Chang, T.Y.& Tsaih, R.H. (2023). Assessing the ecoefficiency of artificial intelligence applications using data envelopment analysis. In Li, E.Y. *et al.* (Eds.) *Proceedings of The International Conference on Electronic Business, Volume* 24 (pp. 629-633). ICEB'24, Zhuhai, China, October 24-28, 2024

Assessing the Eco-Efficiency of Artificial Intelligence Applications Using Data Envelopment Analysis

Tien-Yu Chang ^{1,*} Rua-Huan Tsaih ²

*Corresponding author

¹ Ph.D. candidate, Department of Management Information Systems, National Chengchi University, Taipei, Taiwan , 106356506@nccu.edu.tw

² Professor, Department of Management Information Systems, National Chengchi University, Taipei, Taiwan, tsaih@mis.nccu.edu.tw

ABSTRACT

This study develops a comprehensive framework using Data Envelopment Analysis (DEA) to assess the eco-efficiency of AI applications across various sectors. Through an output-oriented DEA model, we evaluate how AI systems balance performance benefits with environmental impacts, incorporating multiple performance indicators and environmental metrics. The research analyzes data from the healthcare, finance, and industrial sectors, using benchmark data and environmental assessments to determine best practices for sustainable AI implementation. The expected results will indicate that the framework effectively identifies eco-efficient AI practices while highlighting limitations in data availability and evolving technological landscapes. The research will contribute to the theoretical understanding of AI eco-efficiency and practical decision-making, offering organizations insights to optimize AI implementations within ESG parameters, ultimately advancing sustainable AI development practices.

Keywords: Eco-efficiency, artificial intelligence, data envelopment analysis, ESG.

INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technologies across various sectors has led to significant advancements in productivity and innovation (Crawford, 2024). However, this technological progress comes with considerable environmental costs, particularly in energy consumption and carbon emissions. As organizations increasingly adopt AI systems for tasks ranging from medical diagnostics to financial forecasting, balancing performance benefits with environmental impact has become crucial (Guo et al., 2023). This tension between technological advancement and environmental sustainability presents a critical challenge for practitioners and researchers in AI development and deployment.

Current research on AI systems primarily focuses on performance metrics such as task accuracy, scalability, and processing speed (White et al., 2024; Zhang et al., 2022). However, there is a growing body of literature examining the environmental implications of AI technologies. Studies have highlighted the significant energy consumption of large language models (LLMs) and other AI applications (Crawford, 2024). Additionally, frameworks for ethical AI assessment, such as those proposed by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (2022), have begun to incorporate environmental considerations alongside social and governance factors.

Despite the increasing attention to both AI performance and environmental impact, a significant gap exists in methodologies that can effectively evaluate the eco-efficiency of AI applications. While existing studies address performance metrics or environmental impacts separately, there is a lack of comprehensive frameworks that can simultaneously assess both aspects (Lee et al., 2024). Furthermore, the absence of standardized approaches for quantifying the trade-offs between AI system performance and environmental costs hinders effective decision-making in AI deployment.

This study aims to develop a conceptual direction for assessing the eco-efficiency of AI applications using DEA. Specifically, we seek to:

1. Establish a methodology for quantifying and comparing the eco-efficiency of various AI applications across different sectors;

2. Identify and validate relevant performance indicators that encompass both environmental impact and operational benefits;

3. Create a practical practice for organizations and policymakers to optimize AI implementations while mitigating environmental impact.

Our research expects to make several significant contributions to both theory and practice:

Theoretical Contribution: We extend the application of DEA to the domain of AI eco-efficiency evaluation, providing a novel approach that integrates environmental and performance metrics into a single analytical framework, which builds upon existing work in both AI performance evaluation and environmental impact assessment methodologies.

Methodological Contribution: By developing an output-oriented DEA model that can handle multiple performance indicators simultaneously, we offer a robust tool for comparative analysis of AI systems across different sectors. This approach addresses the limitations of current evaluation methods that often focus on single-dimension assessments.

Practical Contribution: Our framework provides organizations with a data-driven approach to balance the benefits and environmental costs of AI deployment, which can inform decision-making processes related to AI implementation and optimization and support the development of more sustainable AI practices.

Through these contributions, our study advances the understanding of AI eco-efficiency and provides actionable insights for stakeholders in both academic and industry settings.

