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Data Envelopment Analysis and Technologies of the Industry of the Future: A Scoping Review

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Abstract
Efficiency is a central driver of the industry of the future, serving as both a strategic transformation goal and a cornerstone of smart manufacturing. Modern data–driven approaches have introduced new ways to analyze efficiency in production processes. This study examines the integration of data envelopment analysis (DEA), a widely applied efficiency evaluation method, and Industry 4.0 technologies. A qualitative review was performed using the Web of Science, Scopus, and IEEE Xplore databases, supported by thematic analysis. Key application areas include robotics and internet of things (IoT) systems. The state–of–the–art analysis enabled the identification of strategies for improving performance assessment in human–centric production systems. Promising directions involve hybrid and ensemble models that merge interpretability and transparency with predictive capabilities, autonomy, and large–scale data processing. These approaches are strengthened by explainable artificial intelligence (XAI), which enhances user understanding and trust in intelligent decision–making systems.

Keywords
Industry 4.0, Efficiency, DEA, Robotics, Internet of Things, AI..

Introduction

The movement toward the industry of the future (also referred to as Industry 4.0 and 5.0) and the overarching sustainability goals pose significant challenges for industry professionals (Figlič et al., 2024). These challenges encompass the complexity of systems, advanced automation and robotization, small batches, high product variability, and the necessity for highly reconfigurable, knowledge–based manufacturing solutions and designs that enable personalization on the production line. Prioritizing efficiency is crucial for the success of the transformation in a global and competitive market, as it enables better resource utilization, waste reduction and reuse, emissions decrease, improvement in employee quality of life, and promotion of innovations to meet current and future requirements.

The literature provides various definitions, metrics, and interpretations of efficiency. The general definition of efficiency is the relationship between the result achieved and the resources used (ISO 9000, 2015). In smart factories, efficiency is crucial at every stage of decision–making: process control, micro– and macro–planning, production planning with scheduling, supply chain management, and enterprise management. Efficiency analysis in the production context requires a broad perspective, focusing on task standardization and automation (Kuryło et al., 2022) with the awareness of the interaction between systems, including customers, employees, business partners, suppliers, and governance. It is imperative to involve issues of sustainable development and inclusive green growth. In the human–centric production paradigm, performance evaluation should be conducted with consideration of the flexibility, inclusiveness, safety, and well–being of workers at all factory levels.

In industrial practice, overall equipment effectiveness (OEE), devised by S. Nakajima (Nakajima, 1988), defined in ISO 22400-1:2014 (ISO 22400-1, 2014), is widely embraced. The method and its variations, e.g., overall labour effectiveness (OLE), and total effective equipment performance (TEEP), are regarded as part of a set of key performance indicators (KPIs) used by companies to monitor and evaluate various aspects of their operations, for example, workforce productivity, process efficiency, supply chain performance, and

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financial profitability (Kochańska & Burduk, 2023). The details of their calculations vary depending on the context. However, they are widely used but often inadequate to analyze the performance of the complex production system (Muthiah et al., 2008; Roda & Macchi, 2019) and do not take into account mutual interactions among technology, people, and processes, as well as exogenous factors. Due to their limitations, attempts are being made to improve or develop new methods for assessing the efficiency and effectiveness of resource use in production processes (Kochańska & Burduk, 2023).

Modern data–driven techniques and methods enable new approaches in efficiency studies (Musial et al., 2024). Currently, artificial intelligence (AI) is the primary approach employed within the industry for data analysis (Rojek et al., 2022; Rojek et al., 2024). A method that has achieved significant success in performance evaluation, confirmed by thousands of publications on both theoretical considerations and real–world applications in various contexts, is data envelopment analysis (DEA). This linear programming technique can handle multiple inputs and outputs, both desirable and undesirable, in monetary and physical terms. It enables the study of the relative efficiency of the decision–making unit (DMU) in performing transformation processes.

Analysis of applications and methodologies used in a production context has revealed that currently, DEA is inferior to other data mining methodologies (Kuo & Kusiak, 2019). However, the development of computer science also opens new possibilities for the application of DEA methods in production research. Network, hybrid, and ensemble DEA models that integrate machine learning algorithms address the challenge of managing large data sets and accurately modeling and predicting performance.

The study aims to examine the current incorporation of DEA method with future industry technologies in the context of production systems, based on a thematic analysis of the content of the Web of Science (WoS), Scopus, and IEEE Xplore databases, as well as a qualitative analysis of selected papers. This facilitates the identification of developmental perspectives and emerging areas for future research within the field of production engineering. The contributions of the article are (i) a concise systematization of the diffuse concepts of efficiency, productivity, and effectiveness of production systems, (ii) identification and summary of DEA efficiency studies of Industry 4.0 (I4.0) technologies, and (iii) highlighting prospective application areas with discussion on potential strategies for enhancing performance assessment methods in human–centric production systems.

The paper opens with an overview that introduces and integrates the concepts of efficiency, DEA, and essential Industry 4.0 technologies. Subsequently, the research framework and results are presented. The article concludes with proposals for future methodological improvements.

