

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON THE EFFICIENCY OF THE OIL AND FAT INDUSTRY: PROBLEM ANALYSIS, INNOVATIVE SOLUTIONS, AND ASSESSMENT METHODOLOGIES

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Abstract

Unlike superficial application of AI, AI implementation implies sustainable implementation, scaling, and profit-making from it. This is achieved through a coordinated system of data, competencies, and processes. In the oil and fat sector, the development stage and ownership structure influence how effectively AI implementation results can be measured and evaluated. Triangle-shaped graphical elements depicting the relationship between potential and results illustrate contradictions, such as efficiency growth, which can lead to increased energy consumption. Unlike superficial application of AI, AI implementation implies sustainable implementation, scaling, and profit-making from it. This is achieved through a coordinated system of data, competencies, and processes. In the oil and fat sector, the development stage and ownership structure influence how effectively AI implementation results can be measured and evaluated. Triangle-shaped graphical elements depicting the relationship between potential and results illustrate contradictions, such as efficiency growth, which can lead to increased energy consumption.

Keywords

artificial intelligence; implementation of AI; digital transformation; production efficiency; productivity measurement; oil and fat industry; organizational skills; MLOps; sustainable development; data management.

INTRODUCTION

The oil and fat industry is a key link in energy and industry. Enterprises strive to optimize their processes using advanced digital technologies, particularly artificial intelligence (AI), to reduce costs, enhance reliability, and reduce emissions at all stages of production. Despite this, research shows that a significant portion (70%) of AI projects in various industries do not achieve the expected results or prove to be ineffective [1]. Although major players in the oil and fat industry have invested in AI startups and formed teams of these specialists, the exact and long-term benefits of such efforts are still difficult to assess [2, 3].

As a result, “technological optimism” arises: companies invest significant resources in digital technologies, but the real growth of productivity is either delayed or its results remain unclear [4, 5].

The question of how to quantify the effectiveness of artificial intelligence and its practical application remains open for scientific discussion. Certain difficulties arise when trying to measure the depth of AI implementation, which, as illustrated by Figure 1, proves to be a key factor in evaluating its performance. Without accurate measurement of AI implementation, it is

impossible to adequately assess its real contribution. The issue of assessing the implementation of artificial intelligence and its commercial success remains debatable, especially in the oil and fat industry with its specific characteristics. Figure 1 demonstrates the direct relationship between the depth of AI implementation and organizational effectiveness, emphasizing the importance of accurately assessing this implementation to determine its real impact on final results.

This study examines four key issues:

1. What are the organizational and contextual conditions that contribute to or hinder the implementation of AI from the pilot project stage into long-term practice?
2. How can the effectiveness of implementing AI in the business environment be measured?
3. How can you determine how much the implementation of artificial intelligence will increase the efficiency of an organization's work?
4. In what specific aspect can fat characteristics, such as oil, influence the AI implementation process and the interpretation of its results?

Within the framework of the study of this problem, an extensive, albeit not fully comprehensive, analysis of existing publications was carried out. The work combined three traditionally considered topics: factors determining the successful implementation of artificial intelligence, its evaluation methodology, and performance indicators.

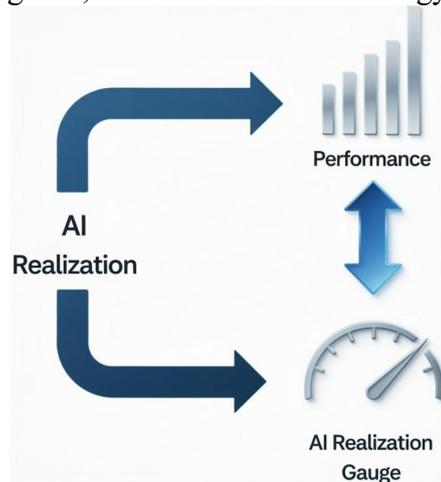


Fig. 1. Implementation of artificial intelligence and its effectiveness.

The development of artificial intelligence is gaining momentum. In this article, we explore its implementation in the oil and fat industry, analyzing examples from various fields. The presented literature review systematizes information on the motives, methods, and results of AI application, as well as examines their practical significance for the oil and fat industry.

The research is of particular relevance due to the lack of scientific works devoted to this topic. Despite the widespread discussion of examples of using artificial intelligence in various fields, such as seismic data analysis, pipeline inspection using drones and AI-controlled sales tables [7, 8], empirical research linking its use to companies' overall performance indicators remains extremely limited. Its scope is defined [9] and includes the stages of value formation and the form of ownership.

The study provides researchers with a structured framework for conducting empirical research aimed at measuring the implementation of artificial intelligence and analyzing its impact on the oil and fat industry. For industry enterprise managers, this work demonstrates that there is no single, universal approach: the effectiveness of measures and the result achieved

depend on the specifics of the company, the available data, and the strategic decisions made. In conclusion, the work offers a number of tips to professionals working in the oil and fat industry on how to more quickly and effectively implement AI in their industry.

