Impact of Artificial Intelligence on Industrial Sustainability

Dr. Divya Chitre[1]
Assistant Professor, School of Information Technology, Indira University, Pune

Ms. Bhakti Govind Shinde[2]
Assistant Professor, School of Information Technology, Indira University, Pune

DOI: 10.29322/IJSRP.16.02.2026.p17012
https://dx.doi.org/10.29322/IJSRP.16.02.2026.p17012

Paper Received Date: 5th January 2026
Paper Acceptance Date: 8th February 2026
Paper Publication Date: 12th February 2026

Abstract

The increasing usage of Artificial Intelligence in the industrial setting has brought about a transformation in the industrial process chain, asset management, and decision-making mechanisms. Though AI-enabled systems are increasingly being regarded as facilitators of industrial sustainability, research evidence regarding the extent to which AI can contribute to industrial sustainability is still limited. This research aims to explore the role of AI in industrial sustainability using both conceptual analysis approaches and insights from existing industrial applications. This study critically analyzes the role of AI-enabled industrial practices in terms of environmental and operation-related dimensions of industrial sustainability. The role of AI-enabled industrial practices in terms of energy performance optimization, resource management, and industrial process reliability is specifically explored. This study analyzes the impact of industrial applications relating to predictive maintenance, intelligent energy management systems, and industrial process optimization on industrial sustainability. The study highlights the role of AI in resulting in improved industrial performance in terms of process optimization, energy conservation, and waste reduction; however, this positive role is overshadowed by the arrival cost based on industrial AI model development. This finding provides the basis for developing a lifecycle-related conceptual model between industrial AI-related process chain stages and industrial performance factors. The framework offers a structured approach towards making sustainability trade-offs to ensure proper decision-making towards the use of sustainable AI. This piece makes a contribution towards the sustainable computing body of knowledge with the provision of an empirically-informed approach that links AI implementation and sustainability goals within the industrial sector.

Keywords - Artificial Intelligence; Industrial Sustainability; Sustainable Computing; Energy Efficiency; Industry 4.0; Lifecycle Assessment

1. Introduction

1.1 Background and Motivation

The current world industrial landscape is moving at a fast pace in the adoption of digital technologies including the use of Artificial Intelligence (AI), the Internet of Things (IoT), and data analysis. Of these, the adoption of AI has become a key facilitator in the adoption of Industry 4.0. This has improved productivity, quality, and the efficiency in the manufacturing, energy, logistics, and process sectors (Jain & Wullert, 2002; Wu et al., 2022).

Conversely, the rising energy consumption rates and the strict environmental standards are exerting more force on industrial sectors to embrace sustainable methods. This is because the industrial sectors contribute immensely to the global carbon emissions (IEA, 2024). A major factor that can optimize the consumption of resources while eliminating industrial wastes effectively through lower carbon emission processes is the application of AI technology. However, the effect brought about by the implementation of AI technology on sustainable performance within the industrial sectors does not always yield positive outcomes.

Current literature emphasizes that while AI-based systems can optimize energy efficiency in terms of operations, their design and subsequent deployment in AI models, especially data-driven and computationally intense tasks, result in their own energy requirements, as well as carbon footprint (Strubell et al., 2019; Henderson et al., 2020). This phenomenon has become a paradoxical issue related to sustainability factors.

1.2 Problem Statement

Though the application of AI has been widely gaining momentum across various industrial sectors, the current literature lacks adequate empirical analysis on the overall effects of AI on the sustainability of industries. Most literature either concentrates on broad industrial sustainability goals or the average environmental impact of the computation process undertaken by the use of AI systems. Nevertheless, the effects related to the overall industrial application of the concerned systems remain underappreciated.

1.3 Research Objectives

The research intends to fulfill the above-given research gap by achieving the following objectives:

1. To analyze existing AI tasks involved in sustainability within an industrial setting.
2. Assess the effects of AI-based industrial processes on sustainability.
3. To determine the trade-offs that could result from the development and implementation of AI models related to sustainability
4. To develop a conceptual framework on sustainable adoption of AI based on its lifecycle.