Key concepts and definitions

Efficiency

Efficiency and related terms, such as effectiveness and productivity, are subjects of extensive research in the context of production processes. The numerical scale of studies from 2012, when the term Industry 4.0 was introduced, until 2025, concerning the industry of the future and related concepts is presented in the quantitative summary of papers in scholarly databases in Figure 1. The data show a consistent increase in the

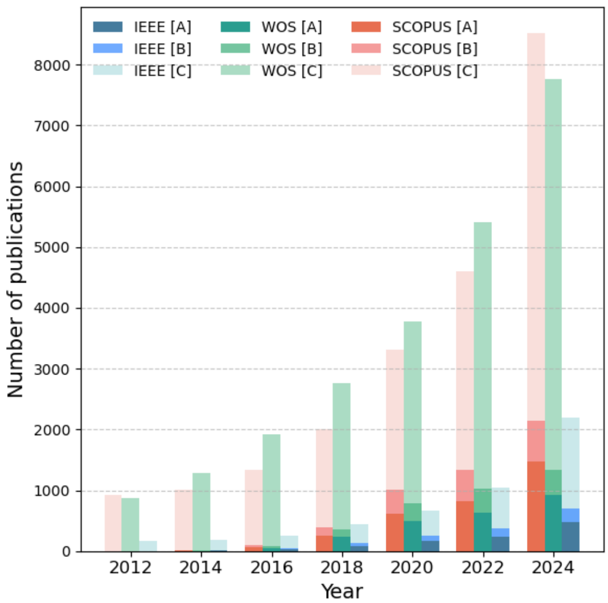

Fig. 1. Increase in the number of publications (without removing duplicates between databases). Search Query: [A]: Data Envelopment Analysis and Technologies of the Industry of the Future: A Scoping Review–ABS–KEY((efficiency) AND ("industry 4.0" OR "industry 5.0")); [B] Data Envelopment Analysis and Technologies of the Industry of the Future: A Scoping Review–ABS–KEY ((effectiveness OR efficiency OR productivity) AND ("industry 4.0" OR "industry 5.0")); [C]: Data Envelopment Analysis and Technologies of the Industry of the Future: A Scoping Review–ABS–KEY((effectiveness OR efficiency OR productivity) AND ("industry 4.0" OR "industry 5.0" OR "smart manufacturing" OR "intelligent production" OR (industry AND future))

number of publications over the years (duplications of papers indexed in databases were not removed; therefore, the graphs illustrate publication trends rather than unique record counts).

There are many works, e.g., (Günter & Gopp, 2022; Tangen, 2005) that summarize the existing meanings of productivity, efficiency, and effectiveness. In general, efficiency should be treated as a quantitative, measurable concept generally defined as the ability to achieve optimal results at minimal cost, which means producing the highest output with the lowest input. Effectiveness relates to achieving goals and desired results (Roghanian et al., 2012). According to the ISO 9000:2015 standard, it is "the extent to which planned activities are realized, and planned results are achieved" (ISO 9000, 2015). Effectiveness captures the link between actual output and potential or intended outcome, with output understood as direct results and outcome as longer–term impacts, which is summarized in the dictionary definition as the ability to be successful ('Effectiveness', 2024). A widespread attempt to distinguish between terms, in line with P. Drucker's thought: "There is surely nothing quite so useless as doing with great efficiency what should not be done at all" (Drucker, 1963), is to perceive effectiveness as doing the right things, while efficiency as doing things right (Sink & Tuttle, 1989). Accordingly, productivity combines effectiveness and efficiency. However, if only doing the right things is controlled, productivity is nothing more than efficiency, defined as the ratio of aggregate output to aggregate input. Figure 2 illustrates these distions. Output is linked to efficiency, as it reflects the immediate results of transforming input into products or services, while outcome is linked with effectiveness, reflecting longer–term impacts and goal attainment.

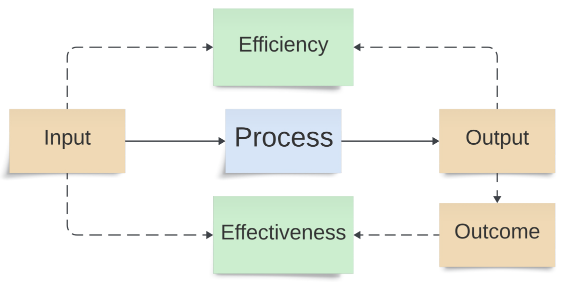

Fig. 2. Efficiency and effectiveness concepts

Figure 3 provides another perspective on the definitions in the literature, where efficiency refers to the management of the resources needed to execute the process, while effectiveness focuses on the results (Tangen, 2005). Productivity combines both terms in the ratio between efficiency and effectiveness, which can be expressed as output achieved per input utilized.

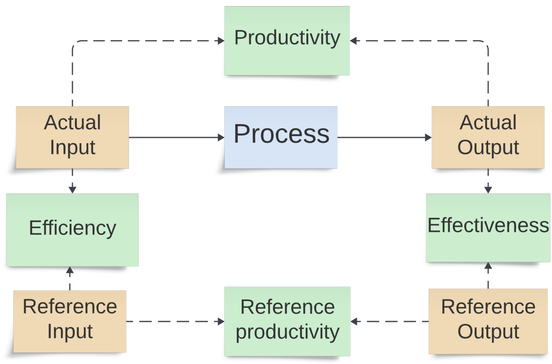

Fig. 3. Productivity, efficiency, and effectiveness concepts

Efficiency is the principle of continuous improvement and a key requirement for achieving operational excellence (Lameijer et al., 2023). Efficiency evaluation in a production environment should acknowledge the need to adapt to changes in priorities and the use of technology as a powerful ally in these activities, with the awareness that productivity growth is often the result of implementing advanced technology (Chen et al., 2018; Kao et al., 1995).

Data envelopment analysis

Productivity from DEA method perspective, is the ratio of the output to the input, and efficiency is defined as the ratio of the minimum input needed to obtain a given output (reference input) to the actual input, but also as the ratio of the actual output to the maximum possible output from a given level of input (reference output) (Chodakowska, 2019). Figure 4 illustrates the concept.