Conceptual foundations. This section establishes fundamental theoretical knowledge that serves as the foundation for all subsequent research. First, the concept of AI is formulated, adapted to the specifics of the company's activities. Then, the distinctive structural features of the oil and fat industry compared to others are considered. In conclusion, examples of implementing artificial intelligence in the oil and fat industry are presented.

Concepts related to artificial intelligence. Artificial intelligence (AI) is the ability of computers to imitate human cognitive functions such as understanding, logical thinking, and problem-solving abilities. As a result, AI allows machines to perform tasks that were traditionally considered the prerogative of human reason [10, 11]. In essence, AI creates intelligent agents capable of processing information and making decisions, similar to human learning and thinking processes [12]. In some works, artificial intelligence is defined as a means of automating routine or complex tasks that humans cannot achieve. Other authors see it as a fundamental scientific discipline or a promising technology with a wide range of applications [13, 14]. In this study, AI is considered as an applied field focused on practical application. Its goal is to equip computers with the ability to discover, process, interpret data, and learn from them to effectively solve problems facing businesses and society. This approach is closely related to our emphasis on quantitative indicators of company performance.

Significant productivity growth is due to the introduction of machine learning and, in particular, deep learning [15, 16]. Machine learning allows models to learn from data by identifying patterns and generating forecasts using statistical algorithms [17]. Deep learning based on multilayered neural networks surpasses this, imitating the work of neural connections in the brain to reveal complex relationships in data arrays [18, 19].

Characteristics of oils depending on their application industry. Industry specificity is due to the wide range of segments involved in the formation of oil value.

Figure 2 illustrates three interconnected flows, each with its own tasks, as well as unique complexities and obstacles.

1. Has a high cost of implementation.
2. Its complexity and technological features necessitate specific skills.
3. There is a significant probability of difficulties in determining available resources and the instability of global prices.

This segment, known as the middle stream, acts as a connecting link between the production of the upper stream and the processing of the lower stream. Its tasks include the movement, storage, and wholesale distribution of oils and fats.

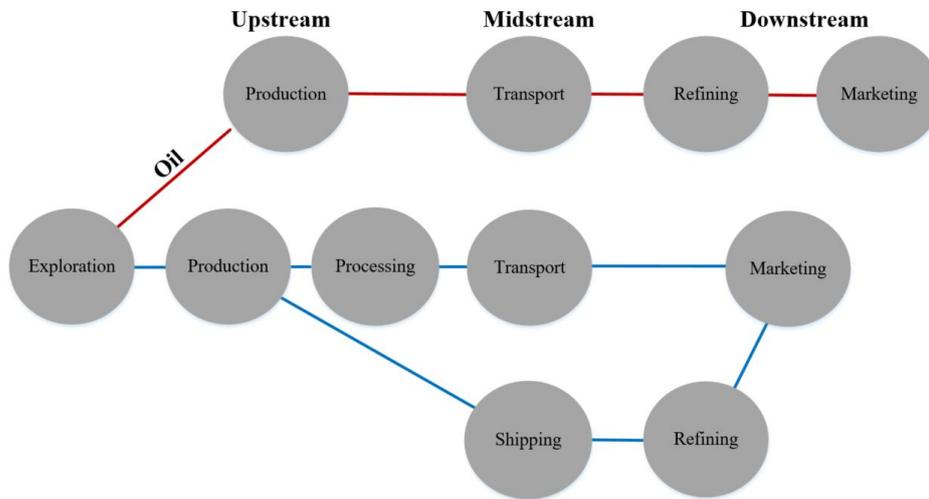


Fig. 2. The industry-adapted value chain is presented in the form of oil.

Important features of this segment are:

- Regulation is characterized by a high degree of strictness.
- It is important that the transport works efficiently.

Environmental and safety risks arising during transportation.

At the final stage of production, attention is paid to the final consumers. In this segment, the transformation of vegetable oil into finished products intended for sale takes place. The segment covers all stages, from refining to distributing and selling the final product. The key features of this segment include:

- Their development is closely linked to fluctuations in market demand, consumer preferences, and existing price mechanisms.
- The effectiveness of refining processes directly affects the profitability of the enterprise.
- Achieving success is due to meeting the market's needs for both energy and non-energy products.
- In addition to the differences in value chain structures, the oil and fat industry exhibits different characteristics in the following aspects:
- At the same time, private companies tend to have more maneuvering opportunities and feel stronger motivation to implement new technologies.
- The scaling of AI solutions by companies depends on the availability of clear financial investment plans and an effective risk management system.
- Data preparation presents a key obstacle due to complexities associated with heterogeneous sensors, the multiphase nature of the flow, and uneven marking [21].

Applications of AI in the oil and fat industry. Artificial intelligence is increasingly finding application in the oil and fat industry, which is covered in a number of review articles. For a more detailed study of this topic, it is recommended to familiarize yourself with the works [2, 22].

