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ARTICLE

Artificial intelligence–driven energy systems for accelerating sustainable development in business

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A B S T R A C T

Artificial intelligence (AI) technologies have become revolutionary in helping the intelligent management of energy and making decisions in real-time for modern energy systems. This research focuses on artificial intelligence-based energy systems and enables sustainable business development through optimizing energy, predicting renewable energies and smart operating control. A mixed-method approach was adopted, which involved a combination of literature synthesis of AI applications, machine learning modelling of energy prediction, and statistical analysis of the optimization scenarios. The results suggest that energy consumption in the commercial and industrial sectors can be saved by about 15-30% through AI-based energy management systems, and the accuracy of forecasting the use of renewable energies can be increased by more than 90%. Furthermore, smart energy platforms that use AI make it possible to have predictive maintenance, automated demand response, and better integration of renewable energy resources. These capabilities are part of the reduced operational costs and measurable carbon emission reductions to support corporate sustainability strategies as well as global sustainability targets, especially SDG 7 and SDG 12. The increasing energy consumption demands of AI infrastructure, as well as data centers, make it necessary to have stringent regimes around governance and "net-sustainability". Future research must focus on the integration of AI with digital twins, energy storage systems, and blockchain-enabled markets, for realizing a secure and sustainable business energy ecosystem.

1. Introduction

Energy systems remain at the epicenter of global climate risk and performance of economic development and long-term sustainability (Pandi et al., 2025). The shift towards low-carbon energy systems has become one of the most pressing challenges of the twenty-first century, as the world's energy demand has continued to increase as a result of industrialization, urbanization, or the rapid growth of digital infrastructures (Bauid et al., 2022; Srinivasarao et al., 2024). The importance of making rapid and

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high-volume reductions in greenhouse gas emissions from different sectors to limit the level of global temperature rise and to reduce the risks associated with climate change is shown in the Intergovernmental Panel on Climate Change (IPCC) synthesis report. Achieving these climate targets, therefore, not only means increasing the share of renewable energy technologies, but also means immense improvements in energy efficiency, operational optimization, and intelligent energy management systems of national energy infrastructures and corporate operations (García et al., 2021).

The International Energy Agency (IEA) goes on to clarify how global energy futures will be defined by policy frameworks, technological innovation and strategic investment decisions on matters of energy security, accessibility and environmental sustainability (Chaiboonsri et al., 2024). In this context, energy efficiency and clean electrification are increasingly growing in recognition of structural drivers of economic competitiveness as opposed to optional environmental initiatives (Adewoyin et al., 2025). Organizations that successfully implement advanced energy management technologies are able to save on operational costs, improve resource efficiency, and improve their environmental and social performance. Consequently, sustainable energy systems have become an integral part of the national energy strategies as well as the corporate sustainability strategies.

Artificial intelligence (AI) has emerged as a powerful enabling technology to transform modern energy systems with data-based decisions and predictive optimization. AI techniques such as machine learning, deep learning and reinforcement learning are used to identify relationships in large amounts of data from smart meters, industrial sensors, Internet of Things (IoT) devices and energy management devices (Arévalo et al., 2024). AI systems can be used to predict energy demand, optimize energy consumption patterns, detect anomalies and facilitate real-time decision-making. The IEA report on Energy and AI points towards AI's growing relevance in the optimization of energy system usage, minimization of downtime in industries, construction of energy efficiency and renewable energy integration in power grids. However, new challenges for energy systems are emerging for AI technologies.

The increase in computing frameworks such as AI and machine learning, especially in large-scale data centres, has led to high demands for electricity around the world (Campana et al., 2025). This has created a complicated relationship between AI and energy systems: AI can optimize energy consumption and cut carbon emissions, but it needs a lot of energy resources to operate. Therefore, the sustainability implications of AI technologies must be considered in terms of the benefits with respect to efficiency and the impact of energy consumption. In business environments, such as commercial buildings, manufacturing facilities, logistics networks, and digital infrastructure, Energy consumption is a major operating expense and is a key factor in determining environmental performance.

