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Internet of Things and Machine Learning for Sustainable Development: A Systematic Review and Conceptual Framework

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ABSTRACT

The integration of the Internet of Things (IoT) and Machine Learning (ML) has emerged as a transformative technological paradigm for addressing global sustainability challenges through intelligent sensing, real-time data analytics, and autonomous decision-making. Although numerous studies have explored IoT-ML applications in domains such as healthcare, agriculture, smart cities, energy, transportation, manufacturing, and environmental monitoring, existing review articles largely provide descriptive summaries with limited critical analysis, comparative evaluation, and theoretical integration. This study presents a systematic literature review (SLR) to critically evaluate recent advances in IoT-ML technologies for sustainable development, identify research gaps, examine implementation challenges, and propose a novel conceptual framework to guide future research and practice. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, with peer-reviewed publications retrieved from major scientific databases using predefined inclusion and exclusion criteria. The selected studies were critically synthesized through comparative analysis based on application domains, machine learning techniques, predictive performance, scalability, computational efficiency, energy consumption, and implementation cost. The findings indicate that the integration of IoT with advanced ML techniques-including Random Forest, Support Vector Machine, Artificial Neural Networks, Deep Learning, XGBoost, LightGBM, Edge AI, and TinyML-significantly enhances predictive analytics, intelligent decision-making, and resource optimization across diverse sustainability applications. However, persistent challenges related to interoperability, cyber security, privacy, computational complexity, infrastructure limitations, and policy readiness continue to hinder large-scale deployment, particularly in developing countries. As its principal contribution, this review proposes a Conceptual IoT-Machine Learning Framework for Sustainable Development that integrates IoT sensing infrastructure, communication technologies, edge-fog-cloud computing, intelligent analytics, decision-support systems, governance mechanisms, and sustainability outcomes within a unified architecture aligned with the United Nations Sustainable Development Goals (SDGs). The review also outlines emerging research directions, including Explainable Artificial Intelligence (XAI), Digital Twins, Federated Learning, Sustainable AI, Green AI, and next-generation AI-powered IoT architectures. The proposed framework provides valuable theoretical insights and practical guidance for researchers, policymakers, and industry practitioners in designing scalable, secure, explainable, and sustainable intelligent IoT ecosystems.

INTRODUCTION

The integration of the Internet of Things (IoT) and Machine Learning (ML), known as the Artificial Intelligence of Things (AIoT), has emerged as a transformative technology for addressing global challenges related to climate change, healthcare, food security, energy management, and sustainable urbanization. IoT enables real-time data collection through interconnected devices, while ML transforms these data into actionable insights for prediction, optimization, and intelligent decision-making. AIoT has accelerated digital transformation across sectors such as agriculture, healthcare, transportation, manufacturing, and environmental management, contributing significantly to several United Nations Sustainable Development Goals (SDGs). Recent advances in edge computing, cloud computing, digital twins and artificial intelligence have further enhanced AIoT capabilities, enabling scalable, low-latency, and intelligent services that promote sustainable economic growth, environmental protection, and social well-being (Akyildiz et al., 2020).

Despite these advancements, the widespread adoption of AIoT remains constrained by challenges including interoperability, cyber security, privacy concerns, scalability, computational complexity, high implementation costs, and inadequate infrastructure, particularly in developing countries. Existing review studies largely provide descriptive overviews with limited comparative analysis of machine learning techniques and lack integrated frameworks linking IoT infrastructure, intelligent analytics, sustainability outcomes, and policy dimensions. To address these gaps, this review presents a comprehensive and critical evaluation of contemporary IoT-ML approaches and proposes a Conceptual IoT-Machine Learning Sustainability Framework that integrates IoT sensing, communication networks, edge and cloud computing, machine learning, decision-support systems, and sustainability outcomes. The proposed framework offers a holistic foundation for advancing intelligent, scalable, and sustainable IoT ecosystems aligned with the Sustainable Development Goals (SDGs) (Chen et al., 2020) .