1.4 Research Questions

- What is the impact of AI implementation on sustainability in industrial operations?
- What are the benefits of AI-based industrial systems in the environment as well as in operations?
- What trade-offs must be made when considering AI performance versus sustainable goals?
- How can the lifecycle-based framework facilitate sustainable AI integration within an industrial setting?

2. Literature Review

2.1 AI and Industrial Transformation

Artificial intelligence has been increasingly used in industry-related fields to provide intelligent automation, prediction, and adaptive control. Such tasks, among them prediction, maintenance, and optimization, have registered a noticeable improvement in increased efficiency and, consequently, reduced costs (Wu et al., 2022). There has been a direct alignment with industry-related goals of sustainability, which include reduced wastage of materials and reduced machine downtime.

2.2 Sustainability Implications of AI Systems

Although AI promotes efficiency in industries, its effect on the environment is becoming a concern for many researchers. It has been shown that the process of training large-scale AI models is quite energy-intensive, leading to carbon emissions (Strubell et al., 2019; Patterson et al., 2021). Wu et al. (2022) have suggested the need for comprehensive analysis in understanding the sustainability of AI solutions for various data streams in their pipeline or hardware used in their operations.

2.3 Industrial Sustainability Metrics

A sustainability analysis of the industry can be made through indicators such as energy efficiency, reduced emissions, resource use, and reliability. However, current sustainability analysis does not take into consideration factors such as computational intensity, volume of data, and infrastructure needs that are unique to artificial intelligence (Henderson et al., 2020).

2.4 Identified Research Gap

As the sustainability and environmental implications of AI have already been covered in the current literature independently, there is a research gap in the development of a comprehensive and validated framework to examine the sustainability dimensions of AI.

3. Proposed Conceptual Framework

3.1 Framework Overview

In this regard, the paper proposes a "Lifecycle-Based Sustainable AI Framework for Industrial Systems" to investigate the sustainability effects of implementing AI in industrial settings. This is because the sustainability effect of AI reaches beyond its use and implementation and is rather embedded within the entire life cycle of the system involved. This is supported by Wu et al. (2022) and Henderson et al. (2020).

Current studies on sustainable AI focus mainly on isolated results like energy optimization or emissions reduced during the operation of industry. However, current studies fail to consider costs involved in sustainable development, like data-intensive preprocessing, complex model training, and infrastructure scaling tasks (Strubell et al., 2019; Patterson et al., 2021). By combining the different phases of AI development with sustainable development aspects of industry, it will be possible to cover all aspects of sustainable development, as mentioned above.

3.2 Framework Components

The framework is made up of two closely related aspects: the stages of AI's lifecycle and the dimensions of industrial sustainability. These two aspects are interconnected in such a way that they offer a framework for sustainability assessment.

3.2.1 AI Lifecycle

Data Acquisition and Processing

Data acquisition and data processing represent the base for AI systems in industrial settings, including data acquisition processes from sensors, machines, and enterprise systems. Although good data is crucial for AI model accuracy, the energy requirements in this stage might be substantial owing to data transmission, storage, and data processing operations in the AI system (Henderson et al., 2020). In the context of sustainability, poorly designed data flows could potentially contribute to increased digital waste, highlighting the need for data minimization practices in AI systems in the industrial domain (Wu et al., 2022).

Model Development and Training

Model development and training are the most computationally intensive part of the AI life cycle. Many industrial AI models are based on huge datasets and profound architecture for high predictive accuracy, which results in high energy consumption and, consequently, acute carbon emissions. This is according to Strubell et al., 2019; Patterson et al., 2021. From this stage, significant choices arise in terms of sustainability, which can be weighed against model complexity and environmental impact. Thus, this framework puts into focus the importance of assessing algorithm efficiency, reusing pre-trained models, and optimizing training strategies to reduce environmental costs.