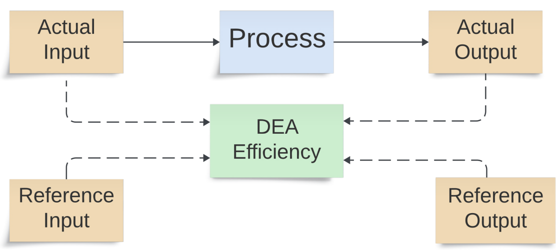

Fig. 4. DEA efficiency concept

The development of the method was initiated by A. Charnes, W.W. Cooper, and E. Rhodes (Charnes et al., 1978), who extended M.J. Farrell's (Farrell, 1957) concept of the best practice frontier. DEA relates the ratio of actual output and input to the reference values from the efficient frontier that envelops the best units in the reference set. The envelope surface shown in Figure 5 is built on the achievements of DMUs A, B, C, D, and E.

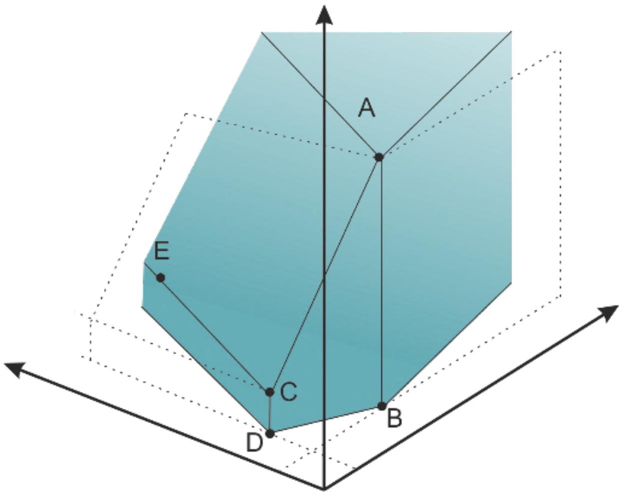

Fig. 5. DEA production frontier concept based on (Mehdiloo & Podinovski, 2021; Zhu, 2015)

Having input vector $\mathbf{x}_j = [x_{1j}, x_{2j}, \ldots, x_{ij}, \ldots, x_{mj}]$ and an output vector $\mathbf{y}_j = [y_{1j}, y_{2j}, \ldots, y_{rj}, \ldots, y_{sj}]$, DEA solves an individual linear programming problem for each DMU j_O (where DMU$_j$; $j = 1, 2, \ldots, n$) and assigns a set of weights λ_j to maximize the technical efficiency score θ ($0 \leq \theta \leq 1$):

$$\begin{aligned}
\min \quad & \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) & \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{ij_O}, & i = 1, \ldots, m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rj_O}, & r = 1, \ldots, s, \\
& \lambda_j \geq 0, & j = 1, \ldots, n, \\
& s_i^- \geq 0, \quad s_r^+ \geq 0, & \forall i, r, \qquad (1)
\end{aligned}$$

where $\varepsilon > 0$ is a non-Archimedean infinitesimal, and s_i^-, s_r^+ are slacks.

DEA has gained wide popularity in many areas, mainly financial and insurance services, education, healthcare, tourism, logistics and transport, supply chains, agriculture, energy sector, and others. It is successfully employed in multi–criteria technological evaluation projects (Chodakowska & Nazarko, 2020). There are proposals to assess digital transformation using DEA methods (Protalinsky et al., 2022). The method has also found applications in strict manufacturing environments (Jain et al., 2023). A variety of extended DEA models have been proposed to address data irregularities and structural complexities within DMUs, as well as combinations with other techniques, to improve DEA performance. These approaches, which merge basic and advanced DEA models with other techniques, can be broadly categorized as machine learning (ML), multi–criteria decision–making (MCDM), and others (miscellaneous) (Fig. 6).

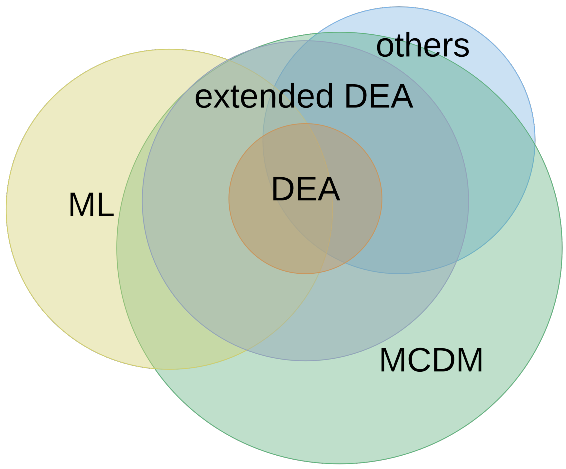

Fig. 6. DEA extension directions

Among the extensions of DEA, models addressing uncertainty – such as stochastic, fuzzy, rough, bootstrap, imprecise, and robust approaches (Chodakowska, 2020; Peykani et al., 2020) – are particularly relevant, as they are crucial for assessing efficiency in Industry 4.0 environments characterized by incomplete, noisy, and variable data from IoT, AI, and cyber–physical systems.

DEA, MCDM, and ML techniques have been used independently in numerous research projects to assess performance, although hybrid and ensemble approaches have been proven to combine benefits and produce synergistic effects. Ensemble models aggregate the results of multiple individual models to enhance the robustness and accuracy of the overall assessment, whereas hybrid models integrate different analytical techniques or algorithms, creating more sophisticated structures that leverage the complementary strengths of the combined methods (Chodakowska et al., 2024).

DEA combined with conceptually different ML algorithms is seen as a future area of intensive development and application (Panwar et al., 2022). These approaches allow for increased applicability and improved reliability in performance assessments. Figure 7 illustrates this scholarly interest, presenting the number of DEA–related publications concerning production efficiency in the period from 2012 to 2024.

The observed slight decline in 2024 may reflect a shift in research interest toward AI–driven methods, as the heightened enthusiasm surrounding AI often accompanies the early stages of technological adoption.