The next stage in the development of artificial intelligence in the food industry will likely be characterized by multimodal and generative methods. Such development will emphasize AI's ability not only to overcome data limitations but also to facilitate more reliable and flexible decision-making in dynamic and complex production environments.

Characteristics of research volumes and approaches. Due to the lack of direct research dedicated to the relationship between the implementation of artificial intelligence, its productivity, and the oil and fat industry, it was impossible to conduct a formal systematic literature review. An exception that partially touches upon this topic is the work. This review sets two objectives. Firstly, he seeks to generalize and systematize existing scientific works on the application of artificial intelligence and its impact on labor productivity. Secondly, he intends to analyze these conclusions in light of the specifics of the oil and fat sector.

The search used a strategy that integrated keywords and logical operators, focusing on three studied topics.

1. Implementation of artificial intelligence (including machine learning and deep learning) in areas such as labor resources, competencies, management, strategic planning, or organizational transformation.

2. Evaluating the effectiveness of artificial intelligence (AI), also known as machine learning or deep learning, by applying appropriate measurement methods.

3. Model performance: focus on the impact of (“artificial intelligence” OR “machine learning” OR “deep learning”) on metrics like (“performance” OR “efficiency” OR “output” OR “reliability”).

During the analysis, key works most relevant to the three identified topics were selected. They became the foundation for compiling a review. Special attention was paid to finding supporting and contextualizing data in non-academic sources. The iterative approach allowed for the consideration of both classical and contemporary significant research.

AI Implementation Drivers in the Oil and Fat Industry. Artificial intelligence alone does not guarantee value. Its successful implementation depends on the close interaction of three main groups of factors. These factors related to human capital, technological base, and management approaches determine the pace of development of necessary data, competencies, and processes within organizations. Each of these groups, being independent, is also closely interconnected and significantly influences the results of AI implementation.

People. The successful implementation of AI in the oil and fat industry directly depends on people. Even the most advanced technologies cannot bring significant results without appropriate competencies, readiness, and the ability to manage them. Three key human aspects determine the pace and effectiveness of AI implementation and integration: the first is the qualifications of specialists. The shortage of specialists with hybrid domain data necessary for seismic analysis of the upper flow, analysis of the integrity of the middle flow, and control of the lower flow processes is a pressing issue [2, 36, 37]. The lack of data science courses in traditional curricula leads to two main challenges: it is necessary to integrate AI courses into the academic environment and ensure that engineers in companies are trained in AI skills [38]. This is important for the successful implementation of AI in the field [38]. The use of AI in field teams can raise concerns if its benefits and safety for workers are not properly demonstrated [56,6]. To reduce negative reactions, it is necessary to ensure transparency in teaching algorithms and their construction. It's also important to consider ethical and legal aspects: a non-functioning AI council can lead to liability disputes between operators, developers, and regulatory bodies. The first studies in the field of responsible AI emphasize the importance of establishing clear rules of transparency and accountability [39].

Technical. The success of implementing AI in the oil and fat industry is closely linked to technical readiness. Quality results, even with experienced management and highly qualified specialists, are impossible without a reliable database, appropriate infrastructure, and effective

algorithms. In this context, three key technical aspects are of particular importance:

1. The reliability and consistency of data coming from sensors, well logs, and commercial reports often encounters problems [40]. Ambiguous marking and fragmented data storage are key obstacles to creating effective models. The second difficulty relates to infrastructure: for large-scale training and operational conclusions, high-speed communication channels between installations, peripheral devices, and cloud services are necessary. Companies must strive for a high degree of maturity in the field of machine learning (ML), covering the entire life cycle of ML models: from data collection and processing to implementation, observation, and continuous improvement. The absence of mature ML processes in firms makes it difficult to maintain the relevance of models. An important aspect is also the use of reliable algorithms.

Manager. Realizing the potential of AI for practical purposes is closely linked to skillful management. A well-thought-out strategy, fruitful interaction between participants, and the ability to adapt to external conditions allow AI projects to go beyond laboratory experiments and ensure their real implementation.

AI implementation measurement. It is impossible to assess the degree to which AI is being implemented in a company's usual work using a single dataset. In this context, previous studies relied on the use of three groups of indicators presented in Figure 3. Initially, the indicators themselves will be considered, and then their relationship with the factors stimulating the development of AI.

