THE ROLE OF AI IN ENERGY USABILITY AND EFFICIENCY: OPPORTUNITIES AND LIMITATIONS

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Artificial Intelligence (AI) is increasingly shaping environmental sustainability, particularly in optimizing energy usability and enhancing energy efficiency. AI-powered solutions, such as smart grids, predictive analytics, and automated energy management systems, enable real-time monitoring and dynamic energy allocation, reducing waste and improving overall efficiency. AI-driven forecasting models also enhance renewable energy integration by predicting fluctuations in solar and wind power generation, ensuring a more stable and sustainable energy supply. Additionally, AI-enabled IoT systems contribute to energy-efficient buildings and industrial processes by autonomously regulating energy consumption based on real-time data. This study employs a mixed-method research approach, combining secondary data analysis with primary research. The primary research component consists of four in-depth interviews with experts in AI, and energy management. These interviews provided qualitative insights into the practical applications, challenges, and future potential of AI-driven energy solutions. The main findings indicate that while AI significantly contributes to energy optimization and stabilization, it also poses sustainability challenges due to its high energy consumption. Experts emphasized that AI-driven solutions must evolve towards greater energy efficiency to offset the environmental impact of AI infrastructure itself.

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1 Introduction

Artificial Intelligence (AI) can be defined as machine intelligence that is able to mimic a human mind's problem-solving and decision-making capabilities to perform various tasks (Kanade, 2025), such as preparing quality any-to-any language translations, and generating, understanding, analysing, or proofreading any text. In simplified terms, artificial intelligence operates on three primary levels. Initially, it assimilates sensory data to perceive its environment. Subsequently, it applies analytical methods to identify patterns and correlations. Finally, it refines its internal knowledge base to enable informed decision-making, thereby facilitating adaptive system optimization (LeCun et al., 2015). It is therefore no coincidence that AI has emerged as a transformative force in the energy sector, offering vast potential to enhance energy usability and improve overall efficiency (Gruetzemacher & Whittlestone, 2019). Through AI-powered solutions, such as smart grids, predictive analytics, and automated energy management systems, the energy landscape is being reshaped to enable real-time monitoring, dynamic energy allocation, and enhanced forecasting capabilities, ultimately reducing waste and optimizing resource utilization (Kumar et al., 2021).

AI exists on a spectrum of capabilities, commonly divided into three levels:

- *Narrow AI (Weak AI):* These systems are designed to perform specific tasks efficiently, such as optimizing heating and cooling in smart buildings or enhancing power distribution in smart grids. Narrow AI is already playing an important role in improving energy efficiency through machine learning algorithms that analyse consumption patterns and adjust systems in real-time. Bankins & Formosa (2023) quote Boden (2016) in their work when stating that this level of AI can be recognised as the *"holy grail"* of this technology. Also, the use of narrow AI allows us to draw on practical examples to ground our works' effectiveness.
- *General AI (Strong AI):* While still theoretical, General AI would possess cognitive abilities akin to human reasoning, thereby enabling autonomous decision-making across multiple domains. In the energy sector, such systems could implement highly adaptive, self-optimizing energy management strategies without human oversight. As Lake et al. (2017) argue, designing machines that learn and think like humans necessitates

integrating perceptual inputs, reasoning, and prior knowledge—capabilities that, if fully realized, could revolutionize dynamic resource allocation and sustainability in energy systems.

– *Super AI:* This hypothetical stage envisions an intelligence that surpasses human cognitive capabilities, with far-reaching implications for innovation. In the context of energy sustainability, a Super AI could theoretically devise novel solutions and radically transform existing paradigms. Chalmers (2016) suggests that such an intelligence might not only optimize established processes but also pioneer entirely new frameworks for energy generation and distribution, thereby addressing complex challenges that currently elude human problem-solving.

In this article, mostly the use of Narrow AI can be taken into consideration. For instance, smart grids, powered by AI algorithms, enable real-time monitoring and dynamic energy allocation, adjusting supply and demand in response to fluctuations (Fang et al., 2012). This dynamic approach maximizes efficiency by reducing energy waste and ensuring a more stable and reliable energy supply. Moreover, AI-driven predictive analytics models can enhance the integration of renewable energy sources, such as solar and wind, by accurately forecasting fluctuations in power generation, allowing for better grid balancing and storage management (Tang et al., 2022). Beyond the power grid, AI-enabled IoT systems also contribute to energy efficiency in buildings and industrial processes. These systems autonomously regulate energy consumption based on real-time data, optimizing lighting, heating, ventilation, and other energy-intensive operations (Alam et al., 2012). While AI has significantly transformed the energy sector, unlocking numerous opportunities for optimization and sustainability, it also poses significant challenges that must be addressed. It is worth to mention that AI has a highly adaptable transformative potential which can enhance energy efficiency and usability, but we have to mention that the widespread adoption of AI-powered solutions carries its sustainability implications. A key concern is the high energy consumption of AI infrastructure itself, which can potentially offset the environmental benefits it aims to achieve (Strubell et al., 2019). As AI systems become more prevalent, their energy demands are likely to increase, highlighting the need for AI-driven solutions to evolve towards greater energy efficiency. As the energy sector continues to undergo digital transformation, the role of AI in enhancing energy usability and efficiency is undeniable.