Fig. 7. Number of publications on DEA within the production context (without removing duplicates between databases). Search Query: TITLE–ABS–KEY((industry OR manufactur* OR production OR factor*) AND (dea OR "data envelopment analysis"))

Technologies of the future

The concept of Industry 4.0 assumes the transformation of industrial production by integrating conventional industry with digital technologies, automation, and robotics (Rojek et al., 2022). I4.0 and its synonyms, such as smart manufacturing and smart production, comprise a variety of technologies (Kamble et al., 2018). The core groups of technologies (versions, elements, and synonyms) most frequently mentioned in the literature are (Ghobakhloo, 2018; World Economic Forum, 2019):

- autonomous robots, soft robotics, advanced robotics, collaborative robots (cobots), autonomous vehicles and drones
- internet of things (IoT), industrial IoT, internet of everything, internet of the body (people), smart sensors, and cyber–physical systems (CPS)
- cloud computing, edge computing, meta cloud, supercloud, and multi–cloud
- additive manufacturing, 3D printing, and rapid prototyping
- augmented (AR), virtual (VR), mixed reality (MR), and metaverse
- horizontal and vertical integration of systems;
- blockchain and cybersecurity
- virtual twins, digital twins, simulation and modeling
- big data, artificial intelligence (AI), machine learning (ML), and advanced analytics

The newest works supplement the list of technologies, such as quantum computing.

I4.0 encompasses not only factories but also supply chains, logistics, transport, and resource management to operate more efficiently, flexibly, and sustainably. The principles of the successor, Industry 5.0 (I5.0), leverage the digital transformation initiated by Industry 4.0, enhancing and reshaping the human role within future–oriented manufacturing environments, while emphasizing sustainability and resilience as core dimensions of industrial evolution.

The study focuses on the application of DEA method to evaluate selected I4.0 technologies. The review covered publications from the announcement of the Fourth Industrial Revolution and the I4.0 concept in 2011. The analysis excluded advances in data analysis, despite their profound impact on production systems and significant potential to boost productivity. These developments are crucial to innovation processes and the transformation of industry. AI and big data tools, in many cases, support the evaluation of other technologies and are frequently used individually or in combination with other methods to analyze efficiency and effectiveness. Therefore, AI and big data could be considered both as technologies to be evaluated and as instruments for the evaluation of other technologies (e.g., robotics, 3D printing, or cyber–physical systems). DEA is employed to assess AI implementations (Y. Chen et al., 2024), and algorithms (Soria et al., 2020). Similarly, in the area of simulation and modeling, including digital and virtual twins, the representation of objects is the subject of performance analysis. There are proposals to integrate designed DEA methodology, e.g., product–service sustainability in a digital twin environment (Jin et al., 2024). Evaluating the efficiency of these technologies falls outside the scope of this study and is left as an area for future research.

Therefore, the analysis focused on the main technology clusters of I4.0. Figure 8 presents the number of Scopus–indexed publications related to these technologies in the context of DEA, covering the period from 2012 to 2024.

The analysis reveals that DEA–related publications primarily focus on robots and vehicles, as well as IoT and smart sensors, whereas other technologies, such as cloud computing, blockchain, AR/VR, additive manufacturing, and system integration, receive comparatively less attention.

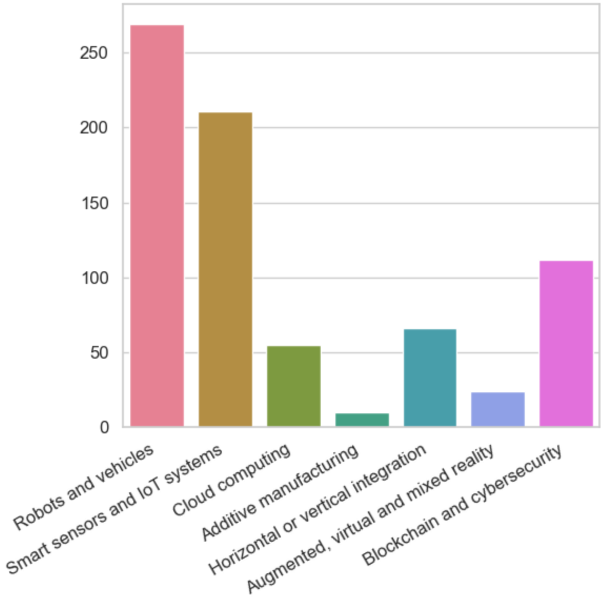

Fig. 8. Number of publications on DEA within the future industry technologies (time frame: 2011–2024, based on Scopus database)

Research framework

The developed research framework is presented in Figure 9.

```
DEFINE technology_set AS list_of_technologies
DEFINE database_results AS EMPTY_LIST
DEFINE current_applications AS EMPTY_LIST
FOR EACH technology IN technology_set DO
BEGIN
DEFINE query AS CONCATENATE
((“DEA” OR “data envelopment analysis”),
technology.descriptors)
FOR EACH database IN [“IEEE”, “WoS”,
“Scopus”] DO
BEGIN
DEFINE search_results AS
SEARCH (database, query)
APPEND search_results TO database_results
END
DEFINE current_application_areas AS
EXTRACT_APPLICATION_AREAS
(database_results)
APPEND current_application_areas
TO current_applications
END
DEFINE prospective_application_areas AS
ANALYZE_PROSPECTIVE_AREAS
(current_applications)
```

Fig. 9. Pseudo code of the research procedure

Presenting the framework in pseudocode highlights its algorithmic nature, making the procedure transparent and reproducible. This approach also facilitates automation, as the steps can be easily translated into a programming environment for large–scale analysis. The procedure involves formulating the search strategy and identifying works that combine I4.0 technology and DEA, enabling the categorization of DEA usability within I4.0 technologies in performance management.