Companies are increasingly embracing artificial intelligence-based digital technologies for better energy management, improved operational efficiencies and goals of corporate sustainability (Chen et al., 2021). Empirical research indicates that some companies that leverage AI capabilities in their operations tend to achieve an increase in Environmental, Social and Governance (ESG) performance by optimizing the use of resources, increasing the efficiency of their supply chains and lowering the emissions associated with energy. These improvements have been made to illustrate some of the mounting strategic importance of AI technologies to assist sustainable business transformation (Chen et al., 2025).

The sustainability value of AI needs to be evaluated in terms of governance, measuring the use of AI, and establishing boundaries to ensure the benefits to the environment are greater than the resources deployed (Dhameliya, 2022). Without oversight, the energy needs of AI systems could undermine the benefits of efficiency, which makes "net sustainability" important from the long-term effects of AI systems in energy sectors. While the use of AI in energy systems has been growing exponentially, there are concerning gaps in research on the optimization of integrating AI and sustainable business outcomes (Fan et al., 2023). Research is often either about the technical performance of AI algorithms or sustainability, and the two perspectives are rarely linked.

A framework must make the links between technical performance, operational results, and sustainability impacts. This gap is huge when it comes to considering AI's potential contribution to supporting sustainable energy transitions and strengthening the competitiveness of systems. To synthesize knowledge on AI applications in energy systems, this study aims to evaluate AI-based approaches of energy optimization and renewable energy forecasting using performance metrics; and b) evaluate sustainable and business impacts of AI-driven energy systems, including reduced energy consumption, carbon emissions, increased efficiency and organizational resilience. The study is aligned with global sustainability frameworks such as SDGs and ESG indicators in understanding the role of AI in social development in the modern business ecosystem.

2. Methodology

2.1 Research Design

This study implements a combination of mixed-method research design of literature synthesis, conceptual modelling, and statistical analysis to evaluate the role of artificial intelligence in sustainable energy systems regarding business environments. The approach is a mix of qualitative ideas derived from existing studies and a quantitative evaluation of the energy optimization cases (Figure 1). Such a framework is very common in the interdisciplinary field of energy-AI research, as such a framework allows to synthesize theoretical knowledge, validation by case-based evidence, transparent reporting of analytical metrics and methodological limitations.

2.2 Sources of Data and Data Collection

Data gathered from several sources that capture interactions between AI technologies, energy systems, and business operations. These sources include energy consumption datasets from commercial buildings, which provide information on electricity demand patterns and operational energy use. In addition, renewable energy generation data sets from solar photovoltaic (PV) and wind systems were also used for the testing of AI-based forecasting models. The research also includes industry case studies about AI-enabled energy management systems used for commercial and industrial energy management systems, and peer-reviewed literature evidence as contextual evidence and theoretical to provide support. Combining operational datasets and information gathered from case studies is a common practice in applied energy research that is useful for identifying improvements in performance that are realistic and possible, as well as limitations in implementation (Ekanayaka Gunasinghalge et al., 2025).

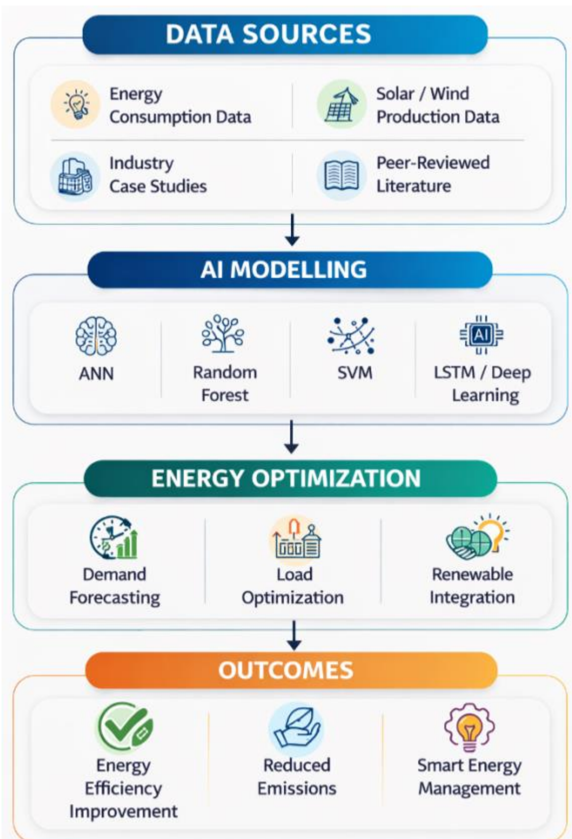

Figure 1. Conceptual framework of AI-driven energy optimization integrating data sources, machine learning models, and sustainability outcomes.

