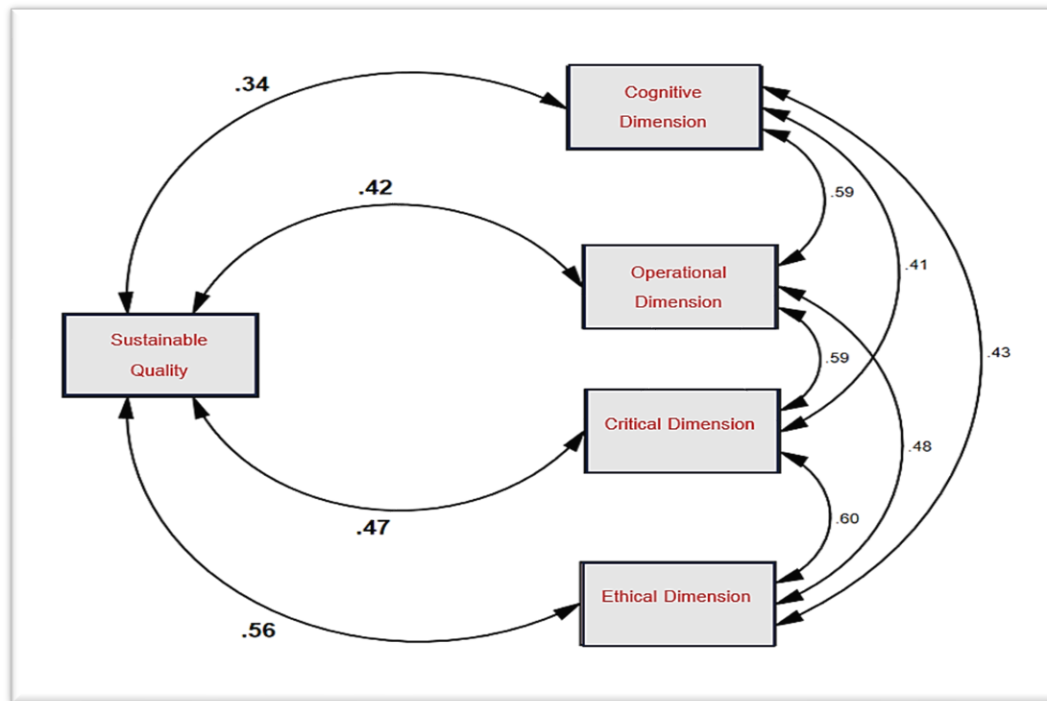


Figure (4): direct and statistically significant correlations between the dimensions of artificial intelligence and sustainable quality- Source: Prepared by the researchers based on the outputs of the AMOS V24 program

Testing the Second Main Hypothesis: There is no effect of the dimensions of the artificial intelligence variable on the sustainable quality variable at a significance level of (0.05).

Based on the results of the multiple linear regression analysis shown in Table (), it was found that the statistical model explains an acceptable proportion of the variance in the sustainable quality variable. The coefficient of determination (R^2) reached a value of 0.358, meaning that 35.8% of the variation in sustainable quality can be explained by the four dimensions of artificial intelligence. The F value of 25.426 at a significance level of (0.000) also showed that the model as a whole is statistically significant, indicating that the combined dimensions have a substantial effect on the dependent variable. At the level of detailed analysis of each dimension, the results showed that the ethical dimension of AI had the greatest impact, with a regression coefficient ($B = 0.440$) and a t-value ($t = 12.266$) with a significant significance ($\text{Sig.} = 0.000$). This indicates that adherence to ethical principles in the use of AI, such as respecting privacy and balancing efficiency and values, contributes significantly and effectively to supporting and developing sustainable quality practices within the organization.

The cognitive dimension also showed a positive and significant impact ($B = 0.325$, $\text{Sig.} = 0.029$), reflecting that increasing knowledge and understanding of AI and keeping up with its developments

clearly impacts raising the level of institutional sustainability, particularly by enhancing technical awareness among individuals.