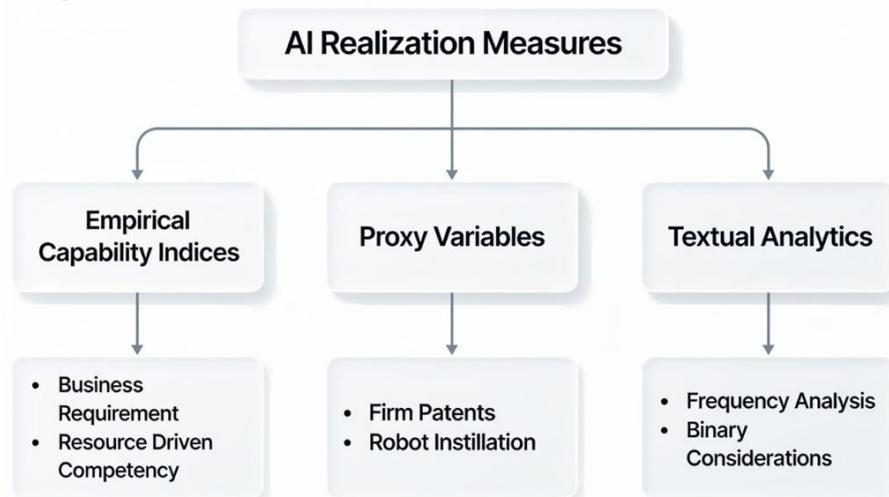


Fig. 3. Key metric categories for evaluating and developing AI solutions in a corporate context.

Empirical capability indices. According to resource theory, companies achieve a competitive advantage by effectively utilizing valuable, unique, and difficult-to-access resources. Similarly, in the context of artificial intelligence, researchers see its ability to transform data, software algorithms, human capital, and business processes as a source of operational value as a key competitive factor. Schmidt [11] defines this skill as the ability to integrate data, algorithms, people, and processes for the successful implementation and effective application of AI tools. Mikalef [6] emphasizes the organization's ability to utilize all available AI resources to optimize work and improve performance. In this context, the concept goes beyond a narrow technological plane and encompasses the entire spectrum of organizational resources necessary for the effective use of AI capabilities. The study's authors distinguish three categories of indices

designed to assess the implementation of AI: resource-driven potential, business-driven capabilities, and AI competence.

Resource management. Assessment of the level of AI development in the company is carried out using the RBT model, which analyzes the company's available resources, as illustrated in Figure 4.

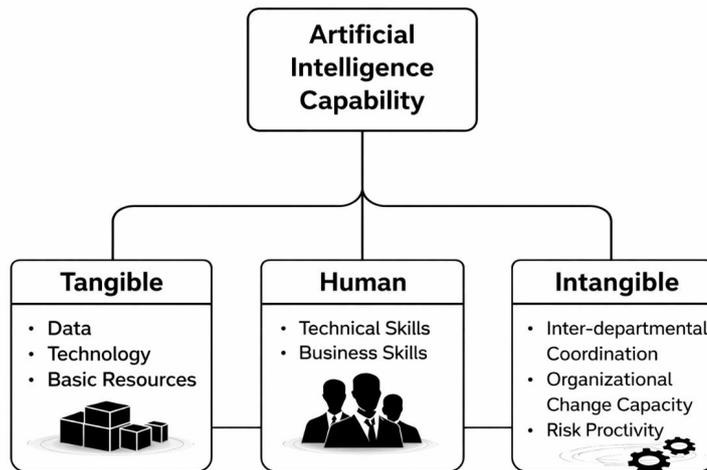


Fig. 4. The potential of using artificial intelligence built on the basis of the RBT model after making the necessary changes to it.

Depending on their nature, resources are divided into three categories: material, human, and non-material [6,56,57]. Material resources include objects such as infrastructure elements and information data. Among human resources, skills and competencies are distinguished, while among non-material resources, coordination mechanisms and the culture that determines them are highlighted. Assessment of material resources, including data, equipment, software, and platform infrastructure, is most often carried out using quantitative indicators, such as the volume of stored information, the number of servers, or cloud platform service costs. Although these measures affect the company's fundamental digital and technological resources, such assets are readily available to everyone and generally do not provide a long-term competitive advantage [6].

Many believe that intangible assets are more difficult to duplicate and are particularly important in an uncertain situation. Compared to material and financial resources, intangible assets are more abstract and variable in nature, making it difficult to identify and evaluate them within the company. The company's intangible resources are formed under the influence of specific factors, such as the history of the organization, its personnel, and internal processes, which gives them a unique and original character. Table 1 shows the quantitative indicators identified during the study of scientific publications, reports, and conducted interviews [56]. To assess the significance of these indicators, special methods have been developed that ensure the possibility of their measurement [6].

Table 1. Formation of AI with emphasis on its resource intensity.

Construct	Definition
Data	Assess an organization's data accessibility, ensuring it's detailed enough for specific needs, and evaluate its capacity to combine and effectively purify data for use in artificial intelligence.
Technological	Indicates if a company possesses the necessary technological infrastructure for

	adaptable data management, examination, and computation, both within its own systems and with external partners.
Technical & Business Skills	Evaluates the level of expertise in AI-related skills possessed by both technical and non-technical employees.
Inter-Departmental Coordination	Evaluates the extent to which departments engage in transparent communication and teamwork, along with the alignment of their collective goals.
Organizational Change	Indicates the ability of a company to adapt quickly to evolving situations, while risk proclivity measures its tendency to embrace ventures with significant potential rewards, albeit accompanied by elevated risks.