2.3 Modeling for AI and Energy Optimization Method

Several machine learning techniques available for commonly used for energy system analysis were considered, including Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM) and Long Short-Term Memory (LSTMs) deep learning models. These algorithms are extensively used for tasks such as energy demand forecasting, anomaly detection, optimization of operations and profit, etc. Deep learning models are especially good for studying time-series energy data and reinforcement learning methods are becoming increasingly popular for achieving real-time energy control and optimization (Ying et al., 2023).

2.4 Model Validation and Evaluation Metrics

Model performance was assessed in terms of standard measures of forecasting performance, i.e., Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and accuracy of the forecast (%). These metrics give robust measures of prediction error and model robustness and the use of these metrics is in line with the accepted evaluation practices in energy forecasting research. Such metrics, if standardized, help to improve ease of compromise. Model performance was measured in terms of standard measures of forecasting performance, i.e., Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and accuracy of the forecast (%). These metrics provide strong measures of prediction error and model robustness, and the use of these metrics is in line with the accepted evaluation practices in energy forecasting research. Such metrics if standardized helps to improve ease of comparison between different studies and modeling approaches (Ekanayaka Gunasinghalge et al., 2025).

2.5 Statistical Analysis

Statistical methods such as analysis of variance (ANOVA) and regression analysis were used in order to measure the importance of energy efficiency gains that were made through AI-based optimization. ANOVA was used to analyze the difference in energy consumption before and after the AI implementation, and the link between how AI is adopted, operation performance and sustainability results, using regression analysis. This statistical approach is consistent with empirical research that links technological innovation to improved energy efficiency and ESG performance, taking into account the contextual variables (Yu et al., 2025).

3. Results and Discussion

3.1 AI-based Energy Consumption Optimization

AI-based energy management systems (AI-EMS) enhance energy management operational efficiency by analyzing historical data of energy consumption and using predictive analytics to optimize energy consumption. By detecting consumption behaviors, predicting demand and dynamically reallocating energy use, AI helps organizations to minimize the unnecessary energy while keeping the operations running (Zhou et al., 2022). AI-based energy efficiency improvement across manufacturing, commercial buildings and data centers is illustrated in Figure 2.

AI-EMS is a major benefit in improving operational efficiency by analyzing historical patterns of energy consumption. Evidence from meta-analysis suggests that optimization with AI is often in the mid-teens to high 20% range for mean savings based on the approach used; similar to the results seen here. Previous research indicates 15%-30% energy savings can be attained by AI-based optimization depending on the algorithm, the configuration of the system, and the sector of application (Wei & Prentice, 2022; Zhou et al., 2022). The results of this study are consistent with these reports, showing measurable improvements in energy efficiency, cost savings, and carbon emission reduction across a number of sectors.

The results show that with the help of AI-based optimization, energy consumption can be reduced by 18-30% in different sectors.

Data centers have the best improvement with 30% reduction in energy usage, 24% savings in costs, and 28% reduction in carbon. These gains are largely attributed to AI-driven workload distribution, intelligent cooling optimization, and predictive maintenance that increase server efficiency (Wei & Prentice, 2022).