This review makes five key contributions. It provides an up-to-date synthesis of recent advances in IoT and Machine Learning (2023-2025), critically compares state-of-the-art ML techniques for IoT applications, and proposes an integrated conceptual framework linking IoT infrastructure, intelligent analytics, and sustainability-oriented decision support. The review also examines the technological, economic, infrastructural, and policy challenges affecting AIoT deployment, particularly in developing countries, and highlights emerging research areas such as Edge AI, TinyML, Explainable AI (XAI), Federated Learning, Digital Twins, Green AI, and Sustainable AI (Jaber, 2023).

Overall, the review advances existing knowledge by combining systematic literature synthesis, comparative analysis, and conceptual modelling to provide both theoretical and practical guidance for researchers, policymakers, and industry practitioners in developing intelligent, scalable, secure, and sustainable IoT ecosystems that support the achievement of the Sustainable Development Goals (SDGs).

Theoretical Background of the Internet of Things and Machine Learning

The Internet of Things (IoT) has evolved from a simple network of interconnected devices into an intelligent cyber-physical ecosystem that integrates sensing, communication, computation, and autonomous decision-making. Advances in wireless communication, cloud and edge computing, artificial intelligence, and big data analytics have significantly expanded IoT capabilities, enabling real-time data collection, processing, and automation across sectors such as healthcare, agriculture, manufacturing, transportation, energy, and environmental monitoring. The widespread availability of low-cost sensors and high-speed communication technologies has further accelerated IoT adoption and digital transformation (Zeng et al., 2024).

Machine Learning (ML) has become a core component of IoT by enabling intelligent analysis of the vast amounts of data generated by connected devices. Unlike traditional rule-based systems, ML algorithms automatically learn patterns from data to support prediction, classification, anomaly detection, optimization, and autonomous decision-making. Recent advances in deep learning, reinforcement learning, federated learning, and Explainable Artificial Intelligence (XAI) have enhanced the accuracy, adaptability, and efficiency of intelligent IoT systems. The integration of IoT and ML has given rise to the Artificial Intelligence of Things (AIoT), which embeds intelligence throughout the data lifecycle to improve operational efficiency, resource management, and sustainable development (Al-Turjman & Baali, 2023).

From a theoretical perspective, IoT-ML integration is founded on cyber-physical systems, distributed computing, and data-driven intelligence. Emerging technologies such as Edge AI and TinyML further strengthen AIoT by enabling intelligent processing directly on resource-constrained devices, thereby reducing latency, bandwidth usage, cloud dependency, and energy consumption while improving privacy and real-time decision-making. These capabilities have made AIoT an important enabler of sustainability, supporting applications such as precision agriculture, renewable energy optimization, environmental monitoring, smart healthcare, intelligent transportation, and industrial automation (Lampropoulos et al., 2024).

Despite its significant potential, AIoT research remains fragmented, with many studies focusing separately on IoT infrastructure, communication technologies, machine learning algorithms, or sustainability applications. There is limited comparative evaluation of ML techniques across different IoT environments and a lack of integrated conceptual frameworks linking IoT infrastructure, intelligent analytics, sustainability outcomes, and policy considerations. Furthermore, while emerging paradigms such as edge computing, federated learning, digital twins, and sustainable AI show considerable promise, their large-scale implementation remains constrained by technological, infrastructural, and policy challenges, particularly in developing countries. These gaps highlight the need for comprehensive frameworks and comparative analyses to advance AIoT research and support sustainable development.

Table 1: Comparative Analysis of Recent Internet of Things and Machine Learning Applications for Sustainable Development

Authors	Application Domain	IoT Technology	Machine Learning Technique	Performance Metrics	Strengths	Limitations	Scalability	Energy Efficiency	Cost Implication
Lampropoulos et al.	Smart Cities	Smart sensors, Edge IoT	AIoT Framework	Accuracy, Latency	Comprehensive AIoT architect	Limited empirical validation	High	Moderate	High