The research process involved analyzing a predefined set of technologies by querying relevant literature databases (IEEE Xplore, Web of Science, Scopus) using keywords related to DEA and technology descriptors. Through iterative refinement of search queries, irrelevant works were eliminated by adding constraints to the technology or method descriptions. Search results were aggregated, and current application areas were extracted. The identified application areas were thoroughly examined to determine prospective opportunities for advancing performance assessment by DEA.

DEA and I4.0 technologies

Robotics and autonomous vehicles

Advanced robots and vehicles play a key role in the context of I4.0, as they drive automation across industrial processes and supply chains. Autonomous robots, including collaborative robots (cobots), are integral to smart manufacturing systems, performing tasks such as assembling, material handling, and quality inspection with precision and adaptability. Autonomous vehicles and drones, on the other hand, revolutionize logistics and intralogistics by ensuring seamless transportation within and between facilities, optimizing delivery times, and reducing operational costs. Robots and vehicles enable the integration of physical and digital systems, ensuring enhanced connectivity, real–time responsiveness, and scalability. Their contributions to enhancing efficiency are significant and are greatly valued.

Attempts to evaluate the performance of robots and robotic systems using DEA predated the announcement of the Fourth Industrial Revolution. The first papers on DEA and robots focused on, e.g., technical specifications (Braglia & Petroni, 1999; Khouja, 1995; Talluri & Paul Yoon, 2000) and efficiency of robotic implementations (Cook et al., 1992). The earliest works focused on the evaluation of robotic systems or used robots as illustrative cases for proposed DEA methodology innovations (Farzipoor Saen, 2006). The topics continue to be investigated. Table 1 lists papers published after 2011, along with their categorizations.

Table 1
Robots and DEA

Authors	Data		Domain		
	A posteriori	A priori	Robotic systems	Industrial processes	Risk analysis
Tao et al., 2012		++		+	
Wu et al., 2012	++	+		+	
Wang et al., 2013	++		+		
Mondal & Chakraborty, 2013	++			+ (P)	
Vaisi et al., 2018	++			+ (P)	
Loske & Klumpp, 2020	++			+ (L)	
Wardana et al., 2020	+	++		+ (P)	
Susarev & Orlov, 2020	++	+	+		
Yan et al., 2021	+	++	+		+
Fazlollahtabar, 2020	+	++		+	
Kao & Liu, 2022	+	++		+ (L)	
Vaisi, 2023	++			+ (P)	
Liu et al., 2023	++	+	+		+
Li & Zhao, 2024	++	+	+		+
Vaisi et al., 2024	++	++	+	+ (P)	+

Legend: Subarea in the industry: P – production, L – logistics; ++ dominant, + existing; a priori – defined in advance at the design stage; a posteriori – determined from the data after the implementation.

The analysis covers strictly industry applications as well as related domains (e.g., robotics in medicine), which have their specific contexts. However, the application of DEA method in robotics is based on the same mathematical principles, regardless of the field. Their joint analysis and interpretation are justified by the similarity of decision variables and the shared goal: supporting the optimization of strategic decisions in the field of robotics.

The papers were classified according to the data used into (i) a priori assessment, e.g., design of systems, performance forecasts, risk assessment at the planning stage, and (ii) a posteriori assessment, e.g., evaluation of systems after implementation, benchmarking, and identification of areas for improvement. The data source in the first case is expert knowledge, technical specifications, and theoretical assumptions, whereas in the second case, it is empirical data, observations, and simulations to verify the scenarios. Many papers combine both a priori and a posteriori elements. Therefore, the dominant approach to the methodology was indicated (symbol ++).

The qualitative review enabled the identification of leading research areas, namely: (i) the development of robotic systems (e.g., robotics in medicine, rescue, and agricultural robots), (ii) optimization of industrial processes (with indication of core production (P) or logistics (L)). The third key area focuses on addressing the issue of risk.

The diversity of approaches to modeling and analysis is indicated by the variables used. The most common approach involves strict technical characteristics (Fazlollahtabar, 2020; L. Li & Zhao, 2024; J. Liu et al., 2023; Loske & Klumpp, 2020; Mondal & Chakraborty, 2013; Susarev & Orlov, 2020; Vaisi, 2023; Vaisi et al., 2018; Y. Wang et al., 2013; Wardana et al., 2020; Wu et al., 2012; Yan et al., 2021). Along with them, financial and economic variables are used (Loske & Klumpp, 2020; Mondal & Chakraborty, 2013; Vaisi, 2023; Vaisi et al., 2018; Wardana et al., 2020; Wu et al., 2012). Additionally, environmental and social variables are also considered (L. Li & Zhao, 2024; J. Liu et al., 2023). Many works involve the integration of quantitative data alongside expert assessments to facilitate an informed evaluation (Fazlollahtabar, 2020; L. Li & Zhao, 2024; J. Liu et al., 2023; Mondal & Chakraborty, 2013; Susarev & Orlov, 2020; Wardana et al., 2020; Wu et al., 2012; Yan et al., 2021).

Considering papers on DEA and robotics, the robots' characteristics are also used only for the purpose of exemplification of advancements in DEA (Y. Fu & Li, 2022; Kao & Liu, 2020; Labijak–Kowalska & Kadziński, 2023). There are also general proposals to integrate DEA into overall intelligent control in the systems (Sun, 2021).

In the context of works on robotization and DEA, noteworthy areas include the assessment of the impact of robotization on productivity growth at micro– and macro–scales (Eder et al., 2024), or a relatively large body of works assessing innovation driven by robotization (S. Wang et al., 2024).