The operational dimension, in turn, showed a significant impact ($B = 0.296$, $\text{Sig.} = 0.047$), indicating that leveraging AI to improve operational efficiency and reduce disruptions contributes to a more sustainable organizational environment. The critical dimension also showed a significant effect ($B = 0.286$, $\text{Sig.} = 0.012$), indicating that adopting critical thinking in evaluating AI technologies and distinguishing between real benefits and temporary trends supports sustainable decisions and improves the effectiveness of using these technologies in environmental and social dimensions.

Based on the above, it can be said that all AI dimensions have a positive and significant impact on achieving sustainable quality, with the ethical dimension being the strongest driver of sustainability, reflecting the importance of building responsible and ethical use of technology in the corporate work environment.

This means rejecting the null hypothesis stating there is no impact and accepting its alternative hypothesis: "There is an impact of the AI dimensions on the sustainable quality variable at significance (0.05).

Table (7): The multiple impact of the dimensions of the artificial intelligence variable on the sustainable quality variable
(Source: Prepared by the researcher based on the outputs of the SPSS V26 program)

Dimension	B	t	Sig.	Coefficient of determination (R^2)	F	Sig.
Constant	1.818	10.231	0.000	0.358	25.426	0.000
Cognitive Dimension	0.325	8.545	0.029			
Operational Dimension	0.296	7.455	0.047			
Critical Dimension	0.286	8.644	0.012			
Ethical Dimension	0.440	12.266	0.000			

Conclusions

The research results in the studied oil company revealed a set of important indicators that reflect the reality and role of employee perceptions of artificial intelligence in enhancing sustainable quality within the company. It was found that there is a clear trend toward adopting AI technologies, supported by technical readiness and a sound understanding of the temporal and transformational impacts associated with AI technologies. This indicates a qualified infrastructure to accommodate digital transformations and keep pace with developments.

At the same time, an urgent need emerged to enhance continuous learning and training on modern AI technologies. This indicates a gap between the technological availability of AI technologies and the human skills necessary to optimally utilize these capabilities. This challenge is considered pivotal in the digital transformation process, especially in the oil sector, which relies heavily on technical competencies and applied knowledge.

A striking aspect of the research results is the company's clear ability to adapt to AI technologies. This is reinforced by a management approach that supports innovation, providing an organizational

environment that encourages the adoption of technological initiatives and transforms them into tools for improving quality and productivity. However, a relative lack of ethical knowledge related to the use of AI technologies was observed, a critical aspect for ensuring the responsible and safe use of these modern tools, especially in complex industrial environments.

With regard to sustainable quality practices, a moderate level of knowledge and application was observed. However, the disparity in organizational vision among stakeholders limits the effectiveness of the Total Quality approach. This requires strengthening organizational communication and unifying visions around sustainable quality standards and objectives, ensuring consistent efforts across all levels of the company.

Based on the above, it can be argued that the company possesses the basic components for transitioning to an AI-driven work environment to enhance and sustain quality. However, this path requires addressing some knowledge and organizational gaps, particularly in ethical and training aspects, and unifying strategic visions among various stakeholders to ensure maximum benefit from AI applications and technologies in promoting sustainable quality.

Recommendations

Based on the research findings, the study recommends strengthening continuous training programs for employees on relevant AI technologies, contributing to bridging the gap between technical readiness and operational knowledge. It also recommends establishing a clear ethical framework for the use of AI technologies, including policies and organizational guidelines that support responsible use and mitigate associated risks. Therefore, the study recommends investing in modern technologies as a strategic tool for enhancing quality within the company, as AI, the Internet of Things, and data analytics can directly contribute to increasing operational efficiency, reducing errors, and improving work outcomes. Strengthening digital infrastructure is also a priority, ensuring systems are ready to support continuous and accurate quality control. It is important to integrate these technologies into quality management and sustainable development systems, ensuring real-time monitoring of performance indicators and improving decision-making processes. The recommendations emphasize the importance of developing specialized training programs that enable employees to understand and effectively use AI technologies in the workplace. It is also recommended to establish multidisciplinary teams that promote integration across different functions to implement technological solutions to improve and sustain quality. Equally important is enhancing the ethical aspect of using these technologies by establishing clear policies governing the handling of data and digital systems. Finally, it is recommended to adopt a culture of innovation and continuous improvement based on artificial intelligence, which will drive the company towards excellence in quality and sustainable performance.