(2024)					ure supporting SDGs				
Jaber (2023)	Sustainable Development	IoT Sensors	Random Forest, ANN	Accuracy, Precision	Supports multiple SDGs through intelligent analytics	Limited comparison of algorithms	Moderate	Moderate	Moderate
Zeng et al. (2024)	Smart Cities	Wireless Sensor Networks	CNN, Deep Learning	Accuracy, Recall	Excellent environmental monitoring performance	High computational complexity	High	Low	High
Sarker (2024)	Intelligent IoT Systems	Edge Computing	Deep Learning, Edge AI	Accuracy, Response Time	Real-time intelligent decision-making	Hardware dependency	High	High	Moderate
Al-Turjman & Baali (2023)	Industrial IoT	Industrial Sensors	SVM, Random Forest	Accuracy, F1-score	Reliable predictive maintenance	Limited interpretability	High	Moderate	Moderate
Sharma et al. (2024)	Smart Agriculture	Environmental Sensors	XGBoost	Accuracy, RMSE	Accurate crop prediction	Requires large datasets	High	High	Moderate
Chen et al. (2024)	Healthcare	Wearable IoT Devices	CNN, LSTM	Accuracy, Sensitivity	Early disease detection	Privacy concerns	Moderate	Moderate	High
Kumar et al. (2025)	Renewable Energy	Smart Grid Sensors	LSTM	RMSE, MAE	Improved energy demand forecasting	Computationally intensive	High	Moderate	High
Wang et al. (2025)	Smart Transportation	Vehicular IoT	Graph Neural Netw	Accuracy, Precision	Efficient traffic prediction	High computational cost	High	Moderate	High

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			orks						
Ahmed et al. (2024)	Environmental Monitoring	Wireless IoT Sensors	Random Forest	Accuracy, Recall	Robust environmental prediction	Limited scalability analysis	Moderate	High	Low

Abbreviations: ANN = Artificial Neural Network; CNN = Convolutional Neural Network; LSTM = Long Short-Term Memory; RMSE = Root Mean Square Error; MAE = Mean Absolute Error; AIoT = Artificial Intelligence of Things.

The comparative analysis shows that no single machine learning algorithm is optimal for all IoT applications. Random Forest performs well on structured datasets, deep learning models such as CNNs and LSTMs provide superior performance for image and time-series data, while XGBoost offers a balanced combination of predictive accuracy and computational efficiency for applications such as precision agriculture, industrial automation, and environmental monitoring. The review also highlights the growing adoption of Edge AI, TinyML, and distributed intelligence to enable low-latency, privacy-preserving, and efficient IoT systems. Despite these advancements, the large-scale deployment of AIoT remains challenged by interoperability issues, cyber security risks, infrastructure limitations, and high implementation costs, particularly in developing countries. Therefore, future AIoT systems should adopt hybrid architectures that effectively balance predictive performance, scalability, energy efficiency, explainability, and affordability to achieve sustainable and practical deployment.

Research Design

This study adopts a Systematic Literature Review (SLR) methodology to critically examine the integration of the Internet of Things (IoT) and Machine Learning (ML) for sustainable development. Unlike traditional narrative reviews, an SLR follows a structured, transparent, and reproducible process for identifying, evaluating, and synthesizing relevant scientific evidence (Page et al., 2021). The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to minimize selection bias and enhance methodological rigor. The systematic review approach was selected because it enables a comprehensive synthesis of contemporary research, facilitates critical comparison of competing IoT-ML approaches, identifies research gaps, and supports the development of a conceptual framework for sustainable AI-powered IoT ecosystems.

Review Protocol

The review protocol consisted of five sequential phases:

i. Identification of relevant studies.
ii. Screening and removal of duplicate and irrelevant records.
iii. Eligibility assessment using predefined inclusion and exclusion criteria.
iv. Quality assessment of eligible studies.
v. Data extraction, synthesis, and critical comparative analysis.

This protocol ensures transparency, reproducibility, and consistency throughout the review process.