Business requirements functionality. In the context of RBT, the implementation of AI in business can be analyzed from three main perspectives, each solving one of the basic business tasks: increasing productivity through robotization, obtaining analytical data for management decisions, and improving customer communication [60]. The application of AI opens up new opportunities for business. Artificial intelligence (AI) opens up opportunities for automating routine processes, freeing employees' time for working on strategic tasks. Thanks to AI's analytical capabilities, you can discover hidden trends and gain valuable insights to make more effective decisions. In the field of interaction with people, AI demonstrates empathy, the ability to build relationships, and adapt its behavior based on user data.

AI Competence. Competence in artificial intelligence (AI) for a company means skillfully applying its own AI solutions, knowledge, and resources to achieve a competitive advantage [57]. To assess this competence, it is important to consider three key aspects: the development of AI infrastructure, the coverage of its use in business processes, and activity in promoting AI initiatives. The development of AI infrastructure implies the creation of a reliable data management system and a technical platform capable of transforming raw data into valuable AI solutions. Business-oriented AI means that management skillfully uses it to implement a business strategy, starting from the concept and ending with its practical implementation. The proactive application of AI implies its use not as a passive tool, but as an active factor that stimulates continuous development and the search for new, innovative approaches.

Using the triangulation method to build intelligent systems. Studying textual data allows us to track the dynamics of artificial intelligence discussions within a company and identify the shift in its strategy focus. The level of key figures mentioned can serve as a basis for comparing AI approaches in various corporate environments. Studying the implementation of AI in the corporate world cannot be carried out based on a single measurement, as it cannot encompass all aspects of this complex implementation. Each individual indicator, moreover, can be distorted by both subjective and objective factors. To increase the reliability of results and minimize systematic errors, researchers should use triangulation, combining various measurement groups (e.g., text data, proxy indicators, and expert surveys) [62,63,64,].

Output data for performance indicators. Only the achievement of visual results in the field of artificial intelligence makes this aspect significant. Previously conducted research revealed three interconnected areas where such results are manifested. Further, a brief description of each area is provided, indicating key indicators, as well as causes and consequences. Figure 5 illustrates how increasing operational efficiency often leads to financial and environmental changes [65]. In the subsequent review, all effectiveness measures will be considered separately.

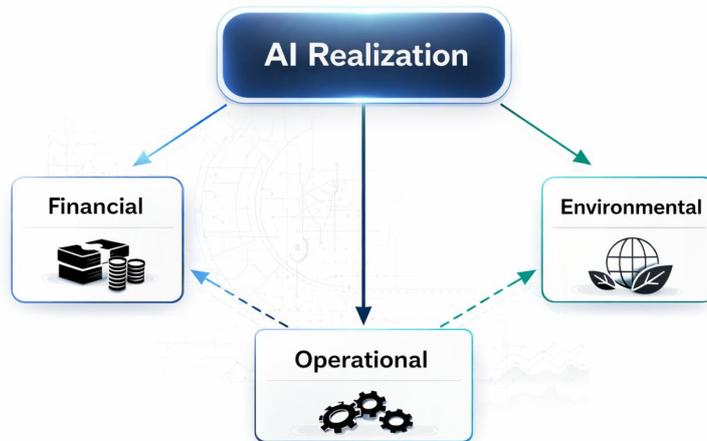


Fig. 5. The impact of implementing artificial intelligence on business efficiency.

Effective indicators in the operational sphere are distinguished by their efficiency. Unlike financial indicators, they can be tracked directly at the work level and generally reflect changes more quickly. Common operational indicators include order fulfillment time, equipment downtime, and employee engagement levels [66, 67]. In the financial aspect, the study examines both internal indicators such as asset profitability and equity profitability, as well as external market metrics such as abnormal return on shares. Although the introduction of AI at an early stage may temporarily negatively impact short-term profits, in the long term, income growth is expected due to increased accuracy in forecasting and cost optimization. Several key signs point to a company's commitment to sustainability, such as its energy efficiency (measured by output generated per kilowatt-hour), carbon dioxide and sulfur dioxide emissions, and the proportion of environmentally friendly patents it holds [34]. Furthermore, analyzing a company's sustainability reports for terms and expressions associated with the shift towards renewable energy can reveal its underlying business goals [9].

The principle of triangular interpolation in performance evaluation. To objectively assess the effectiveness of artificial intelligence, it is necessary to consider not only its operational performance and financial indicators, but also its environmental impact. While increasing operational efficiency can bring profit, it can simultaneously increase data processing and energy consumption, which in turn can harm the environment. Increased return on investment and other financial bonuses can be achieved through continuous innovation in operational activities and meeting customer needs. The environmental impact, expressed in emission reduction, is especially valuable if combined with improved operational performance and cost-effective implementation. Separating these points from the overall picture distorts their interconnection and deprives us of a full understanding of the true value of AI.