AI Performance Evaluation Indicators

LITERATURE REVIEW

In addressing the eco-efficiency of AI applications, output-oriented performance evaluation is essential, particularly in environmental, social, and governance (ESG) concerns. Unlike input-oriented approaches, which focus on minimizing resources such as energy and material use, output-oriented models concentrate on maximizing desirable outcomes like task accuracy, scalability, and the positive social and economic impact of AI systems (Crawford, 2024; Hernández-Orallo, 2017; Lee et al., 2024; Meltzer, 2019; Yang et al., 2023). For instance, AI systems that improve diagnostic accuracy and patient outcomes are prioritized in healthcare, as these outputs directly affect social benefits and overall efficiency (Yang et al., 2023). Similarly, in smart cities, AI applications that enhance public safety and resource management serve as critical performance indicators, aligning with ESG goals (Perez-Des Rosiers, 2021). The selection of output-oriented performance metrics, including social welfare improvements and enhanced decision-making capacity, reflects the broader trend in ESG frameworks, where AI systems are evaluated based on their contributions to sustainable development (Kulkov et al., 2024; Lee et al., 2024).

DMU and Data Sources for Analysis

Given the difficulty in collecting input data, an output-oriented DEA analysis can leverage several well-known datasets that provide robust metrics on AI systems' performance and their broader social and economic impacts. One such dataset is the significant language models benchmark, which provides comprehensive data on LLMs AI model performance regarding scalability, task accuracy, and processing speed across various sectors (White et al., 2024; Zhang et al., 2022). Additionally, the Environmental Performance Index (EPI) offers valuable data on how AI technologies impact environmental metrics like energy efficiency and carbon emissions, particularly in sectors like manufacturing and finance (Guo et al., 2023). Another critical resource is the Ethical Impact Assessment (EIA) of UNESCO, which compiles case studies and reports on the social impacts of AI applications, including ethical governance, public safety, and social welfare contributions (Chui et al., 2018; Mantelero, 2018; UNESCO, 2022). These data sources and sector-specific AI adoption reports provide a rich foundation for conducting DEA analysis, allowing researchers to quantify AI's social and economic benefits while addressing ESG-related objectives.

DEA Model Descriptions and Suggestions

The use of output-oriented DEA models in the context of ESG focuses on maximizing the desirable outputs of AI systems while addressing sustainability goals. Output-oriented DEA models are particularly well-suited for evaluating AI technologies because they prioritize AI systems' social and economic benefits, such as enhanced decision-making capacity, improved public welfare, and better healthcare outcomes (Chung & Chen, 2024; Hu & Chang, 2023).

METHODOLOGY

Overview of the Experiment

This study employs a DEA model to assess the eco-efficiency of AI applications. The primary goal is to evaluate how effectively AI systems across different sectors, including healthcare, finance, and manufacturing, can balance task performance with environmental sustainability. Using a novel output-oriented DEA approach, the model maximizes beneficial outputs such as task accuracy, social benefits, and economic value while minimizing environmental impacts like energy consumption and carbon emissions.

Population/Sample

The AI applications analyzed in this study are drawn from sectors with high AI adoption rates, such as healthcare, smart cities, finance, and manufacturing. These sectors are selected based on their potential environmental impact and significant reliance on AI technologies for operational efficiency. Data is collected from case studies, environmental assessments, and benchmark performance reports of AI systems deployed in these industries.

Restrictions/Limiting Conditions

The study's primary limitation is data availability and quality variability across different sectors and organizations. AI technologies are rapidly evolving, which may result in outdated findings. Additionally, some aspects of AI's environmental

impact, such as indirect effects on human behavior or long-term ecological consequences, are difficult to quantify in the short term.

Sampling Technique

A purposive sampling technique is applied to select AI applications representing significant industries contributing to environmental and social sustainability challenges. AI systems were chosen based on their high deployment rates and availability of detailed environmental performance data, ensuring the robustness of the sample.

Datasets

Data for this study sourced from a combination of:

- Published benchmarks and performance papers of AI systems, such as the LLMs Benchmark (Chen et al., 2024).
- Environmental impact assessments of AI infrastructure, particularly data centers, through resources like the Environmental Performance Index (EPI) (Guo et al., 2023).
- Surveys of AI practitioners, sustainability experts, and case studies from organizations implementing AI systems.
- Ethical impact assessments from entities like UNESCO's AI Ethics Guidelines (UNESCO, 2022).