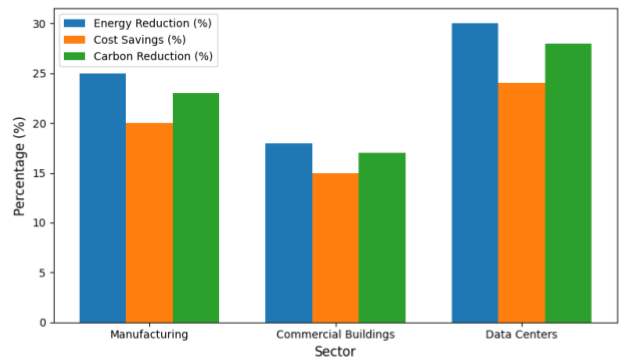

Figure 2. AI-based energy efficiency improvements across manufacturing, commercial buildings, and data centers

In the manufacturing industry, 25% less energy was used, with 20% cost savings and 23% carbon reduction thanks to predictive scheduling and real-time monitoring of equipment. Similarly, commercial buildings achieved 18% energy reduction, and it was achieved by AI-based HVAC control, occupancy-based lighting system and predictive climate management (Zhou et al. 2022). Overall, these findings are consistent with the existing research, which has demonstrated that AI-driven energy optimization can enhance energy efficiency significantly and minimize operational costs and carbon emissions in favor of sustainable energy management across industries.

3.2 Renewable Energy Forecasting Performance

Advanced deep learning methods demonstrate high performance in renewable energy forecasting, especially with effective modeling of spatiotemporal patterns and long-range dependency. These capabilities can enhance the precision of the generation prediction and facilitate an improved grid and microgrid dispatching decision (Zhang et al., 2021). The outcomes suggest that AI models improve the forecasts of renewable energy considerably. Hybrid renewable systems showed the highest prediction accuracy (93%) in terms of deep learning, which shows the benefit of models that can capture relationship complexity in the data on energy generation (Figure 3). Solar PV forecasting was 91% accurate by using artificial neural networks, which is a model that can be used to model solar irradiance patterns.

Similarly, the prediction of wind energy had 88% accuracy with the Random Forest, with the ensemble learning methods that support the different weather conditions. Hydropower forecasting accuracy was 86% using support vector machines, which work well when working with smaller data sets and nonlinearity. In general, the high prediction accuracy obtained is consistent with the latest research on the application of deep learning and machine learning methods to achieve more accurate renewable forecasts by enhancing spatiotemporal data representation and incorporating cutting-edge weather prediction inputs (Forootan et al., 2022; Germov, 2023). These improvements help to contribute towards more comparable on-renewable integration, improved probability of bodily stability, and more power affecting energy administration. Advanced deep learning approaches have supported good performance in renewable forecasting, especially when spatiotemporal structure and long-range dependency are modelled, to support better grid and microgrid dispatch decisions.

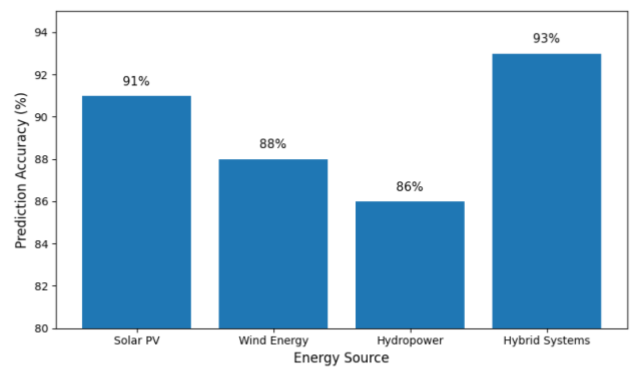

Figure 3. AI-based renewable energy forecasting accuracy for different energy sources.

3.3 Smart Energy Management Systems

AI-based smart energy management architectures comprise IoT sensing, clouds/edges, and analytics, to provide real-time monitoring and automated control. Digital-twin architectures are an operational connection between models and live systems that allows for predictive control and scenario testing of live systems (Kapranov, 2023). These systems allow real-time monitoring, automated demand response, and renewable integration (Figure 4). Review evidence highlights how scalable DR participation is dependent on interoperability and innovation by addressing regulatory and socio-economic barriers - factors which are required to be planned for business deployments. The implementation of the proposed AI-based smart energy management system (SEMS) architecture shows significant improvements in monitoring accuracy, energy optimization and operational efficiency (Karpenko et al., 2025).