Creating conceptual integrity. Figure 2 illustrates key concepts that will help understand the implementation of AI and its impact on the oil and fat industry. Successful AI integration depends on three key factors: personnel competencies, availability of data and technological base, and management approach. The implementation of these opportunities will lead to significant advantages in three main areas. The first noticeable results will be operational benefits such as accelerating cycles and reducing the number of unexpected downtime. Such advantages contribute to improving financial indicators (increasing ROA, strengthening cash flow) and reducing environmental impacts (reducing energy intensity per barrel, reducing CO₂ emissions).

To build a conceptual synthesis, three types of drivers are used, which ultimately form three key areas of performance. The study of AI implementation can be carried out using various

tools: a survey of opportunities, analysis of patent documentation, evaluation of robotic achievements, as well as the study of public statements of the company on the main directions of development, acting as indicators of its intentions. Despite the extensive applicability of the described synthesis, the oil and fat industry faces unique features that influence its driving forces and achievable results, as illustrated in Figure 6.

The value chain is divided into three interconnected levels, each of which sets specific tasks for artificial intelligence and uses its own performance indicators. At the initial level, AI focuses on improving the quality of research work, at the middle level – on improving logistics chains and minimizing risks, and at the final level – on improving products and implementing innovations designed to meet consumer demands.

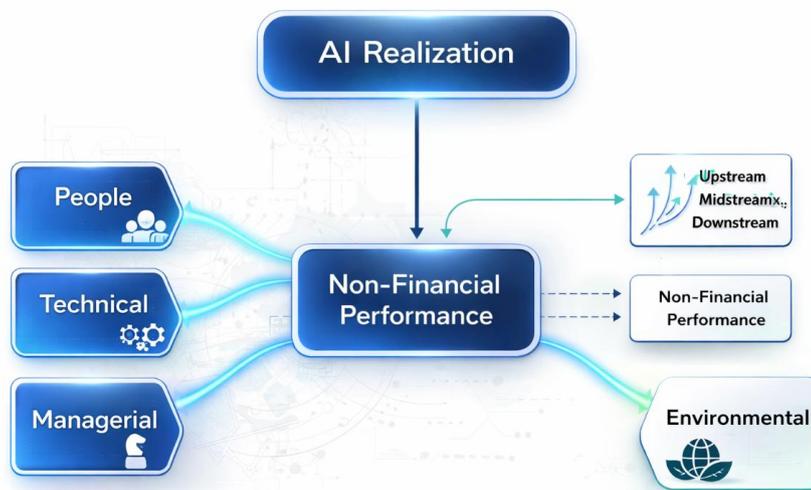


Fig. 6. A theoretical approach that identifies three key elements that determine the impact of artificial intelligence on the efficiency of oil and fat industry enterprises.

To achieve practical benefits from artificial intelligence, managers need to consider strategic resource allocation: investing in people, data, and innovative technologies. In addition, it is necessary to restructure the management structure, taking into account the industry characteristics and the company's position in the product or service creation chain. The evaluation of the effectiveness of investments in AI should be multidimensional, covering not only financial and environmental aspects but also the impact on the company's operational efficiency. Leaders' open statements about intentions to use AI should be clear and specific, as they serve as key indicators of real achievements in this field. The use of proxy indicators, although it can indicate the general trend of AI development, does not provide the same accurate assessment of its maturity as indices reflecting the actual capabilities of AI systems, which most fully correspond to their level of development.

Tips for enterprises working with oils and fats. Combine operational, financial, and sustainability data into a single system to ensure a unified representation for all departments [40]. This approach will enhance interaction, encourage innovation, reduce costs, and increase operational transparency. Implement annual potential scanning. A brief questionnaire on such parameters as skills, data quality, infrastructure, and management will allow for the assessment of "readiness to use AI"; monitoring this assessment over time will reveal weaknesses at the initial stage [6].

Proposals for improving the oil and fat industry sector. In the oil and fat industry,

professional associations, such as SPE, can significantly advance the implementation of AI. For this, they need:

Study the dynamics of the life cycle of property objects and land plots. Evaluate how effectively artificial intelligence (AI) pays off when applied to IOCs, NOCs, green fields, and fields at different maturity stages [20,67]. Share and play. Organize open consortia that will facilitate the exchange of source data, supporting materials, and brand information. Additionally, encourage companies to publish code where permitted by regulations, which will expedite the review and decision-making process [33,43]. Improve your AI competencies. Include Data Science courses in the training programs for engineers and supply chain specialists to analyze the relationship between training volume and company performance indicators [36,37]. Implement a transparent reporting system. Standardizing the disclosure of information about AI projects, including timelines and format, will help reduce information noise and ensure objective comparison of results [47].

The collected data will strengthen the evidence base, close existing gaps in functional capabilities, and ensure the transformation of AI potential into a stable competitive advantage for the oil and fat industry.