Procedures

The study follows a two-phase approach. In the first phase, relevant data on AI applications is collected and standardized for comparison across sectors. Due to the challenges in gathering input data, an output-oriented DEA analysis might use several existing datasets; thus, we focus on output performance indicators like task accuracy, economic value generated, and social benefits (e.g., healthcare improvements). In the second phase, the DEA model is applied to evaluate the eco-efficiency of each AI system, identifying the most efficient systems in balancing performance and environmental impact.

Statistical Treatment

Data collected from various sources is processed using DEA software to model and compare the eco-efficiency of AI systems. The DEA model allows for handling multiple outputs without requiring prior assumptions about their relationships. Control variables, such as the organization size, industry type, and technological maturity, are factored into the analysis to ensure the robustness of the results. Additionally, temporal analysis captures trends over two years, assessing how AI technology advancements affect eco-efficiency.

EXPECTED RESULTS AND CONTRIBUTIONS

Expected Theoretical Results and Contributions

This study is expected to significantly contribute to the theoretical understanding of AI eco-efficiency, particularly concerning output-oriented DEA models. By developing a framework that integrates ESG considerations into AI performance metrics, the research will expand current DEA models that primarily focus on technical performance and resource efficiency. The novel combination of environmental impacts (e.g., carbon emissions) and social benefits (e.g., improved healthcare outcomes) in a DEA model will provide a more comprehensive view of AI's broader societal effects. Additionally, incorporating temporal analysis will offer new insights into the evolution of AI eco-efficiency over time, contributing to the body of knowledge on how technological advancements affect sustainability metrics. This study will also help bridge the gap between AI performance evaluation and ESG-related theoretical frameworks, offering a method for quantitatively assessing AI's role in sustainable development.

Expected Practical Results and Contributions

Practically, the study is expected to provide actionable insights for organizations and policymakers aiming to optimize the ecoefficiency of AI applications. The output-oriented DEA model will allow businesses to identify best practices in AI deployments that maximize social and economic benefits while minimizing environmental impacts. In sectors like healthcare, finance, and manufacturing, the model can help organizations pinpoint areas for improvement, such as reducing energy consumption without compromising task accuracy or scalability. By quantifying the eco-efficiency of AI applications, the research will offer a practical tool for decision-makers to balance performance and sustainability goals. Moreover, the case study on AI applications in medical imaging diagnostics will highlight real-world applications of the model, showcasing its ability to drive improvements in healthcare delivery while addressing environmental concerns. The study's focus on output metrics relevant to ESG objectives will further support policy development to promote sustainable AI innovations.

Conclusion

CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

This study has proposed a comprehensive framework for evaluating the eco-efficiency of AI applications through an outputoriented DEA model. The research integrates ESG performance indicators to assess how AI technologies balance task performance with their environmental and societal impacts. The results of this study are expected to help organizations optimize their AI implementations by maximizing beneficial outputs like economic value and social welfare improvements while minimizing environmental costs such as energy consumption and carbon emissions. The development of this research result will offer a valuable contribution to both theoretical and practical discussions on sustainable AI development, providing a practice that supports decision-making in various sectors, including healthcare, finance, and manufacturing.

Limitations

Several limitations need to be acknowledged in this study:

Data Availability: Collecting high-quality, comparable data across various sectors is challenging. The variability in data availability, particularly when measuring AI's environmental impacts across different regions or industries, could impact the robustness of the findings.

Rapid Technological Changes: The fast-evolving nature of AI technologies means that some of the findings could quickly become outdated as new AI models and environmental standards emerge. Continuous research will be required to keep the model up to date.

Indirect Environmental Effects: The study may not fully capture the indirect environmental effects of AI systems, such as longterm ecological impacts or changes in human behavior induced by AI usage. This aspect requires further exploration and could limit the scope of the current analysis.

Future Research

Based on the limitations identified, several avenues for future research are proposed:

Sector-Specific DEA Models: Future studies could refine the DEA model to account for the unique characteristics of specific industries, such as finance, healthcare, or smart cities, which may face different ESG challenges and require tailored evaluation metrics.

Incorporating Life Cycle Assessment (LCA): Integrating LCA methodologies into the DEA framework could provide a more comprehensive evaluation of AI's environmental impacts by considering resource extraction and end-of-life disposal factors.

Indirect and Long-Term Impacts: Research should also aim to develop methods for measuring AI technologies' indirect and long-term environmental impacts, enabling a deeper understanding of how AI influences broader societal trends and long-term sustainability goals.