Robotization is invariably linked with mobility (Susarev & Orlov, 2020). Mobile and transport robots have emerged as a prominent research topic over the last decades (Qiu & Wang, 2022). Autonomous vehicles and drones are increasingly being utilized in various fields, including transportation, logistics, inspection, and surveillance. These technologies enable operations with minimal human intervention, thereby enhancing efficiency and reducing the likelihood of human error. As with robotics, the first works in this area also predate the announcement of the I4.0 (F.–H. F. Liu & Kuo, 2007).

Consistent with the study's focus, the search query primarily focused on applications in the production environment. Table 2 presents vehicle–related works.

The articles in Tab. 2 encompass a wide range of applications of DEA in evaluating and optimizing transport systems, AGVs, autonomous technologies, and agricultural systems. The works have been clustered with respect to data (a priori and a posteriori) and according to the domain into (i) smart farming systems, (ii) automated transport systems and logistics, (iii) product–service systems and multi–criteria optimization. The common goal is to improve efficiency, minimize costs, and support multi–criteria decisions in various production and logistics environments.

In the literature, DEA is widely used in the assessment of transport systems, including economic benefits, environmental performance, and safety (Gupta et al., 2021). Explored areas include optimal planning of electric vehicle facilities (Wang et al., 2018) or location of logistic centers (Yazdani et al., 2020). Numerous studies have examined the efficiency of container ports (Nguyen et al., 2020) and airports (Toloo et al., 2022), as well as supply chains in the automotive industry (Li et al., 2019). Another area of interest is also transportation routes, including multimodal or parcel delivery with drones (Cavone et al., 2021). A relatively uncommon but interesting approach is to analyze human–AI collaboration for truck drivers using DEA (Loske & Klumpp, 2021). The proposed solutions or their scaled–up versions can be effectively implemented in the production environment. DEA might evaluate whether drones and autonomous vehicles reduce delivery times between production lines, determine which vehicle routes can be optimized, compare the efficiency of different drones and vehicles depending on the task and conditions, and assess cost and time savings. Based on the literature, the potential of DEA within operational management challenges

Table 2
Vehicle and DEA

Authors	Data		Domain		
	A posteriori	A priori	Smart Farms	Transport and logistics systems	Product–service systems
bin Md Fauadi et al., 2012		++		+	
Chang et al., 2014		++		+	
Pjevcevic et al., 2017	++			+	
Chen & Ming, 2020	+	+			+
Seo & Umeda, 2021	++		+		
Yu et al., 2021	++	+		+	
Chen et al., 2022	+	+			+
Lyu et al., 2023	++			+	
Wang et al., 2023	++	+			+
Zhou et al., 2024	++		+		

Legend: ++ dominant, + existing; a priori – defined in advance at the design stage; a posteriori – determined from the data after the implementation.

– encompassing vehicle allocation, routing, selection, and maintenance – as well as infrastructure and energy efficiency assessment, remains largely underutilized.

Smart sensors and IoT systems

Smart sensors serve as physical measurement points in IoT, providing the infrastructure for data integration, analysis, and interpretation. They form the backbone of Industry 4.0, enabling real–time connectivity and data exchange necessary for automation, operational efficiency, and the integration of cyber–physical systems in modern industrial environments. Studies suggest that IoT technology may improve the overall performance of manufacturing processes (Jang et al., 2022), industries (Y. Li et al., 2022), and entire supply chains, aligning with the principles of green and sustainable development.

IoT systems are evaluated as standalone systems using DEA, including, for example, anomaly detection (S. Park & Lee, 2021). More commonly, DEA is used to evaluate the influence of IoT on efficiency, with IoT serving as a data source for assessing the performance of other processes and systems (Kaiser et al., 2022; Pérez–Pons et al., 2020), or IoT–related metrics are incorporated into DEA assessments (Woo et al., 2021).

Table 3 includes works related strictly to efficiency evaluation and optimization in IoT–enabled production systems using DEA.

The articles listed in Tab. 3 cover a range of industrial and technological contexts. The qualitative review clusters the studies into three domains: (i) IoT, (ii) market technologies, and (iii) risk analysis. The works span multiple disciplines, including engineering, management, information technology, and risk analysis.

Digital technologies and IoT can provide a significant competitive edge by improving efficiency, primarily through the reduction of operators and labor costs. In addition to the works in Tab. 3, it is noteworthy that numerous articles examine the impact of IoT on productivity, including studies concerning plants (Torregrossa et al., 2018), ports (Castellano et al., 2019), enterprises in general and industries (Fan et al., 2021; Wang & Chen, 2021), sectors (Zhang et al., 2018), and entire countries (Kweh et al., 2022; Zhang & Wang, 2019). Additionally, IoT systems serve as data sources for DEA analyses, as exemplified by the evaluation of supply chains using electronic vehicle identification (Hu et al., 2016).

Table 3
Vehicle and DEA

Authors	Data		Domain		
	A posteriori	A priori	Industry and IoT	Technologies and markets	Risk
Siok & Tian, 2011	+		+ (P)		
Chen & Huang, 2012	+			+	
Lim & Anderson, 2014		+		+	
Yoon & Anderson, 2014	+			+	
Ajibesin et al., 2014	+		+ (IoT)		
Hu et al., 2016	+	++	+		
Gong et al., 2016		+		+	
Tan et al., 2017	++	+	+ (IoT)		
Khanduzi et al., 2018		+	+ (IoT)		+
Tselentis et al., 2019	+		+ (P)		
Woo et al., 2021		+		+	
Sinchangreed et al., 2022	+		+ (IoT)		
Cavalcanti et al., 2022	+		+ (P)		
Morinibu & Morita, 2022	+		+ (P)		
Chnina & Daneshvar, 2024	+	+	+ (IoT)		+

Legend: Subarea in the industry: IoT, P – production; ++ dominant, + existing; a priori – defined in advance at the design stage; a posteriori – determined from the data after the implementation.