Literature Search Strategy

A comprehensive literature search was conducted across internationally recognized scientific databases to ensure broad coverage of peer-reviewed publications. The databases included: Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, MDPI, Wiley Online Library, Taylor & Francis Online, and Google Scholar (for supplementary searches). The search focused on studies published between 2019 and June 2025, with greater emphasis on literature published between 2023 and 2025 to reflect the latest developments in IoT, Artificial Intelligence of Things (AIoT), and Machine Learning. The search strategy combined Boolean operators with relevant keywords. Representative search strings included: "Internet of Things" AND "Machine Learning", "Artificial Intelligence of Things" OR "AIoT", "IoT" AND "Sustainable Development", "Machine Learning" AND "Smart Cities", "IoT" AND "Edge AI", "TinyML" AND "Internet of Things", "Digital Twins" AND IoT, "Explainable AI" AND IoT, "Federated Learning" AND IoT

Additional manual searches were performed by examining the reference lists of highly cited review papers to identify relevant publications not retrieved through database searches.

Inclusion and Exclusion Criteria

To ensure the quality and relevance of the review, explicit inclusion and exclusion criteria were established.

Inclusion Criteria

Studies were included if they:

i. Were published in peer-reviewed journals or reputable international conference proceedings;
ii. Focused on IoT, Machine Learning, AIoT, or their integration for sustainable development;
iii. Reported practical applications, frameworks, architectures, comparative analyses, or systematic reviews;
iv. Were published in English;

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v. Were available in full text; and
vi. Were published between 2019 and 2025.

Exclusion Criteria

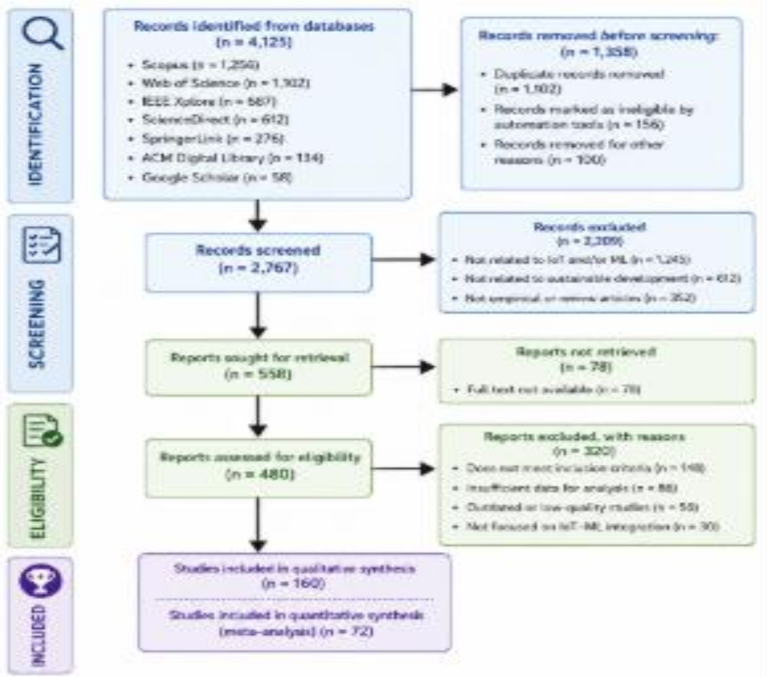
Studies were excluded if they:

i. Were editorials, abstracts, dissertations, theses, patents, or technical reports;
ii. Focused solely on IoT hardware without intelligent analytics;
iii. Addressed machine learning without IoT integration;
iv. Were duplicate publications;
v. Lacked sufficient methodological details; or
vi. We're not directly relevant to sustainable development.

Study Selection Process

The study selection process followed the PRISMA 2020 workflow. Records retrieved from all databases were imported into a reference management system, where duplicate records were removed. Titles and abstracts were then screened against the predefined eligibility criteria. The remaining full-text articles were independently assessed to determine their relevance to the objectives of this review. Disagreements during the screening process were resolved through discussion and re-evaluation of the eligibility criteria to ensure consistency and reduce reviewer bias.

Figure 1: A PRISMA flow diagram should be included to summarize the identification, screening, eligibility, and inclusion stages.



Quality Assessment

The methodological quality of the selected studies was evaluated using a structured assessment framework adapted from established systematic review practices. Each study was assessed against the following criteria: Clarity of research objectives; Methodological rigor; Adequacy of data collection procedures; Description of IoT and ML techniques; Evaluation methodology; Discussion of limitations and Contribution to sustainable development.