References

1. Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. *Journal of Cleaner Production*, 437, 140527.
2. Agrawal, A., Gans, J., & Goldfarb, A. (Eds.). (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press.
3. Ahmadi, A.; Meybodi, M.R.; Saghiri, A.M. Adaptive search in unstructured peer-to-peer networks based on ant colony and Learning Automata. In *Proceedings of the 2016 Artificial Intelligence and Robotics*, Qazvin, Iran, 9 April 2016.
4. Anderson, R. N. (2017, December). 'Petroleum Analytics Learning Machine' for optimizing the Internet of Things of today's digital oil field-to-refinery petroleum system. In *2017 IEEE International Conference on Big Data (Big Data)* (pp. 4542-4545). IEEE.
5. Anifowose, F. A., Labadin, J., & Abdulraheem, A. (2017). Ensemble machine learning: An untapped modeling paradigm for petroleum reservoir characterization. *Journal of Petroleum Science and Engineering*, 151, 480-487.
6. Arend, R. J. (2014). Entrepreneurship and dynamic capabilities: how firm age and size affect the 'capability enhancement-SME performance' relationship. *Small Business Economics*, 42, 33-57.
7. Baird, A., & Maruping, L. M. (2021). The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS quarterly*, 45(1).
8. Balakrishnan, T., Chui, M., Hall, B., and Henke, N. 2020. *The State of AI in 2020*, McKinsey & Company (<https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020>).
9. Bellamy, R.K.; Dey, K.; Hind, M.; Hoffman, S.C.; Houde, S.; Kannan, K.; Lohia, P.; Martino, J.; Mehta, S.; Mojsilović, A. AI Fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias. *IBM J. Res. Dev.* 2019, 63, 4:1-4:15. [CrossRef].
10. Bernardo, G. L., Jomori, M. M., Fernandes, A. C., & Proença, R. P. D. C. (2017). Food intake of university students. *Revista de Nutrição*, 30(6), 847-865.
11. Binu, D.; Rajakumar, B.R. *Artificial Intelligence in Data Mining: Theories and Applications*; Academic Press: Cambridge, MA, USA, 2021.
12. Cheng, X.; Lin, X.; Shen, X.-L.; Zarifis, A.; Mou, J. The dark sides of AI. *Electron. Mark.* 2022, 1-5. [CrossRef].
13. Cuomo, S., Biagini, G., & Ranieri, M. (2022). Artificial Intelligence Literacy, che cos'è e come promuoverla. Dall'analisi della letteratura ad una proposta di Framework. *Media Education*, 13(2), 161-172.

14. De Mattos, C. A., Correia, F. C., & Kissimoto, K. O. (2024). Artificial Intelligence Capabilities for Demand Planning Process. *Logistics*, 8(2), 53.
15. Došilović, F. K., Brčić, M., & Hlupić, N. (2018, May). Explainable artificial intelligence: A survey. In 2018 41st International convention on information and communication technology, electronics and microelectronics (MIPRO) (pp. 0210-0215). IEEE.
16. Druga, S., Vu, S. T., Likhith, E., & Qiu, T. (2019). Inclusive AI literacy for kids around the world. In *Proceedings of FabLearn 2019* (pp. 104-111).
17. Evans, S. J. (2019, April). How digital engineering and cross-industry knowledge transfer is reducing project execution risks in oil and gas. In *Offshore Technology Conference* (p. D022S057R014). OTC.
18. Fogel, D. B. (2022). Defining artificial intelligence. *Machine Learning and the City: Applications in Architecture and Urban Design*, 91-120.
19. Fundin, A., Bergquist, B., Eriksson, H., & Gremyr, I. (2018). Challenges and propositions for research in quality management. *International Journal of Production Economics*, 199, 125-137.
20. Hamzeh, H. (2016). Application of big data in petroleum industry. Department of Electronics and Computer Engineering Istanbul Sehir University hamedhamzeh@ std. sehir. edu. tr.
21. Hanif, M.A.; Khalid, F.; Putra, R.V.W.; Rehman, S.; Shafique, M. Robust machine learning systems: Reliability and security for deep neural networks. In *Proceedings of the 2018 IEEE 24th International Symposium on On-Line Testing and Robust System Design (IOLTS)*, Platja d'Aro, Spain, 2–4 July 2018; pp. 257–260.
22. Kim, S., Jang, Y., Kim, W., Choi, S., Jung, H., Kim, S., & Kim, H. (2021, May). Why and what to teach: AI curriculum for elementary school. In *proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 35, No. 17, pp. 15569-15576).
23. Koroteev, D., & Tekic, Z. (2021). Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future. *Energy and AI*, 3, 100041.
24. Lantham, A. (2019). Why explorers are in the grip of an existential crisis: exploration's role to undergo profound change as energy transition gains pace. *Wood Machenzie. Society of Petroleum Engineers*.
25. Lee, J., Park, J., & Mostafa, N. A. (2025). Artificial Intelligence Dimensions and Design Features for the Knowledge-based Work of the Future: A Socio-Technical Perspective. *Data Science and Management*.
26. Li, H., Yu, H., Cao, N., Tian, H., & Cheng, S. (2021). Applications of artificial intelligence in oil and gas development. *Archives of Computational Methods in Engineering*, 28, 937-949.