REFERENCES

- Chen, J., Lin, H., Han, X., & Sun, L. (2024). Benchmarking Large Language Models in Retrieval-Augmented Generation. *Proceedings of the AAAI Conference on Artificial Intelligence, 38*(16), 17754-17762. https://doi.org/10.1609/aaai.v38i16.29728
- Chui, M., Harrysson, M., Manyika, J., Roberts, R., Heteren, R.C.A.v., & Nel, P. (2018). Applying artificial intelligence for social good. *McKinsey & Company*. Retrieved from https://www.mckinsey.com/featured-insights/artificial-intelligence/applyingartificial-intelligence-for-social-good#/ (accessed 11 November 2024).
- Chung, W., & Chen, Y.-T. (2024). Development of ESG Performance and Sustainability Indicators: A Data Envelopment Analysis Approach with Overlapping Criteria. In *Handbook on Data Envelopment Analysis in Business, Finance, and Sustainability* (pp. 459-488). World Scientific Publishing Co Pte Ltd. https://doi.org/10.1142/9781800615786_0015
- Crawford, K. (2024). Generative AI's environmental costs are soaring And mostly secret. *Nature*, 626(693). https://doi.org/10.1038/d41586-024-00478-x
- Guo, Q., Zeng, D., & Lee, C.-C. (2023). Impact of smart city pilot on energy and environmental performance: China-based empirical evidence. *Sustainable Cities and Society*, *97*, 104731. https://doi.org/10.1016/j.scs.2023.104731
- Hernández-Orallo, J. (2017). Evaluation in artificial intelligence: From task-oriented to ability-oriented measurement. *Artificial Intelligence Review*, 48(3), 397-447. https://doi.org/10.1007/s10462-016-9505-7
- Hu, J.-L., & Chang, T.-Y. (2023). Energy Resilience: A Cross-Economy Comparison. *Energies*, 16(5), 2214. https://doi.org/10.3390/en16052214
- Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustainable Development*, 32(3), 2253-2267. https://doi.org/10.1002/sd.2773
- Lee, S.U., Perera, H., Liu, Y., Xia, B., Lu, Q., Zhu, L., Cairns, J., & Nottage, M. (2024). Integrating ESG and AI: A Comprehensive Responsible AI Assessment Framework. *ArXiv*, *abs/2408.00965*. https://doi.org/10.48550/arXiv.2408.00965
- Mantelero, A. (2018). AI and Big Data: A blueprint for a human rights, social and ethical impact assessment. *Computer Law & Security Review*, 34(4), 754-772. https://doi.org/10.1016/j.clsr.2018.05.017
- Meltzer, J.P. (2019). Artificial intelligence primer: What is needed to maximize AI's economic, social, and trade opportunities. *Global Economy and Development*, *12*, 1-23.
- Perez-Des Rosiers, D. (2021). AI Application in Surveillance for Public Safety: Adverse Risks for Contemporary Societies. In T. Keskin & R. D. Kiggins (Eds.), *Towards an International Political Economy of Artificial Intelligence* (pp. 113-143). Springer International Publishing. https://doi.org/10.1007/978-3-030-74420-5 6
- UNESCO. (2022). *Recommendation on the Ethics of Artificial Intelligence*. United Nations Educational, Scientific and Cultural Organization.
- White, C., Dooley, S., Manley, R., Pal, A., Feuer, B., Jain, S., Shwartz-Ziv, R., Jain, N., Saifullah, K., Naidu, S., Hegde, C., LeCun, Y., Goldstein, T., Neiswanger, W., & Goldblum, M. (2024). LiveBench: A Challenging, Contamination-Free LLM Benchmark. ArXiv, abs/2406.19314. https://doi.org/10.48550/arXiv.2406.19314

- Yang, W., Wei, Y., Wei, H., Chen, Y., Huang, G., Li, X., Li, R., Yao, N., Wang, X., Gu, X., Amin, M.B., & Kang, B. (2023). Survey on Explainable AI: From Approaches, Limitations and Applications Aspects. *Human-Centric Intelligent Systems*, 3(3), 161-188. https://doi.org/10.1007/s44230-023-00038-y
- Zhang, Z., Xiao, Y., & Niu, H. (2022). DEA and Machine Learning for Performance Prediction. *Mathematics*, 10(10), 1776. https://doi.org/10.3390/math10101776