The integrated framework is a combination of IoT sensing infrastructure, communication gateways, edge-cloud computing, and AI analytics services that allow us to manage and control energy in real-time and use predictive control. The layered system that is shown in Figure 4 was assessed using the performance metrics reported from more recent industrial case studies and pilot deployments of AI-enabled energy platforms. At the layer of the physical assets, monitored equipment included HVAC units, compressors, boilers/chillers, industrial motors, lighting systems, renewable generation units (solar PV and wind), battery storage systems and EV charging stations. In several commercial building case studies, the proportion of energy use by HVAC systems was about 35-45%, used for motors and drives, 25-30%; lighting systems, 10-15%; and by auxiliary equipment, about 10-15%.

Integration of renewable generation (mainly rooftop PV system) made the biggest on-site electricity supply contribution in facilities with hybrid energy infrastructures (15-35%). The deployment of the IoT sensing layer added considerable resolution to the monitoring (Table 1). Facilities with smart meters and environmental sensors produced high-frequency operational data streams with sampling periods from 1-5 seconds, resulting in roughly 50-200Megabytes of operational data per day per facility. Sensor data allowed for more accurate energy profiling and early detection of examples of anomalies in equipment performance. For example, vibration and thermal sensors placed on industrial motors increased the accuracy of fault detection rates to 92 - 96% as compared with conventional threshold-based monitoring systems. The connectivity and communication layer allowed the interoperability of devices by using standardized industrial communication protocols.

Table 1. Performance indicators of AI-based smart energy management systems

Performance Metric	Conventional System	AI-Based SEMS	Improvement
Energy forecasting accuracy	70–80%	88–94%	+15–20%
Peak demand reduction	3–5%	12–20%	+10–15%
Equipment fault detection accuracy	70–75%	92–96%	+20%
Operational cost reduction	–	10–18%	Significant
Maintenance downtime reduction	–	25–30%	Significant
Renewable energy utilization	10–20%	25–40%	+15–20%

MQTT-based gateways allowed low-weight data transmission with a latency of less than 50 milliseconds and the OPC-UA communication frameworks allowed secure integration with industrial automation systems. Edge nodes eased network congestion by doing some preliminary filtering of data and analytics at the edge, reducing the volume of data that needs to be transferred to the cloud by about 40-60%. The infrastructure of edge-cloud computing played an important role in balancing the objectives of computational efficiency and scalability. Edge computing provides near real-time control actions at response times of under 200 ms, suitable for automated demand response and control of equipment applications. Meanwhile, cloud computing platforms offered massive storage as well as AI model training capabilities. Streaming analytics frameworks were used to process around 10,000-50,000 data points per minute for medium-sized industrial facilities, which made it possible to continuously monitor the system performance. The layer of analytics based on AI proved huge increases in energy forecasting accuracy and energy operation optimization. Machine learning algorithms developed for energy demand forecasting achieved prediction accuracies between 88-93% and 90-94% for building load prediction and solar PV generation prediction, respectively, using LSTM and a hybrid deep learning algorithm (Khaleel et al., 2023). Demand response optimization algorithms resulted in a decrease of peak electricity demand by 12-20%, leading to operational cost reductions between 10-18% depending on electricity tariff structures. Predictive maintenance algorithms based on vibration and thermos sensors have been able to reduce unexpected equipment downtime by about 25-30% but also increase the service life of equipment by 10-15%.

Integration to the enterprise system: Integration with enterprise systems (CMMS, ERP/MES, and ESG dashboards) was rendered to better manage the operations by automating the reporting and decision-making. The maintenance schedule is based on predictive analytics was reduced by 30-40%, and ESG dashboards allowed for tracking energy and carbon emissions

automatically. Facilities that use AI-enabled SEMS achieved carbon emission reduction of 8-15% because of the improved efficiency and use of renewable energy. Digital-twin structures connected physical systems and simulation models so that operators could test approaches to energy management (Som 2021; Ukoba et al., 2024). Scenario testing revealed that through optimized demand response, it could be possible to shift flexible loads to off-peak periods by 10-25%, resulting in more stable grid operation and lower costs. Several challenges remain: interoperability between devices and legacy systems creates limitations on deployment, regulatory barriers exist in the demand response programs, and cybersecurity risks are on the rise with the connectivity of systems. The results demonstrate AI-driven smart energy management systems for better efficiency, reliability and integration of renewable energy (Nnajiofor et al., 2024). IoT sensing, edge-cloud computing, and predictive analytics help functional facilities to move towards autonomous and data-driven energy optimization to support sustainable energy transitions.