Deployment and Inference

Deployment represents the process of integrating the trained model with the industrial systems to enable tasks like predictive maintenance and scheduling. This phase is contributing to sustainability in the industrial applications and results in the minimization of equipment downtime and the efficient use of materials and energy. But there could be new power consumption requirements involved with the continuous inference of the model. The model takes into consideration the new consumption involved with the inference of the model.

Monitoring and Optimization

For monitoring and optimization, it ensures continuous functioning of AI in dynamic industrial environments. Tasks like performance monitoring, system retraining, and system fine-tuning are ensured in order to avoid deterioration of the AI model and inefficient resource use. Analysis from the sustainability perspective views monitoring as crucial in avoiding unnecessary retraining sessions and computation overheads. It thus supports long-term efficiency (Henderson et al., 2020). This phase confirms sustainability through monitoring.

Model Reuse or Retirement

In the final stage of the life cycle, long-term management regards reuse, transfer, or retirement of the AI models. According to Wu et al. (2022), model reuse across similar contexts reduces computational and energy costs related to retraining by a significant amount. On the other hand, improper retirement will lead to infrastructure waste and inefficient use of technology. The framework therefore demonstrates that long-term environmental and economic impacts can be minimized with responsible decommissioning and lifecycle planning.

3.2.2 Sustainability Dimensions

The framework evaluates AI lifecycle stages across three key sustainability dimensions:

Environmental Sustainability

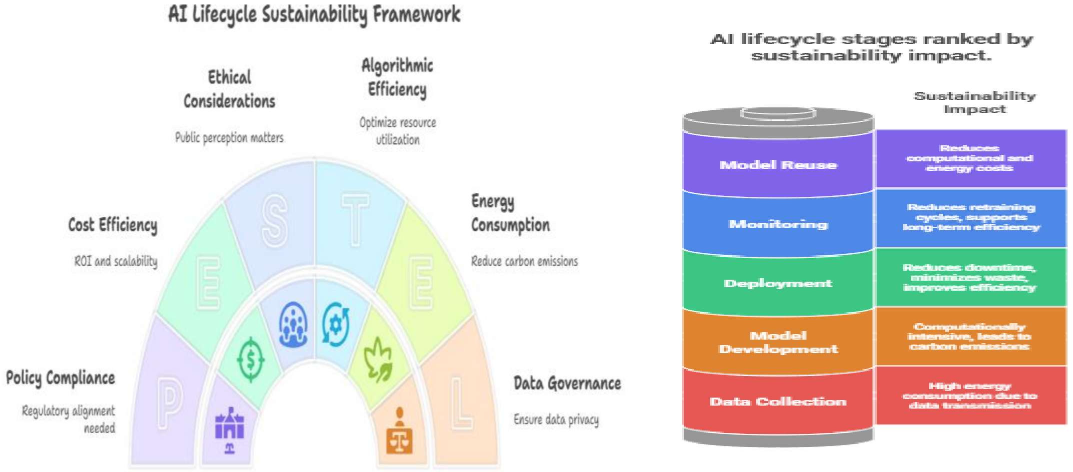
The major concern regarding environmental sustainability is related to indicators of energy use, carbon emission, and waste management. The study of these indicators in relation to the entire lifecycle of AI can thus help determine areas of highest impact in terms of environment and plan strategies accordingly (Strubell et al., 2019; Patterson et al., 2021).

Operational Sustainability

Operational sustainability involves the use of AI systems in enhancing the efficiency, reliability, and resilience of industrial operations. The metrics on downtime reduction, system stability, and process efficiency are different measures used to benchmark the longitudinal operational values of the AI-enabled solution (Jain & Wullert, 2002).

Economic Sustainability

Economic sustainability studies the benefits of cost savings, increased productivity, or ROI related to the implementation of artificial intelligence. For sustainable artificial intelligence solutions to be adopted on an industrial scale, they must prove to be economically viable (Wu et al., 2022)



3.3 Figure Description

A representation of the proposed framework based on the AI system stages mapped to the dimensions of industrial sustainability is shown in Figure 1. It is evident from the representation in the figure that the effects of sustainability are associated not only with the deployment stages of the AI system but with every other stage as well.