27. Li, Q., Zhang, Y., & Um, G. (2025). Intertwining Artificial Intelligence and Efficiency: An Empirical Analysis of AI Focus and Operational Efficacy in Chinese Listed Firms. *Finance Research Letters*, 107451.
28. Lu, H., Guo, L., Azimi, M., & Huang, K. (2019). Oil and Gas 4.0 era: A systematic review and outlook. *Computers in industry*, 111, 68-90.
29. Mata, J., De Miguel, I., Duran, R. J., Merayo, N., Singh, S. K., Jukan, A., & Chamania, M. (2018). Artificial intelligence (AI) methods in optical networks: A comprehensive survey. *Optical switching and networking*, 28, 43-57.
30. Mhlanga, D. (2023). Artificial intelligence and machine learning for energy consumption and production in emerging markets: a review. *Energies*, 16(2), 745.
31. Monteith, S., Glenn, T., Geddes, J. R., Achtyes, E. D., Why brow, P. C., & Bauer, M. (2023). Challenges and ethical considerations to successfully implement artificial intelligence in clinical medicine and neuroscience: a narrative review. *Pharmacopsychiatry*, 56(06), 209-213.
32. Murphy, K. P. (2012). *Machine learning: a probabilistic perspective*. MIT press.
33. Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, 100041.
34. Pagano, T. P., Loureiro, R. B., Lisboa, F. V., Peixoto, R. M., Guimarães, G. A., Cruz, G. O., ... & Nascimento, E. G. (2023). Bias and unfairness in machine learning models: a systematic review on datasets, tools, fairness metrics, and identification and mitigation methods. *Big data and cognitive computing*, 7(1), 15.
35. Pesämaa, O. (2017). Personnel-and action control in gazelle companies in Sweden. *Journal of Management Control*, 28(1), 107-132.
36. Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J. F., Breazeal, C., ... & Wellman, M. (2019). Machine behaviour. *Nature*, 568(7753), 477-486.
37. Ranängen, H. & Zobel, T. (2014). Revisiting the ‘how’ of corporate social responsibility in extractive industries and forestry. *Journal of Cleaner Production* 84, 299-312. <https://doi.org/10.1016/j.jclepro.2014.02.020>
38. Resen, E. J., Razzaq, M. S. A., & Abbood, H. Q. (2023). Environmental Impact Assessment for Industrial Organizations using Rapid Impact Assessment Matrix. *Ecological Engineering & Environmental Technology*, 24.
39. Robinson, J., 2014. Likert Scale. In: Michalos, A.C. (Ed.), *Encyclopedia of Quality of Life and Well-Being Research*. Springer Netherlands, pp. 3620–3621. https://doi.org/10.1007/978-94-007-0753-5_1654.