CONCLUSION

Companies operating in the food industry, as well as in other sectors, invest in AI only if this guarantees tangible and long-term productivity growth. To achieve such results, it is necessary to fully integrate artificial intelligence: implement data, models, and advanced work processes at all levels of business, and not limit oneself to pilot projects. AI implementation performance evaluation involves rigorous metrics that reflect both the degree of implementation and the resulting performance improvement. This study analyzes the applied methods of implementing AI, studies their impact, and identifies the main elements that determine its overall significance for the organization. Companies operating in the oil and fat industry or other sectors consider investing in AI only when they see it as an opportunity for a clear and long-term improvement in efficiency. Real results are achieved not through one-time projects, but through the comprehensive implementation of AI, encompassing data, models, and business processes at all levels. To assess the effectiveness of AI implementation, it is important to have clear indicators reflecting both implementation quality and performance changes. This research explores various approaches to assessing the effectiveness of artificial intelligence implementation and their resulting impacts. It also outlines crucial elements that empower businesses to unlock the full, enterprise-wide value of artificial intelligence.

Currently, experts identify three key levels of AI development in the context of its performance. The first level is determined by three main factors: personnel competencies, technical infrastructure, and management support. It is they that determine how successfully an organization can move from individual AI pilot projects to its universal implementation. Also, progress in AI is assessed through the analysis of textual data from corporate documents, proxy indicators, such as AI technology patents or the number of robots, as well as indices formed based on surveys. Additionally, the impact of implemented artificial intelligence is becoming noticeable in operational, financial, and environmental spheres. It is precisely in the oil and fat sector that the success factors, key indicators, and company achievements are further dependent on two industry nuances: its position in the supply chain (at the initial, middle, or final stage) and the management type: the state's NOC or the commercial NOC.

To successfully implement AI in the company's daily operations, the oil and fat industry

management must focus on all three categories of drivers. AI development engineers require practical experience with drivers, convincing evidence of tool effectiveness, and clear frameworks for ethical and responsible AI application. Technical implementation involves cleaning and integrating data storage facilities, creating robust MLOPS infrastructures, and ensuring the exchange of data sets and models between various system components. Leadership in managing the implementation process of artificial intelligence begins with establishing open information exchange, overcoming inter-functional barriers, and forming partnerships with suppliers and educational institutions. It is necessary to assess the progress and impact of AI comprehensively using triangulation – a comparison of at least two AI implementation indicators with several key performance indicators.

For successful triangulation, companies must ensure consistency in their operations, financial indicators, and systems aimed at sustainable development. Furthermore, they should develop a brief overview of "AI Readiness," which will cover key aspects such as competencies, data quality, IT infrastructure, and management, and periodically update it to assess development dynamics. Interaction and cooperation between industry companies also play an important role in sustainable progress. Specialized organizations, such as the Society of Engineers, can act as intermediaries between the NOC and the IOC, facilitating the safe transmission of information, encouraging universities to include practical courses on artificial intelligence in their programs, and developing more transparent reporting standards. These actions provide managers with more reliable tools for evaluating and improving the real effectiveness of AI. Accurate triangulation requires consistent data, so companies should integrate their operational, financial, and sustainable development management systems so that all departments work with a unified information base. After this, organizations can develop a brief overview of "Readiness for AI Implementation," where competencies, data quality, infrastructure status, and management level will be analyzed. This review needs to be updated annually to identify weaknesses in a timely manner. Achieving sustainable progress is impossible without interaction between industries. The interaction of professional organizations allows decision-makers to be provided with more reliable data for assessing and improving the real impact of AI.

After this, organizations can develop a brief overview of "Readiness for AI Implementation", where competencies, data quality, infrastructure status, and management level will be analyzed. This review needs to be updated annually to identify weaknesses in a timely manner. Achieving sustainable progress is impossible without interaction between industries. The interaction of professional organizations allows decision-makers to be provided with more reliable data for assessing and improving the real impact of AI. AI activators, which include data, competencies, and aligned strategic efforts, can be considered as factors influencing the realization of AI capabilities, which, in turn, act as intermediate links in this process. Firm indicators covering the financial sector (e.g., ROA), operational activities (e.g., capacity), and environmental aspects (e.g., CO₂ emission levels) can be used as target variables for analysis. The influence of context, such as the form of ownership and the level of regulation, can modify the nature of connections, strengthening or changing their direction. The structure can be evaluated using structured surveys, using standardized scales (e.g., AI Ability Index), and additionally confirming performance data and public company reports. In-depth conversations with organization leaders allow for valuable insights into its internal structure and decision-making processes, enriching understanding of statistical data and making conceptual synthesis more applicable in practice.