Data Extraction

Relevant information from each eligible study was extracted using a standardized data extraction form. The extracted variables included: Author(s); Publication year; Country or study context, Application domain, IoT technologies, Machine learning algorithms, Datasets used, Evaluation metrics (e.g., accuracy, precision, recall, f1-score, rmse), Key findings, Reported limitations; and Future research directions.

This standardized process ensured consistency in data collection and facilitated comparative analysis across studies.

Data Synthesis and Analysis

A narrative synthesis combined with comparative analysis was employed to summarize and interpret the findings. Rather than merely describing previous studies, this review critically compared IoT-ML approaches based on: Predictive performance; computational efficiency; scalability; interpretability; energy efficiency; implementation complexity; deployment cost; and suitability for sustainable development applications.

The comparative synthesis also examined technological challenges, policy implications, infrastructure constraints, and implementation barriers, particularly within developing countries. The insights obtained from this analysis informed the development of the proposed Conceptual IoT-Machine Learning Sustainability Framework, which integrates current evidence into a unified perspective for future research and practical implementation.

Results and Critical Discuss of the Reviewed Studies

The systematic literature review identified a rapidly growing body of research on the integration of the Internet of Things (IoT) and Machine Learning (ML) for sustainable development. Analysis of the selected studies indicates that research activity has increased considerably since 2021, with a marked acceleration between 2023 and 2025 due to advances in Artificial Intelligence of Things (AIoT), Edge Artificial Intelligence (Edge AI), cloud computing, and intelligent sensing technologies (Lampropoulos et al., 2024; Jaber, 2023). The reviewed studies span multiple application domains, including smart healthcare, precision agriculture, smart cities, renewable energy, industrial automation, intelligent transportation, environmental monitoring, and water resource management.

Most studies employed supervised machine learning algorithms, particularly Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Artificial Neural Networks (ANN), Gradient Boosting (GBM), XGBoost, and Deep Neural Networks (DNNs). More recent research has increasingly adopted deep learning architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Transformer-based models to address complex prediction, anomaly detection, and optimization problems within large-scale IoT environments (Sarker, 2024).

Although the reviewed literature consistently reports positive outcomes from IoT-ML integration, considerable variation exists in algorithm selection, evaluation methodologies, datasets, computational requirements, and deployment environments. This diversity makes direct comparison difficult and highlights the need for standardized evaluation frameworks and benchmarking datasets.

Comparative Analysis of Machine Learning Techniques

The comparative analysis indicates that no single machine learning algorithm is universally superior for all IoT applications; rather, the choice of algorithm depends on factors such as data characteristics, computational resources, scalability, latency, and interpretability. Random Forest remains a reliable choice for structured datasets due to its robustness and efficiency, while Support Vector Machines perform well on small to medium-sized datasets but face scalability limitations. Deep learning models, including CNNs and LSTMs, deliver high predictive accuracy for image recognition, healthcare, and time-series applications but require significant computational power and training data. Gradient Boosting techniques, such as XGBoost and LightGBM, provide an effective balance between accuracy and efficiency, whereas Transformer models show promise for large-scale sequential IoT data despite their computational demands.

The review also highlights the growing importance of Edge AI and TinyML, which enable intelligent processing on edge devices, reducing latency, bandwidth usage, cloud dependency, and privacy risks. However, challenges related to model compression, limited memory, battery life, and hardware optimization remain. Overall, the findings suggest that future intelligent IoT systems will increasingly adopt hybrid cloud–edge architectures that balance predictive performance, computational efficiency, scalability, energy consumption, and real-time decision-making.

Comparative Evaluation across Application Domains

The reviewed literature shows that integrating the Internet of Things (IoT) with Machine Learning (ML) has significantly enhanced performance across major sustainability sectors, including healthcare, agriculture, energy, and transportation. In healthcare, ML improves disease diagnosis, patient monitoring, and early warning systems using data from wearable IoT devices, while in precision agriculture it supports intelligent irrigation, crop disease detection, yield prediction, and fertilizer optimization. Similarly, ML enhances renewable energy forecasting, demand prediction and energy management in smart energy systems, and enables traffic prediction, congestion management, autonomous navigation, and route optimization in intelligent transportation systems.