40. Saghiri, A. M., Vahidipour, S. M., Jabbarpour, M. R., Sookhak, M., & Forestiero, A. (2022). A survey of artificial intelligence challenges: Analyzing the definitions, relationships, and evolutions. *Applied sciences*, 12(8), 4054.
41. Savino, M. M., & Batbaatar, E. (2015). Investigating the resources for Integrated Management Systems within resource-based and contingency perspective in manufacturing firms. *Journal of cleaner production*, 104, 392-402.
42. Shafiee, M., Animah, I., Alkali, B., & Baglee, D. (2019). Decision support methods and applications in the upstream oil and gas sector. *Journal of Petroleum Science and Engineering*, 173, 1173-1186.
43. Silva, C. S., Magano, J., Matos, A., & Nogueira, T. (2021). Sustainable quality management systems in the current paradigm: The role of leadership. *Sustainability*, 13(4), 2056.
44. Sircar, A., Yadav, K., Rayavarapu, K., Bist, N., & Oza, H. (2021). Application of machine learning and artificial intelligence in oil and gas industry. *Petroleum Research*, 6(4), 379-391.
45. Smuha, N. A. The EU approach to ethics guidelines for trustworthy artificial intelligence. *Comput. Law Rev. Int.* 2019, 20, 97–106. [CrossRef]
46. Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., ... & Teller, A. (2022). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. *arXiv preprint arXiv:2211.06318*.
47. Strubell, E.; Ganesh, A.; McCallum, A. Energy and policy considerations for deep learning in NLP. *arXiv* 2019, *arXiv:1906.02243*.
48. Su, J., Zhong, Y., & Ng, D. T. K. (2022). A meta-review of literature on educational approaches for teaching AI at the K-12 levels in the Asia-Pacific region. *Computers and Education: Artificial Intelligence*, 3, 100065.
49. Tan, K. H., & Lim, B. P. (2018). The artificial intelligence renaissance: deep learning and the road to human-level machine intelligence. *APSIPA Transactions on Signal and Information Processing*, 7, e6.
50. Tekic, Z., & Koroteev, D. (2019). From disruptively digital to proudly analog: A holistic typology of digital transformation strategies. *Business Horizons*, 62(6), 683-693.
51. Temizel, C., Canbaz, C. H., Palabiyik, Y., Putra, D., Asena, A., Ranjith, R., & Jongkittinarukorn, K. (2019, March). A comprehensive review of smart/intelligent oilfield technologies and applications in the oil and gas industry. In *SPE Middle East Oil and Gas Show and Conference* (p. D042S087R001). SPE.
52. Tingström, O., Wesula Lwande, O., Näslund, J., Spyckerelle, I., Engdahl, C., Von Schoenberg, P., ... & Bucht, G. (2016). Detection of Sindbis and Inkoo virus RNA in genetically typed

- mosquito larvae sampled in Northern Sweden. Vector-Borne and Zoonotic Diseases, 16(7), 461-467.
53. Vandenbrande, W. W. (2021). Quality for a sustainable future. Total Quality Management & Business Excellence, 32(5-6), 467-475.
54. Wang, C., & Wang, Z. (2025). Investigating L2 writers' critical AI literacy in AI-assisted writing: An APSE model. Journal of Second Language Writing, 67, 101187.
55. Wang, C., & Wang, Z. (2025). Investigating L2 writers' critical AI literacy in AI-assisted writing: An APSE model. Journal of Second Language Writing, 67, 101187.
56. Wang, P. (2019). On defining artificial intelligence. Journal of Artificial General Intelligence, 10(2), 1-37.
57. Wirtz, B.W.; Weyerer, J.C.; Sturm, B.J. The dark sides of artificial intelligence: An integrated AI governance framework for public administration. Int. J. Public Adm. 2020, 43, 818–829. [CrossRef]
58. Zeadally, S., Adi, E., Baig, Z., & Khan, I. A. (2020). Harnessing artificial intelligence capabilities to improve cybersecurity. Ieee Access, 8, 23817-23837.
59. Zeadally, S., Adi, E., Baig, Z., & Khan, I. A. (2020). Harnessing artificial intelligence capabilities to improve cybersecurity. Ieee Access, 8, 23817-23837.