



## RESEARCH ARTICLE

### THE USE OF ARTIFICIAL INTELLIGENCE IN DATA ENVELOPMENT ANALYSIS

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#### ABSTRACT

**Background:** Artificial Intelligence is gaining momentum in various application domains and has a big potential in business analytics and decision making. **Objective(s):** The objective of this paper is to assess the use and potential of Artificial Intelligence in enhancing Data Envelopment Analysis, ultimately advancing business analytics and decision making. **Methods:** Various tools, technologies and case studies are reviewed to assess the potential of Artificial Intelligence in Data Envelopment Analysis. A SWOT (Strength, Weakness, Opportunities, Threats) analysis is conducted. **Results:** Artificial Intelligence has growing potential in Data Envelopment Analysis. **Conclusions:** The growing use of Artificial Intelligence in Data Envelopment Analysis will largely shape decision making and business analytics in the future.

## INTRODUCTION

Artificial Intelligence (AI) plays a significant role in enhancing Data Envelopment Analysis (DEA) through structural and methodological innovations. The integration of AI, particularly Artificial Neural Networks (ANNs), with DEA enhances predictive capabilities and efficiency assessments. For instance, Yeh *et al.* highlight that combining DEA and ANN allows for the identification of performance levels among nations by utilizing optimization processes that account for multiple outputs and relevant variables (Yeh *et al.*, 2024). Similarly, Jomthanachai *et al.* develop a hybrid model demonstrating how the combination of DEA and various machine learning techniques improves logistics performance predictions when data is limited, although their work primarily focuses on economic attributes in logistics (Jomthanachai *et al.*, 2023). Moreover, Wu *et al.* discuss the effectiveness of neural networks in estimating efficiency frontiers more reliably than traditional methods by leveraging comprehensive datasets, thereby retaining crucial information (Wu *et al.*, 2006). In addition, the work of Jauhar *et al.* exemplifies a practical application in the pulp and paper industry, showing that deep learning combined with DEA can support performance evaluation and decision-making processes (Jauhar *et al.*, 2022). Collectively, these advancements underscore the transformative impact of AI on DEA methodologies across various sectors, including economics, logistics, and specific industry applications.

## MATERIALS AND METHODS

We reviewed more than 50 papers related to the use of Artificial Intelligence in Data Envelopment Analysis. Our review covered various areas including tools, technologies, and applications across various domain verticals.

A SWOT (Strength, Weakness, Opportunities, Threats) analysis is conducted to assess the use and potential of Artificial Intelligence in enhancing Data Envelopment Analysis for advancing business analytics and decision making.

## REVIEW AND RESULTS

**REVIEW OF Data Envelopment Analysis:** Data Envelopment Analysis (DEA) is a prominent non-parametric technique widely employed in management sciences to evaluate the relative efficiency of Decision Making Units (DMUs) that operate under multiple inputs and outputs. Originally developed to assess productivity in various organizations, DEA constructs a production frontier which serves as a benchmark for efficient performance. Efficient DMUs form the frontier, while inefficient ones lie below it, enabling a clear comparative analysis of operational effectiveness (Jahanshahloo *et al.*, 2007; Navabakhsh *et al.*, 2007). DEA methodologies leverage linear programming to determine optimal weights assigned to inputs and outputs, thereby necessitating no transformation of these variables during evaluation. This characteristic allows for direct comparison among DMUs across diverse sectors, leading to comprehensive insights into performance metrics (Yao, 2013; Cooper *et al.*, 2011). The applicability of DEA ranges from assessing commercial bank branches to broader organizational performance, reflecting its versatility and robustness as an analytical tool.

**REVIEW OF AI Tools Used in Data Envelopment Analysis:** Artificial Intelligence (AI) has become increasingly prevalent in enhancing Data Envelopment Analysis (DEA) methodologies. Various AI techniques, such as machine learning algorithms, play essential roles in improving the efficiency and accuracy of DEA

applications. For example, kernel methods, including Support Vector Machines (SVM) and decision trees, have been applied to optimize the evaluation of decision-making units by refining the performance measures obtained through DEA (Pandey *et al.*, 2024).

Moreover, feature selection and extraction techniques are critical for preprocessing the data, ensuring only relevant variables are included in the DEA model, which leads to a more nuanced understanding of efficiency (khan, 2022). The integration of metaheuristic algorithms with machine learning approaches enables hybrid models that can enhance diagnostic accuracy and efficiency in various applications (Yağmur *et al.*, 2023). Additionally, foundational research on fuzzy logic and neural networks contributes to the extraction of logical rules from complex data environments, facilitating improved decision-making through clearer interpretability of the DEA results (Duch *et al.*, 2000).

**Case Studies of the Use of AI in Data Envelopment Analysis:** Recent case studies illustrate the impactful integration of Artificial Intelligence (AI) with Data Envelopment Analysis (DEA) across various fields. One notable example is Inazumi *et al.*, who developed a case-based decision support system using DEA and Genetic Algorithms (GA) to enhance efficiency assessments in organizational settings, such as hospitals and schools (Inazumi *et al.*, 2020.). This study demonstrates the effectiveness of combining traditional DEA frameworks with AI techniques for optimized decision-making.