Although predictive performance has improved substantially, different ML algorithms are better suited to specific applications. Deep learning models excel in healthcare and time-series analysis, Random Forest and Gradient Boosting perform well in agricultural applications, and LSTM, Graph Neural Networks, and reinforcement learning show strong results in energy forecasting and intelligent transportation. However, most existing studies focus primarily on predictive accuracy while giving limited attention to computational efficiency, scalability, explainability, deployment cost, and environmental sustainability, highlighting the need for more balanced and practical AIoT solutions.

Deployment Challenges and Implementation Trade-Offs

Despite significant advances in Artificial Intelligence of Things (AIoT), several challenges continue to hinder its large-scale deployment. Key barriers include interoperability among heterogeneous IoT devices, cyber security and privacy risks, the high computational and energy demands of deep learning models, and the limited interpretability of many "black-box" machine learning algorithms. In addition, developing countries face significant obstacles due to inadequate infrastructure, high implementation costs, shortages of skilled personnel, and limited research funding.

These findings highlight the need for future AIoT systems to adopt balanced approaches that optimize predictive accuracy while ensuring computational efficiency, explainability, security, affordability, and sustainability. Addressing these challenges is essential for enabling the scalable and practical deployment of intelligent IoT ecosystems across diverse application domains.

Implications for Sustainable Development

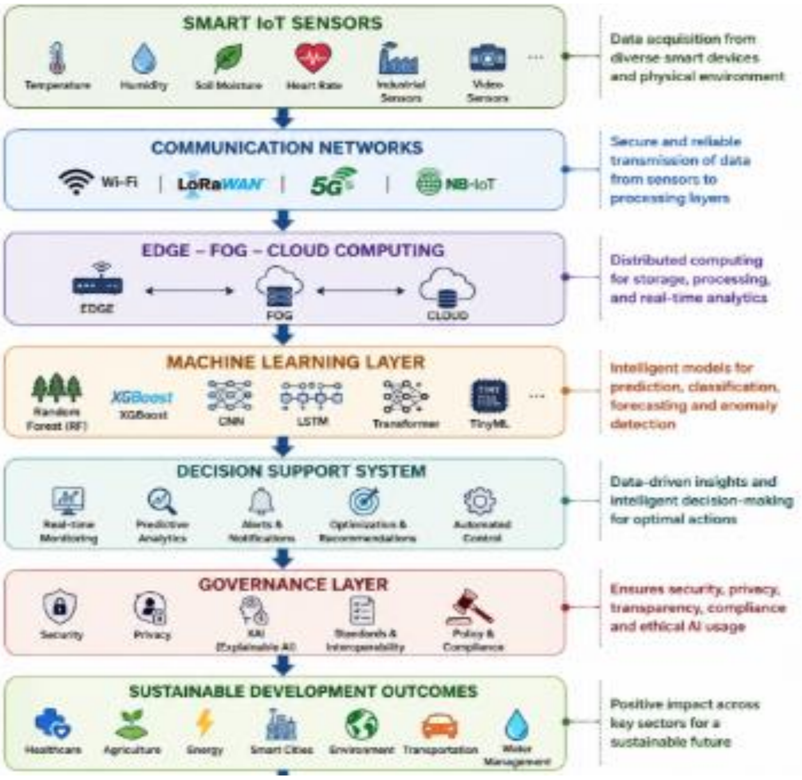
The findings indicate that integrating the Internet of Things (IoT) and Machine Learning (ML) has significant potential to advance sustainable development through intelligent resource management, predictive decision-making and autonomous system optimization. However, successful implementation requires not only technological innovation but also supportive policies, investment in digital infrastructure, workforce development, interoperable standards, and strong cyber security governance. The review also highlights that existing research is largely technology-focused, with limited consideration of socio-economic factors, implementation feasibility, and long-term sustainability, especially in low-resource settings. Therefore, future research should adopt multidisciplinary approaches and develop integrated frameworks that combine IoT infrastructure, intelligent analytics, decision-support systems, and sustainability outcomes to address both technological and practical challenges.