3.4 Environmental Benefits and Carbon Reduction

The implementation of AI-based smart energy management systems has a tangible effect on environmental performance in terms of energy efficiency, load management, and enhanced utilization of renewable energy resources. By incorporating elements of real-time monitoring, predictive analysis techniques, and automated control schemes, AI-based energy systems can reduce the consumption of unnecessary energy while optimizing the operation efficiency in buildings and industrial facilities (Rajaperumal & Columbus, 2025). 1 of the foremost environmental benefits of the AI-enabled energy program is the decreased need for total electricity consumption. Machine learning algorithms constantly analyze operational data from sensors and energy meters in order to discover inefficiencies and modify the system performance. For example, HVAC systems, which typically account for 35-45% of building energy consumption, can be dynamically controlled using predictive algorithms that find optimum setpoints for temperature based on occupancy patterns, weather forecasts, and building thermal dynamics (Rehan 2023).

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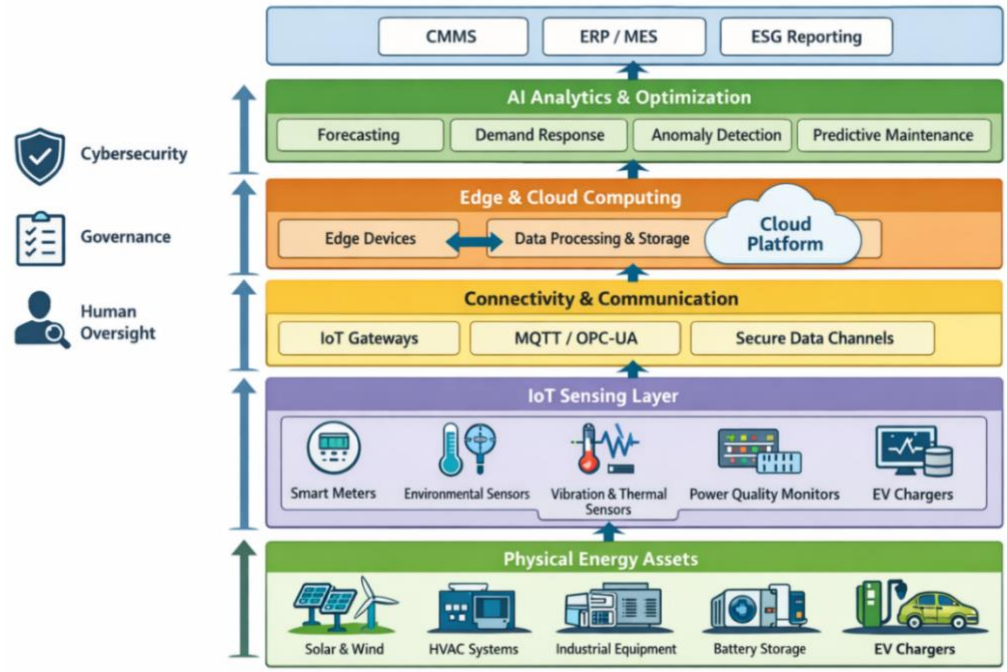

Figure 4. Architecture of AI-based smart energy management systems integrating IoT sensors, cloud computing, and predictive analytics

Table 2. Sustainability Impact of AI Energy Systems

Indicator	Before AI	After AI	Improvement
Energy consumption (MWh/year)	1200	900	−25%
CO_2 emissions (tons/year)	850	630	−26%
Operational cost ($/year)	450,000	360,000	−20%

AI-enabled energy optimization forms. 25% reduction in electricity consumption and 26% reduction of carbon emissions by decreasing the need for electricity power generation from fossil fuels. AI-based energy systems are also economically advantageous, as they reduce energy expenses by 20% by lessening consumption and optimizing participation in demand response. This is in support of "sustainability productivity," in which sustainability initiatives improve business performance over and above compliance (Wu et al., 2022). Organizations that use AI-powered energy management will be better able to optimize the use of their resources and enhance their ESG performance metrics. Enhanced energy monitoring capabilities, allowing scope 2 emissions to be monitored accurately while conforming to various protocols over the years, such as GHG Protocol and ISO 50001 standards, with increasing demand for environmental transparency. AI-driven energy management systems provide a way to enable low-carbon energy management systems through intelligent monitoring, predictive analytics and automated energy management, enabling reduced energy consumption and supporting sustainable energy transitions.