Cloud computing

Technologies such as cloud computing, edge computing, meta–cloud, supercloud, and multi–cloud are key in I4.0. They are often linked with IoT and robotics, serving as both the infrastructure and method for storing and processing data. Cloud computing enables effective collection, processing, and analysis of data in both real–time and centralized or distributed manners. This increases the speed of decision–making, improves operational flexibility, minimizes delays, and supports the reliability and scalability of systems, directly leading to an increase in production and management efficiency.

The literature contains numerous studies that evaluate cloud service providers from various perspectives. In many cases, they use customized and adapted DEA models. Among the studies addressing these issues indexed in the scholarly databases are: (Azadi et al., 2022; Azadi et al., 2023; Azadi et al., 2024; Azadi et al., 2025; Bilecki & Fiorese, 2016; Cho et al., 2016; De Moraes et al., 2018; De Moraes et al., 2022; Fernández–Cerero et al., 2018; Filiopoulou et al., 2021; Georgios et al., 2021; Jatoth et al., 2017; Pawar et al., 2022; Poordavoodi et al., 2020; Swami Das et al., 2019; Vo et al., 2023; Wang et al., 2021; Xu et al., 2015).

Similar to IoT, in the context of cloud computing, the influence of digital infrastructure adoption and digitization, including cloud computing, on efficiency is also frequently examined (Afgani et al., 2024; Fu et al., 2024; Guo et al., 2023; Hu et al., 2025; Liu & Qu, 2023; Tang & Yang, 2023; Zheng et al., 2022).

The implementation of cloud computing technology enables organizations to dynamically allocate resources according to demand, thereby enhancing operational efficiency and scalability. The resource allocation evaluation is represented by (Cho et al., 2016; Krishnaswamy & Sundarraj, 2017; Rahimi Zadeh et al., 2016). The efficiency of cloud systems was also examined (De Moraes et al., 2022; Shaheen & Kumar, 2022). DEA has been applied to evaluate protocols in virtual networks (Júnior et al., 2019). Early studies examined trust in cloud computing technology using DEA (Raja & Ramaiah, 2016).

In the case of cloud computing, there is a notable lack of research on applying cloud computing in production systems *sensu stricto*.

Additive manufacturing

In the context of a scoping review on additive manufacturing, including 3D printing, rapid prototyping, and DEA, the overall volume of literature is limited. DEA has been used to evaluate the efficiency of different part orientations in 3D printing (Ransikarbum et al., 2021; Ransikarbum & Kim, 2017). DEA was applied to assess the technical efficiency of printers, with results validated against expert benchmarks (Papatheodorou et al., 2021). A decision–making framework combining MCDM and DEA was proposed to select optimal production strategies, demonstrating that additive manufacturing is effective for small–scale production (Achillas et al., 2015).

Augmented, virtual, mixed reality, and metaverse

The application of DEA in the context of immersive technologies such as virtual reality (VR), augmented reality (AR), and mixed reality remains a relatively underexplored area, yet existing studies highlight its growing analytical potential. For instance, DEA has been used to examine team dynamics in VR environments, emphasizing that VR can enhance communication and collaboration (Sparks et al., 2025). Similarly, DEA has been applied to evaluate the performance of training programs for tunnel construction workers, confirming the effectiveness of VR–based training programs (Guo et al., 2024).

Horizontal or vertical integration of systems

The integration of cyber–physical systems within I4.0 frameworks enables seamless vertical and horizontal data exchange, which is foundational for smart manufacturing and adaptive production systems (Zubrzycki et al., 2021). Research highlights the relevance of DEA in evaluating organizational efficiency within the context of structural integration. DEA–based studies have demonstrated that horizontal and vertical integration among hospitals can enhance both productivity and value (Bao & Bardhan, 2025; Zeng et al., 2024). In aquaculture, vertical integration has also been shown to improve economic efficiency, while horizontal integration yielded similar effects (Dridi et al., 2023). A DEA–based Nash bargaining model was introduced to support merger target selection under both horizontal and vertical integration scenarios (Chang et al., 2023). In the petroleum sector, simulated mergers between specialized upstream and downstream firms revealed through DEA that vertical integration could substantially improve structural efficiency (Sharma & Gundimeda, 2023). High–speed rail systems also benefit from vertical integration, which has been identified as a strategic reform direction to enhance operational efficiency in China (Zong et al., 2023).

Blockchain and cybersecurity

In the context of blockchain integration into production systems, the literature on DEA reveals a dominant focus on higher–level aggregated systems rather than on core production processes. A large portion of the studies concentrate on supply chain and logistics systems, where blockchain is used to enhance transparency, traceability, and resilience, while DEA serves as a tool for evaluating operational efficiency and sustainability (Babaei et al., 2025; Yousefi & Tosarkani, 2025). Another significant group of studies addresses finance and accounting, where blockchain supports innovations and DEA is used to assess institutional or system–level efficiency (Charkha & Kale, 2024; Ristanović et al., 2025; Sarwar et al., 2024). There are also studies that analyze the efficiency of investing in blockchain technologies (Zhou et al., 2020).

Regarding works focused on industry and manufacturing, DEA and blockchain are used to support planning, sustainability, and strategic transformation. For example, a DEA–based model for production and distribution planning under uncertainty, enhanced by blockchain transparency, was proposed (Babaei et al., 2025). The integration of blockchain technology and DEA was also explored within the context of lean manufacturing and decentralized management systems (Krenický et al., 2023).

Prospective application areas

Efficiency is a fundamental principle driving the industry of the future, allowing it to meet the economic, social, environmental, and technological challenges. In production engineering research, a transition is observed from analytical–based models towards a data–driven approach (Kuo & Kusiak, 2019). Data analytics and AI play a crucial role in Industry 4.0 by providing real–time insights and predictive analysis to support decision–making (Ahmmed et al., 2024).