Proposed Conceptual IoT-Machine Learning Framework for Sustainable Development

The systematic review and critical analysis conducted in this study reveal that existing Internet of Things (IoT) and Machine Learning (ML) research has made substantial contributions toward intelligent automation and sustainable development. However, most previous studies focus on isolated application domains such as healthcare, agriculture, energy management, transportation, or smart cities, with limited efforts devoted to integrating these findings into a unified conceptual framework. Furthermore, existing reviews primarily describe technological developments without explaining how IoT infrastructure, intelligent analytics, decision-support mechanisms, and sustainability objectives interact to produce measurable societal outcomes (Jaber, 2023; Lampropoulos et al., 2024).

To address this issues, this paper proposes a Conceptual IoT-Machine Learning Framework for Sustainable Development. The framework synthesizes evidence from the reviewed literature into a holistic architecture that integrates intelligent sensing, communication technologies, edge intelligence, cloud computing, machine learning, decision support, governance, and sustainability outcomes. Unlike previous review studies, the proposed framework not only summarizes current knowledge but also provides a roadmap for designing scalable, secure, explainable, and sustainable AIoT ecosystems.

Figure 2: Architecture of the Proposed Framework



The proposed framework consists of seven interconnected layers that collectively transform raw environmental data into intelligent and sustainable decisions.

Layer 1: Smart Sensing Layer

The first layer comprises IoT-enabled sensing devices responsible for collecting real-time information from physical environments. These include environmental sensors, wearable healthcare devices, smart meters, industrial sensors, drones, cameras, autonomous vehicles, and wireless sensor networks. The diversity of sensing devices enables continuous monitoring across sectors such as healthcare, agriculture, energy, transportation, manufacturing, and environmental protection.

Layer 2: Communication and Connectivity Layer

Data generated by IoT devices are transmitted through heterogeneous communication technologies including Wi-Fi, Bluetooth Low Energy (BLE), ZigBee, LoRaWAN, NB-IoT, 5G, and emerging 6G networks. Reliable communication infrastructure is essential for maintaining interoperability, scalability, and real-time data exchange among distributed IoT systems.

Layer 3: Edge-Fog-Cloud Computing Layer

Rather than transmitting all sensor data directly to centralized cloud platforms, the framework adopts a distributed computing architecture combining edge computing, fog computing, and cloud computing. Edge devices perform preliminary data filtering, aggregation, compression, and anomaly detection near the data source, thereby reducing latency, bandwidth consumption, and communication costs. Computationally intensive tasks such as deep learning model training and long-term storage are executed within cloud infrastructures.

Layer 4: Intelligent Analytics Layer

The intelligent analytics layer forms the core of the proposed framework. Machine learning algorithms analyse IoT-generated data to support prediction, classification, clustering, optimization, anomaly detection, and autonomous decision-making.

Depending on application requirements, multiple categories of algorithms may be employed, including:

i. Supervised Learning (Random Forest, XGBoost, Support Vector Machine, CatBoost, LightGBM)
ii. Deep Learning (CNN, LSTM, GRU, Transformer Networks)
iii. Unsupervised Learning (K-Means, DBSCAN, Autoencoders)
iv. Reinforcement Learning
v. Federated Learning
vi. TinyML and Edge AI

This hybrid analytical approach enables intelligent systems to adapt to changing environmental conditions while minimizing computational overhead and maximizing predictive accuracy.

Layer 5: Decision Support Layer

The outputs generated by intelligent analytics are transformed into actionable knowledge through intelligent decision-support systems. This layer provides predictive dashboards, visualization platforms, early warning systems, optimization engines, recommendation systems, and automated control mechanisms capable of supporting evidence-based decision-making by governments, industries, healthcare professionals, farmers, environmental agencies, and urban planners.

Layer 6: Governance and Security Layer

Effective deployment of AIoT ecosystems requires robust governance mechanisms addressing cyber security, privacy protection, interoperability standards, ethical artificial intelligence, regulatory compliance, and data governance. Explainable Artificial Intelligence (XAI) should be integrated to improve model transparency, accountability, and stakeholder trust, particularly within high-risk applications such as healthcare, transportation, and public administration.