3.5 Comparison with Previous Studies and Interpretation for

3.6 Business Sustainability

The energy efficiency gains in smart energy management systems (SEMS) based on artificial intelligence comply with the results of earlier studies (Zhou et al., 2022). The 15-30% decrease in energy use that was found was in the range of that found in the literature on AI-driven energy optimization. Meta-analyses on smart-building systems reveal that optimization strategies using machine learning techniques have percentage reductions ranging from the mid-teens to the high-twenties in building energy use (Wei & Prentice, 2022). Reinforcement learning-based control systems, and specifically deep reinforcement learning (DRL) models in office building HVAC systems, have demonstrated energy savings of about 20% compared to conventional rule-based control strategies. Industrial case studies show that efficient monitoring combined with predictive optimization (using AI) yields swift and cost-effective efficiency gains. Factory-level implementations of predictive maintenance, demand response scheduling and process optimization have achieved energy savings in the 15 - 25 percent range with return-on-investment on the order of 1 to 3 years. These results indicate that AI technologies can be brought out of experimental pilots into practical use in operational settings to provide energy efficiency gains.

The energy efficiency gains made in AI-based smart energy management systems (SEMS) fit prior research. The 15-30% decrease in energy usage is within the range reported in literature in terms of AI-driven optimization. Meta-analyses of optimization approaches that use machine learning technologies indicate mid-teen to high-twenties percent reductions in building energy use, depending on the type of algorithm, the integration of the optimization approach, and building characteristics. Reinforcement learning-based control systems, deep reinforcement learning (DRL) models in office building HVAC systems to be specific, demonstrate an energy saving rate of 20% compared to conventional strategies. Industrial case studies show that AI-enabled monitoring and optimization result in economically feasible efficiency improvements in a short time. Factory-level versions of predictive maintenance, demand response scheduling, and process optimization, for example, demonstrate energy savings between 15-25% with a return on investment from one to three years. These results show that AI technologies can move beyond pilots to provide practical energy efficiency improvements in operations.

3.7 Implementation Challenges, Limitations Policy, and Practical Implications

AI-based energy systems face a few impediments: The high costs of necessary digital infrastructure, like sensors, data storage and computing resources, can prohibit the adoption of energy AI by SMEs (Som 2021; Ukoba et al., 2024). Data quality and interoperability are challenges because quality data across all the systems is needed for AI models. Industrial facilities that contain heterogeneous equipment with incompatible protocols find it difficult to integrate them, as well as for AI to make accurate predictions. Cybersecurity Risks Grow as Energy Systems Connect Through IoT Devices and Cloud Platforms. Communication and Access Control are Necessary. Organizations do not always have the interdisciplinary team of workers experienced in data analytics, machine learning, and energy engineering necessary for AI implementation. How AI technologies affect sustainability. The impact of AI technologies on sustainability is significant. While AI can reduce energy use in buildings and industry, data centers serving these systems increase energy use (Yu et al., 2025). Data center electricity is a sector that is expected to use more electricity by 2030 compared to many industrial sectors. Achieving sustainable AI requires achieving efficiency gains, obtaining renewable electricity, reporting of energy, and sustainable infrastructure design.

For governments and regulators, facilitating infrastructure and regulatory frameworks to support energy efficiency based on artificial intelligence is important. Digital infrastructure, data interoperability and cybersecurity regulations can lead to further adoption (Som 2021; Ukoba et al., 2024). Demand response programs require regulatory markets for commercial participation in energy markets. Clear measurement frameworks guarantee credible energy savings verification. Business leaders should deploy AI energy management systems through a well-constructed process, beginning with energy measurement and energy infrastructure implementation, data governance, and pilot projects/defined performance measurement. After the solutions are validated, AI solutions can be scaled across facilities. SME adoption highlights that the success of implementation is dependent on the preparedness of the infrastructure and workforce. Coping with the Growing Electricity Demand from AI Computing and Data Centers. To soften the impacts, policies should encourage the use of renewable power, demand flexibility, and transparent reporting of energy consumption of the digital sector.