REFERENCES



1. J. Weiner, Why AI/Data Science Projects Fail: How to Avoid Project Pitfalls, Springer Nature, 2022.
2. K. Abdelhamid, T.B. Ammar, L. Kenioua, Artificial intelligent in upstream oil and gas industry: a review of applications, challenges and perspectives, in: Lecture Notes in Networks and Systems, 2022, pp. 262–271.
3. E. Strantzali, K. Aravossis, Decision making in renewable energy investments: a review, *Renew. Sustain. Energy Rev.* 55 (2016) 885–898, <https://doi.org/10.1016/j.rser.2015.11.021>.
4. OECD Economics Department, Reviving productivity growth, Working Paper, Organisation for Economic Co-Operation and Development, 2024.
5. E. Brynjolfsson, D. Rock, C. Syverson, Artificial Intelligence and the Modern Productivity Paradox: a Clash of Expectations and Statistics, Working Paper 24001, National Bureau of Economic Research, 2017.
6. P. Mikalef, M. Gupta, Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance, *Inf. Manag.* 58 (2021) 103434, <https://doi.org/10.1016/j.im.2021.103434>.
7. A. Cunha, A. Pochet, H. Lopes, M. Gattass, Seismic fault detection in real data using transfer learning from a convolutional neural network pretrained with synthetic seismic data, *Comput. Geosci.* 135 (2020) 104344, <https://doi.org/10.1016/j.cageo.2019.104344>.
8. I.M. Enholm, E. Papagiannidis, P. Mikalef, J. Krogstie, Artificial intelligence and business value: a literature review, *Inf. S T. Eriksson, A. Bigi, M. Bonera, Think with me, or think for me? On the future role of artificial intelligence in marketing strategy formulation, TQM J.* 32 (2020) 795–814, <https://doi.org/10.1108/tqm-12-2019-0303>.
9. Q. Demlehner, S. Laumer, Shall we use it or not? Explaining the adoption of artificial intelligence for car manufacturing purposes, in: Proceedings of the 28th European Conference on Information Systems (ECIS), ECIS 2020, Association for Information Systems (AIS), 2020, pp. 1–16.
10. R. Schmidt, A. Zimmermann, M. Möhring, B. Keller, Value creation in connection-ist artificial intelligence: a research agenda, in: Proceedings of the 2020 Americas Conference on Information Systems (AMCIS), Association for Information Systems (AIS), 2020, pp. 1–10, https://aisel.aisnet.org/amcis2020/ai_semantic_for_intelligent_systems/ai_semantic_for_intelligent_systems/7, paper 7.
11. R. Afiouni, Organizational learning in the rise of machine learning, 2019. C. Janiesch, P. Zschech, K. Heinrich, Machine learning and deep learning, *EM* 31 (2021) 685–695, <https://doi.org/10.1007/s12525-021-00475-2>.
12. M. Soori, B. Arezoo, R. Dastres, Artificial intelligence, machine learning and deep learning in advanced robotics: a review, *Cogn. Robot.* 3 (2023) 54–70, <https://doi.org/10.1016/j.cogr.2023.04.001>.
13. C. Ley, R.K. Martin, A. Pareek, A. Groll, R. Seil, T. Tischer, Machine learning and conventional statistics: making sense of the differences, *Knee Surg. Sports Traumatol. Arthrosc.* 30 (2022) 753–757, <https://doi.org/10.1007/s00167-022-06896-6>.
14. J. Zhang, Y. Li, W. Xiao, Z. Zhang, Non-iterative and fast deep learning: multilayer extreme learning machines, *J. Franklin Inst.* 357 (2020) 8925–8955, <https://doi.org/10.1016/j.jfranklin.2020.04.033>.
15. M.M. Bejani, M. Ghatee, A systematic review on overfitting control in shallow and deep neural networks, *Artif. Intell. Rev.* 54 (2021) 6391–6438, <https://doi.org/10.1007/s10462-021-09975-1>.



16. C.J. Baby, F.A. Khan, J.N. Swathi, Home automation using IoT and a chatbot using natural language processing, <https://doi.org/10.1109/IPACT.2017.8245185>, 2017.
17. A. Darko, A.P.C. Chan, M.A. Adabre, D.J. Edwards, M.R. Hosseini, E.E. Ameyaw, Artificial intelligence in the aec industry: scientometric analysis and visualization of research activities, *Autom. Constr.* 112 (2020) 103081, <https://doi.org/10.1016/j.autcon.2020.103081>.
18. A.C. Silva, J. Machado, P. Sampaio, Predictive quality model for customer defects, *TQM J.* 36 (2024) 155–174, <https://doi.org/10.1108/tqm-09-2023-0302>.
19. M. Hussain, S. Yang, U.S. Maqsood, M. Ammar, Tapping into the green potential: the power of artificial intelligence adoption in corporate green innovation drive, *Bus. Strategy Environ.* (2024), <https://doi.org/10.1002/bse.3710>.
20. A.N. Okon, S.E. Adewole, E.M. Uguma, Artificial neural network model for reservoir petrophysical properties: porosity, permeability and water saturation prediction, *Model. Earth Syst. Environ.* 7 (2021) 2373–2390.