However, precisely due to these factors, a vicious cycle emerges, posing a significant challenge in finding a viable solution. While artificial intelligence (AI) systems and models are increasingly employed to enhance energy efficiency, the energy demand of AI systems themselves is escalating at an alarming rate on a global scale.

2 Literature review

The literature on the intersection of artificial intelligence, energy efficiency, and environmental sustainability reveals a multifaceted and, at times, paradoxical relationship. On one hand, numerous studies demonstrate that AI applications – ranging from predictive analytics and dynamic energy allocation to the deployment of smart grids – have been instrumental in optimizing energy management and integrating renewable sources. For instance, Phuangpornpitak et al. (2013) and Ukoba et al. (2024) illustrate how AI-driven algorithms can adjust supply and demand in real time, thereby enhancing grid stability and reducing energy wastage. These innovations enable more resilient and adaptive energy systems, which are essential for meeting the demands of modern power infrastructure. Conversely, the rapid advancement and scaling of AI technologies have raised critical concerns regarding their intrinsic energy consumption. Jiruwala (2024) argue that the energy required to train large-scale neural networks, such as those powering natural language models (referred as LLMs), can result in carbon emissions on a scale comparable to those of traditional industrial processes. This view is corroborated by Strubell et al. (2020), whose research highlights the significant environmental costs associated with deep learning, particularly in the context of computational resource demands. Furthermore, Bender et al. (2021) have sparked an important debate by emphasizing that while AI can unlock transformative efficiencies across various sectors, the computational and energy costs associated with these systems necessitate a rigorous re-examination of their long-term sustainability. In response, recent investigations by Moon et al. (2019) have focused on reducing the energy footprint of deep learning architectures through algorithmic optimizations and the integration of energy-efficient hardware. Such approaches are critical in bridging the gap between the immediate benefits of AI applications and their broader environmental impact. Practical applications of AI in energy management further underscore both the promise and the challenges inherent in this technological paradigm. Zhao (2022) demonstrates that AI-driven optimization in industrial production can lead to notable reductions in energy consumption, while Ali et al. (2024) provide evidence that intelligent building systems – through continuous monitoring and automated control – can significantly lower operational carbon footprints. In the transportation domain, Ponnusamy et al. (2024) and Cavus et al. (2025) have documented how AI-based traffic management and predictive maintenance systems can contribute to more efficient energy use, thereby mitigating congestion and reducing emissions. Despite these promising developments, Chen (2023) cautions that the overall benefits of AI in promoting energy efficiency must be carefully balanced against its own escalating energy demands. The dual challenge lies in harnessing AI's potential to drive sustainability while simultaneously developing methods to curtail the energy intensity of AI systems themselves. As such, the literature points to a critical need for interdisciplinary research that not only expands the application of AI in energy systems but also prioritizes the creation of lower-energy-consuming models and infrastructures.

It can be stated that even if AI offers transformative potential for enhancing energy efficiency and advancing environmental sustainability, its application is marked by an inherent paradox: the very systems designed to reduce energy consumption can themselves be energy intensive. A holistic balance must be reached which can ensure that the pursuit of technological efficiency does not inadvertently exacerbate global energy challenges.

3 Methodology

This study employs a mixed-method research approach, integrating secondary data analysis with primary qualitative research. The primary research component is based on semi-structured in-depth interviews conducted with four experts in artificial intelligence and energy management. These interviews were designed to elicit comprehensive insights into the practical applications, challenges, and future potential of AI-driven energy solutions, with particular attention to sustainability issues arising from the high energy consumption associated with AI infrastructure. The semi-structured interview format was chosen to balance the need for consistency across interviews with the flexibility to explore emerging topics in greater depth. In the interview guide we formulated 20 questions to address three central thematic areas: the general understanding and conceptualization of artificial intelligence, the specific applications and operational modalities of AI within the interviewees' organizations – especially as they pertain to energy efficiency –, and the strategies employed by these organizations to integrate AI in optimizing energy consumption. This structure allowed us to evaluate both the depth of the experts' knowledge on AI and the extent to which their organizations have implemented AI-driven solutions in the energy domain.

The central research question guiding this study was the following:

Q1: To what extent can AI-driven solutions optimize energy management while mitigating the sustainability challenges posed by the companies represented by the research participants' energy consumption?

Participants were selected through purposive sampling, ensuring that each interviewee had demonstrable expertise in either AI technology, energy management, or both. This strategic selection was necessary to collect relevant data. All interviews were recorded and transcribed verbatim to ensure the accuracy and reliability of the data. The resulting transcripts were subjected to thematic analysis, a qualitative method that involved coding the data and identifying recurring themes and patterns. Ethical considerations were rigorously observed throughout the research process. Participants were fully informed about the study's objectives, and their informed consent was obtained prior to the interviews. Confidentiality was strictly maintained by anonymizing personal identifiers and ensuring that any potentially sensitive organizational information was handled with care.