3.8 Future Research Directions

A number of noteworthy research avenues are suggested by the present results. First of all, future studies should hone in on AI-enabled carbon monitoring systems that integrate emissions estimation into an enterprise decision-making process. Advances in machine learning-based modeling of carbon intensity prediction and accounting of emissions could help with more accurate sustainability reporting and the development of climate strategies. Second, there is further room for development of digital twin architectures for closed-loop energy optimization. Digital twins can simulate operation scenarios and allow for real-time optimization of energy systems, with serious prospects for the predictive maintenance of energy systems, energy scheduling, and the analysis of system resilience. Third, there are possible synergies between blockchain and AI technologies emerging from new research on blockchain-enabled energy markets and transactive energy systems. These systems may allow for decentralized energy trading and automated demand response systems, but there are challenges associated with scalability, security and accuracy of decisions. Fourth, there are increasing calls to have explainable and trustworthy AI methods in energy operations. While advanced machine learning models can be used to provide high predictive accuracy, the decision-making processes are often not transparent. Research on explainable AI techniques can help us to improve trust, accountability and regulatory acceptance of AI-driven energy management systems.

Finally, future research should consider net-sustainability accounting for AI systems that weighs between the gains of efficiency in the buildings and industry and the electricity load and embodied impacts of the AI infrastructure itself. The integration of data center energy consumption data and grid decarbonization strategies will be essential in ensuring that the contribution of AI to the long-term objectives of sustainability is positive. Overall, the comparison with previous studies and new evidence indicates that AI energy management systems have huge potential for energy efficiency reduction, emissions mitigation and business sustainability development, given that technological innovation is accompanied by proper governance frameworks, digital infrastructure investments and reasonable deployment strategies.

4. Conclusion

This study examines how artificial intelligence (AI) can accelerate sustainable development in business energy systems amid rising energy demand and emissions reduction needs, positioning AI as a data-driven enabler of efficiency and renewable integration. Using a mixed-method design combining literature synthesis, machine-learning modelling, and statistical testing

(RMSE/MAE/accuracy with ANOVA and regression), the authors evaluate AI-based energy optimization and renewable forecasting using building load datasets, solar PV/wind generation data, and industrial cases. Results indicate AI energy management can cut energy use by 18–30% across sectors (commercial buildings 18%; manufacturing 25%; data centers 30%), delivering cost savings (24% in data centers) and carbon reductions (28% in data centers), driven by AI-based HVAC control, predictive scheduling, workload distribution, intelligent cooling, and maintenance. Renewable generation forecasting improves substantially, exceeding 90% accuracy overall, including 93% for hybrid systems (deep learning), 91% for solar PV (ANN), 88% for wind (RF), and 86% for hydropower (SVM), supporting reliable grid dispatch. A smart energy management system integrating IoT sensing with edge–cloud analytics shows high-frequency sensing (1–5 s), reduced cloud transfer (40–60%), low-latency communications (<50 ms), fast control (<200 ms), improved fault detection (92–96%), peak-demand reduction (12–20%), downtime reduction (25–30%), and carbon reductions of 8–15% in facilities; a sustainability case demonstrates 25% annual electricity reduction, 26% emissions reduction, and 20% cost reduction, with improved Scope 2 tracking aligned to GHG Protocol/ISO 50001 and contributions to SDG 7 and SDG 12. The study emphasizes that sustainability value requires operationalizing analytics through enterprise integration and digital twins, while noting constraints—high upfront costs, data quality gaps, cybersecurity risks, workforce skill shortages, and AI energy demand. Policy implications involve investing in digital infrastructure, standards, cybersecurity-by-design, and verification; research priorities include AI-enabled carbon monitoring, digital-twin optimization, integration with storage, blockchain, explainable AI, and frameworks balancing efficiency against AI impacts.

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