Similarly, Arabjazi *et al.* applied DEA to analyze the performance of social security organizations, where fuzzy measures helped address uncertainty in evaluating multiple inputs and outputs (Arabjazi *et al.*, 2022). Their approach underscores the versatility of DEA when combined with AI to offer clearer insights into organizational efficiency amidst complex factors. In the education sector, Zhang and Sun highlighted the use of AI-infused DEA models to evaluate college English teaching quality, emphasizing enhancements in accuracy and efficiency through new algorithmic approaches (Zhang & Sun, 2025). These innovations illustrate how AI supports the assessment processes in educational contexts. Additionally, Hashemi and Khorsandi introduced a two-stage network structure assessing systems with undesirable outputs, showcasing the application of AI to effectively analyze outputs that complicate DEA evaluations (Hashemi & Khorsandi, 2022). Their work exemplifies the challenges inherent in performance assessments and the potential solutions offered by AI methodologies.

**AI Software used in Data Envelopment Analysis:** The integration of Artificial Intelligence (AI) into Data Envelopment Analysis (DEA) has prompted the development and use of various software solutions specifically designed for performance evaluation and efficiency analysis. Prominent software options include DEAP (Data Envelopment Analysis Program), which supports standard DEA models and has been widely referenced in efficiency studies Đelović (2023). Additionally, Excel Solver and GAMS (General Algebraic Modeling System) are commonly used optimization tools that facilitate the implementation of DEA through linear programming techniques (Daraio *et al.*, 2018).

Moreover, specialized software packages have emerged that focus on productivity and efficiency analysis. For instance, the exploratory bibliographical survey conducted by Daraio *et al.* highlights multiple software solutions tailored for DEA models and stochastic frontier analysis, underscoring the evolution of tools available for researchers and practitioners (Daraio *et al.*, 2018). Such advancements streamline the application of complex DEA methodologies by integrating AI capabilities to enhance prediction accuracy and data processing efficiency. Furthermore, the development of hybrid systems that combine machine learning approaches with traditional DEA frameworks is gaining traction, allowing for more nuanced analyses of decision-making units. This trend is evident in diverse applications across industries, emphasizing the importance of robust software tools in optimizing performance evaluations (Akçay&Etiz, 2020).

## DISCUSSION

The integration of artificial intelligence (AI) in Data Envelopment Analysis (DEA) presents several strengths, weaknesses, opportunities, and threats. Strengths of this integration include enhanced decision-making capabilities derived from advanced machine learning (ML) algorithms, which provide robust statistical analyses that traditional DEA methods may overlook, particularly in managing complex and non-linear data environments (Ermolieva *et al.*, 2022). Moreover, AI's capacity for continual learning can improve the accuracy of performance measurements for small and medium enterprises (SMEs), potentially leading to more sustainable practices within this sector (Malesios *et al.*, 2018). However, weaknesses are evident, such as the potential over-reliance on AI models, which may lead to misinterpretations if not properly understood or managed (Ermolieva *et al.*, 2022). Opportunities lie in the evolving technological infrastructure that supports AI integration, promising improved efficiency and insight generation (Akpan *et al.*, 2025). Conversely, threats include the rapid advancements in AI technologies that could outpace current DEA methodologies, potentially leading to obsolescence or misalignment with emerging data paradigms (Zhou, 2024). Overall, balancing these factors is crucial for fully realizing the benefits of AI in DEA. Table 1 presents a SWOT Analysis of Artificial Intelligence in Data Envelopment Analysis.

**Table 1. SWOT Analysis of Artificial Intelligence in Data Envelopment Analysis**

Category	Description
<b>Strengths</b>	AI enhances efficiency and accuracy in Data Envelopment Analysis (DEA) through advanced algorithms and data processing capabilities (Ghazinoory <i>et al.</i> , 2011). Additionally, it offers the ability to analyze vast datasets, identifying patterns that may not be immediately apparent through traditional methods (Benzaghta <i>et al.</i> , 2021).
<b>Weaknesses</b>	Dependence on high-quality datasets is a critical weakness; inadequate data can lead to erroneous conclusions in DEA (Benzaghta <i>et al.</i> , 2021). There is also a risk of overfitting the models, which may lead to misleading efficiency scores (Ghazinoory <i>et al.</i> , 2011).
<b>Opportunities</b>	The integration of AI can open up new applications in diverse sectors, driving innovation in DEA methodologies (Ghazinoory <i>et al.</i> , 2011). Moreover, AI can provide predictive insights and support decision-making processes in complex environments, enhancing organizational performance (Benzaghta <i>et al.</i> , 2021).
<b>Threats</b>	Rapid technological changes pose a risk of obsolescence in AI tools (Benzaghta <i>et al.</i> , 2021). Furthermore, the implementation of AI in DEA may lead to ethical dilemmas, particularly concerning data privacy and bias (Wang <i>et al.</i> , 2024). The requirement for continuous training and updates could strain resources (Ghazinoory <i>et al.</i> , 2011).

This SWOT analysis underscores the multifaceted nature of employing AI in DEA, reflecting both its potential and challenges.

## CONCLUSION

The convergence of AI tools with DEA methodologies presents a powerful synergy, optimizing performance evaluation across various sectors. The case studies considered collectively illustrate how AI methodologies facilitate more robust, effective, and nuanced applications of DEA across various sectors. Various AI-driven software solutions significantly enhance the application of DEA methods, offering researchers the tools to conduct comprehensive analyses of efficiency in multiple contexts.

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