Hybrid and ensemble models create a synergistic bridge connecting the interpretability and transparency of analytical models, fostering human trust in the solutions, with the capabilities of detecting patterns and predictions, self–learning, and handling large data sets. It is assumed that trust in AI/ML–based solutions increases when the path to the generated results is transparent and explainable (Mypati et al., 2023).

The review shows that DEA method is applied in assessing strictly I4.0 technologies but is used less extensively compared to the assessment of enterprises, including manufacturing companies involved in new technologies in the context of technology changes (Hu & Xu, 2022; L. Zhang, 2019) or entire supply chains (Kao & Liu, 2020).

The diverse strengths of DEA models – such as their ability to incorporate sustainability, environmental performance, and energy efficiency – are still underexploited in technology assessment. Integrating DEA with other analytical techniques within hybrid and ensemble systems presents a promising direction. These approaches, already well–established in areas like country or sector evaluation, enable synergistic effects and flexible, needs–oriented solutions. Their application in technology assessment would allow for more comprehensive and adaptive evaluations, balancing multiple decision–making perspectives in a multi–criteria environment and significantly improving decision quality.

Mathematical models play a crucial role in automating processes for sustainable production. Promising fields for efficiency evaluation by DEA in designing, monitoring, and managing smart factories include:

- Human–centric AI integration issues, including analysis focused on: (i) human–AI collaboration, (ii) human–machine interfaces (HMI), and (iii) building trust through explainable AI and interpretable models
- Predictive analytics and system proactive maintenance, including: (i) scheduling optimization, (ii) anomaly detection, and (iii) forecasting future performance and reliability of systems with integration with industrial internet of things (IIoT) and within digital twin–based environments
- Environmentally and socially responsible efficiency assessment supporting green technology evaluation and eco–efficiency

Efficiency and automation are becoming increasingly crucial to industrial competitiveness. DEA integrated with AI can address the need for comprehensive and detailed efficiency evaluation, supporting the validation of new methods and proposed improvements in manufacturing engineering.

The integration of AI with DEA can occur at both the preprocessing and postprocessing stages, significantly enhancing the analytical depth and practical utility of efficiency assessments. At the preprocessing stage, AI methods – particularly machine learning algorithms such as XGBoost, Random Forest, and LightGBM – can be used for: (i) feature selection, identifying the most relevant input variables for DEA models; (ii) dimensionality reduction, simplifying complex datasets without losing critical information; (iii) detecting nonlinear and multicollinearity relationships between variables (X. Liu et al., 2022; Zhu, 2022). At the postprocessing stage, AI can be employed to further interpret and operationalize DEA results. This includes: (i) classification of decision–making units (DMUs) based on their efficiency scores (e.g., using CART or clustering algorithms); (ii) prediction of future performance trends using time–series models or neural networks; (iii) policy recommendation generation by linking DEA outcomes with contextual variables and stakeholder needs (Osman et al., 2019; Z. Zhang et al., 2022).

Moreover, explainable AI offers substantial potential when combined with DEA to improve the interpretability and transparency of efficiency assessments. XAI–based DEA frameworks could provide understandable reasoning behind efficiency scores, supporting human trust in AI–driven decision–making. In this context, hybrid DEA–XAI models represent a particularly promising direction for explainable benchmarking of production units and robotic systems, thereby reinforcing the human–centric production paradigm within Industry 5.0.

Efficiency assessment is often just the first step, and the key objective is to uncover the underlying causes of inefficiency. Consequently, the application of DEA should be complemented by advanced data analysis and logical reasoning to develop intelligent decision–support systems within the manufacturing domain.

Conclusions

Industry 4.0 integrates advanced technologies to create value and improve production process efficiency. The qualitative review demonstrates that DEA remains a mature and flexible tool for assessing performance in manufacturing engineering, particularly in scenarios requiring the combination of multiple inputs and outputs and the management of data uncertainty. Extensions of DEA (including stochastic, fuzzy, bootstrap, and network models) are well–suited to the challenges of I4.0 environments, where data originate from IoT, CPS, and AI systems.

Quantitative and qualitative analyses demonstrate that the best–documented DEA application areas in the context of I4.0 technologies are robotics (including cobots and mobile systems). However, operational and infrastructure management issues (allocation, routing, maintenance, energy efficiency) remain underexplored. IoT and sensor systems serve both as objects of assessment and as sources of data for measuring process performance.

At the same time, the review reveals significant gaps. DEA is less frequently used to evaluate cloud computing applications in the strict sense of production systems (despite the growing literature on cloud providers), additive manufacturing, and horizontal and vertical integration. In the context of blockchain and cybersecurity, DEA also applies to aggregated higher–level systems, rather than to production–level processes directly.

The most promising development directions involve hybrid and ensemble models that combine DEA with machine learning methods – from feature selection and dimension reduction (preprocessing) through nonlinearity detection to DMU classification, trend forecasting, and recommendation generation (postprocessing). Explainable AI (XAI) offers significant potential when combined with DEA to improve the interpretability of efficiency scores and provide transparent reasoning for decision makers. Future research could focus on hybrid DEA–XAI frameworks enabling explainable benchmarking of production units or robotic systems, thereby enhancing human trust in AI–supported performance assessment. Priority application areas include: (i) human–AI collaboration and HMI design, (ii) predictive analytics and proactive maintenance (including integration with IIoT and digital twins), and (iii) eco–efficiency and green technologies assessment.

In summary, DEA combined with AI techniques can constitute a robust component of intelligent decision support systems in factories of the future. Challenges include building reference datasets for I4.0 technologies, standardizing indicators (including social and environmental ones), and pilot implementations in cloud–edge environments and autonomous logistics systems.

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