4 Results

The primary qualitative investigation involved four in-depth interviews with experts representing international companies operating in Hungary. Two of these companies belong to the telecommunications sector, while the remaining two are IT enterprises, each employing over 250 individuals. The interviews were designed to capture the current utilization of AI-driven solutions in energy management as well as the associated sustainability challenges.

A key finding from the study is that three of the four interviewees reported regular use of AI tools – engaging with these technologies for at least four hours per day and employing a minimum of three different large language models (LLMs). In contrast, one participant described a more variable usage pattern, noting, *"There are* *times when I don't need to use it even once a week, but there are times when I need to use it for 8 hours a day".* This divergence in usage frequency underscores the heterogeneous integration of AI within similar organizational contexts.

When exploring the practical impact of AI on energy management, responses varied considerably among the participants. One interviewee expressed reservations regarding AI's long-term viability in optimizing energy consumption, stating, *"To my knowledge, AI systems consume a great deal of energy, so I do not believe that this would be a long-term solution for improving energy management. (...) I am not aware of this aspect being prioritized in our company's primary strategy".* This perspective highlights concerns regarding the sustainability of AI systems, particularly in terms of their energy demands.

Conversely, another expert emphasized the innovative potential of AI to uncover novel methods for reducing energy consumption. This respondent noted, *"AI's detection capabilities are remarkably precise in uncovering new innovative methods that could achieve real and more effective energy reductions, even at our company. However, at present, this is a secondary consideration because most employees are not yet at that stage".*

A third interviewee provided evidence of proactive sustainability measures within their organization, stating, *"In our company, we already have solar panels that are specifically intended to sustainably meet the energy demands of the AI systems we use (...) currently only partially, but it is already operational".* This response indicates that some companies are beginning to integrate renewable energy solutions specifically to offset the energy demands of AI systems.

Finally, the fourth participant drew attention to the rapid escalation of energy consumption associated with large language models, particularly in light of recent technological advancements such as ChatGPT. This interviewee remarked, *"By the end of 2022, when ChatGPT was introduced, we already knew that this technology would have an enormous energy demand. Just consider that every LLM system doubles its capacity every three months, which consequently increases energy consumption. However, our engineers have prepared for this in time, so we use a hardware park that consumes significantly less energy, and we strive to power it entirely with sustainable energy sources".* This insight underscores the urgency of addressing AI's energy requirements through innovative, energy-efficient technological and infrastructural solutions.

These thoughts indicate that even among large multinational companies, there is significant variability in how energy efficiency is prioritized within the context of AI deployment. While some organizations are actively pursuing sustainable practices to mitigate the environmental impact of their AI systems, others appear less committed to this aspect.

5 Discussion

Several corporate examples illustrate how AI-driven solutions can optimize energy management while addressing sustainability challenges. For instance, Vodafone, a leader in telecommunications, has implemented advanced AI algorithms for network optimization and predictive maintenance, and invested in a dedicated solar park to power its data centres, thereby reducing reliance on non-renewable energy sources (Lawrence & Durana, 2021).

In the IT sector, IBM and Intel leverages AI for intelligent building management. The facilities of these companies utilize AI-driven systems to monitor and regulate energy consumption in real time – adjusting heating, ventilation, and lighting – while integrating solar panels to ensure sustainable energy sourcing (Mahzar et al., 2022).

Additionally, leading logistics companies such as DHL and Alibaba, employ AI-based traffic management systems to optimize route planning and reduce fuel consumption. DHL is also piloting solar-powered charging stations for its electric vehicle fleet, underscoring its commitment to merging AI innovations with renewable energy solutions (Ozturk, 2024).

These examples highlight the potential of AI to enhance energy efficiency across various industries while mitigating environmental impacts. However, they also emphasize the need to balance technological advancement with sustainable practices, ensuring that the energy demands of AI systems do not offset their environmental benefits.

6 Conclusion

This study successfully achieved its objective by elucidating the dual role of AI-driven solutions in optimizing energy management and highlighting the sustainability challenges posed by their energy consumption. The integration of AI in energy systems – evident in corporate practices at Vodafone, IBM, and DHL – demonstrates that while AI can significantly enhance energy efficiency and resource allocation, its deployment is not without environmental costs. The mixed-method research approach, particularly the use of semi-structured in-depth interviews, proved advantageous in capturing nuanced perspectives from industry experts. These qualitative insights provided a rich understanding of both the practical applications and the limitations of AI in the context of energy management.

The research question is answered by the findings. The evidence suggests that while AI technologies are capable of optimizing energy consumption and improving operational efficiencies, their energy demands remain a critical concern. The divergent experiences of the interviewees indicate that the effectiveness of AI in promoting sustainability is highly dependent on the strategic integration of renewable energy sources and energy-efficient infrastructures within organizations.

To further validate these preliminary findings, a subsequent survey is planned to target a broader sample of employees – including managerial staff – to analyse and statistically validate the exploratory insights generated by these interviews.

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