4. Expected Contributions

4.1 Theoretical Contributions

This paper adds to the sustainable AI literature by broadening the scope of sustainable evaluation to the industrial domains. The lifecycle framework advances the current literature on sustainable AI through the connection to the dimensions of sustainability during the design, implementation phase to the dimensions mentioned above instead of being specifically focused on one environmental or technical point covered within previous literature (Wu et al., 2022; Henderson et al., 2020).

4.2 Practical Contributions

From a practical standpoint, the proposed framework is an organized tool that benefits the industrial community in terms of assessing the sustainability implications of implementing AI. It enables engineers, managers, and policymakers to trade off the optimization of performance with sustainability. Moreover, this framework helps in synchronizing the use of AI in Industry with the requirements of regulations and sustainability in organizations (IEA, 2024).

5. Conclusion

This study shows that Artificial Intelligence can strongly support industrial sustainability when it is used thoughtfully and evaluated in a holistic manner. The findings indicate that AI applications such as predictive maintenance, intelligent energy management, and process optimization help industries reduce energy consumption, minimize material waste, improve operational reliability, and enhance overall efficiency. These outcomes clearly demonstrate AI’s potential to support environmental and operational sustainability goals.

At the same time, the study highlights an important concern. While AI improves sustainability during industrial operations, the processes involved in building and running AI systems—such as large-scale data processing, model training, infrastructure expansion, and continuous monitoring—consume significant energy and generate carbon emissions. This creates a clear trade-off, where the benefits of AI must be weighed against its environmental cost. Therefore, AI should not be viewed as automatically sustainable; its impact depends largely on how it is designed, deployed, and managed.

By taking a lifecycle-based perspective, this research emphasizes that sustainability impacts arise at every stage of an AI system, from data collection to model retirement. The proposed framework helps industries evaluate these impacts in a structured way by considering environmental, operational, and economic dimensions together. It encourages informed decision-making, allowing organizations to balance performance improvements with long-term sustainability through practices such as efficient model design, reuse of existing systems, and responsible decommissioning.

In conclusion, AI can act as a powerful enabler of sustainable industrial development when lifecycle awareness is integrated into its adoption. A balanced and responsible approach to AI implementation is essential to ensure that technological progress aligns with sustainability objectives, supporting both industrial growth and environmental responsibility.

References

1. Jain, A., & Wullert, J. R. (2002). Challenges: Environmental design for energy efficiency. Computer, 35(7), 24–26. https://doi.org/10.1109/MC.2002.1016908
2. Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (pp. 3645–3650). https://doi.org/10.18653/v1/P19-1355
3. Henderson, P., Hu, J., Romoff, J., Brunskill, E., Jurafsky, D., & Pineau, J. (2020). Towards the systematic reporting of the energy and carbon footprints of machine learning. Journal of Machine Learning Research, 21(248), 1–43.
4. Kiela, D., Bartolo, M., Nie, Y., Kaushik, D., Santurkar, S., Wallace, E., Parikh, D. (2021).
5. Dynabench: Rethinking benchmarking in NLP. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (pp. 4110–4124).
6. Patterson, D., Gonzalez, J., Le, Q. V., Liang, C., Munguia, L. M., Rothchild, D., … Dean, J. (2021). Carbon emissions and large neural network training. arXiv preprint arXiv:2104.10350. https://arxiv.org/abs/2104.10350
7. Wu, C.-J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., … Hazelwood, K. (2022).
8. Sustainable AI: Environmental implications, challenges, and opportunities. In Proceedings of the 5th Conference on Machine Learning and Systems (MLSys). https://proceedings.mlsys.org
9. World Bank Group. (2023). Measuring the emissions and energy footprint of the ICT sector: Implications for climate action. Washington, DC: World Bank. https://documents.worldbank.org
10. Information Technology Industry Council. (2024). Understanding AI's role in the energy transition: Sustainable technology policy guide. Washington, DC: ITI.https://www.itic.org
11. International Energy Agency. (2024).Electricity 2024: Analysis and forecast to 2026. Paris: IEA.https://www.iea.org.