Layer 7: Sustainable Development Outcomes

The final layer represents measurable sustainability impacts generated through intelligent IoT ecosystems. These include:

i. Smart Healthcare
ii. Precision Agriculture
iii. Renewable Energy Management
iv. Smart Manufacturing
v. Smart Transportation
vi. Environmental Monitoring
vii. Water Resource Management
viii. Smart Cities
ix. Circular Economy
x. Climate Change Mitigation

Collectively, these outcomes contribute directly to achieving multiple United Nations Sustainable Development Goals, including SDGs 2, 3, 6, 7, 9, 11, 12, and 13.

Mathematical Representation of the Proposed IoT-Machine Learning Framework

To improve the analytical rigor of the proposed framework, this section presents the mathematical formulation describing the interaction among IoT sensing, data preprocessing, machine learning, decision support, and sustainability outcomes. The formulations provide a generalized representation applicable to multiple IoT application domains including healthcare, smart agriculture, renewable energy, transportation, environmental monitoring, and smart cities.

IoT Data Acquisition

Assume that an IoT system consists of **N** interconnected sensing devices.

The complete sensor dataset is represented as

$$D = \{x_1, x_2, \ldots, x_N\}$$

Where

(D) Denotes the complete IoT dataset;

(x_i) Represents an individual observation;

(N) is the total number of IoT sensing devices.

Each sensor observation is defined as

$$x_i = (t_i,\ s_i,\ l_i,\ a_i)$$

Where

x_i = the i-th IoT sensor observation

t_i = timestamp of the observation

s_i = sensor measurement/value

l_i = geographical location

a_i = additional contextual attributes

The collected data are continuously transmitted to the intelligent processing layer through wireless communication technologies including Wi-Fi, ZigBee, LoRaWAN, NB-IoT, Bluetooth Low Energy, and 5G networks.

Data Pre-processing

Raw IoT data frequently contain noise, missing values, redundant observations, and inconsistent measurements. Therefore, preprocessing is performed before model training.

The transformed dataset is expressed as

$$D_p = f(D)$$

Where

D_p = processed IoT dataset

D = raw IoT dataset

f(·) = data preprocessing function, including data cleaning, normalization, missing-value treatment, feature extraction, and dimensionality reduction.

For normalization,

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Where

x′ = normalized value

x = original data value

x_{min} = minimum value in the dataset

x_{max} = maximum value in the dataset.

Machine Learning Prediction Model

The intelligent prediction function is represented by

$$\hat{Y} = F(D_p, \theta)$$

Where

Y^ = predicted output generated by the machine learning model

F(·) = machine learning prediction function

Dp = preprocessed IoT dataset

θ = learned model parameters or weights.

Depending on the application, (F) may represent Random Forest, Support Vector Machine, Artificial Neural Network, XGBoost, CatBoost, LightGBM, Convolutional Neural Network, Long Short-Term Memory, and Transformer Networks.

Model Optimization

The optimal parameter set is obtained by minimizing the prediction error

$$\theta^{*} = \arg\min_{\theta} L(Y, \hat{Y})$$

Where

θ∗ = optimal model parameters

θ = model parameters being optimized

L(Y,Y^) = loss function measuring the difference between actual and predicted outputs

Y = actual/observed output

Y^ = predicted output

For regression problems,

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

Where:

n = total number of observations

Yi = actual/observed value for observation i

Y^i = predicted value for observation i

Yi−Y^i = prediction error

(Yi−Y^i)2 = squared prediction error

For classification,

$$\text{CrossEntropy} = -\sum_{i=1}^{n} Y_i \log\left(\hat{Y}_i\right)$$

Where:

n = number of observations or classes, depending on the classification formulation

Yi = actual/true label

Y^i = predicted probability for the corresponding class

log(Y^i) = logarithm of the predicted probability

These optimization functions enable the learning algorithm to iteratively improve predictive performance.

Decision Support Function

The optimized prediction is transformed into actionable decisions through

$$S = g(\hat{Y})$$

Where

S = intelligent decision-support output

g(·) = decision function or decision-making rule

Y^ = predicted output generated by the machine learning model

Typical decisions include disease alerts, irrigation scheduling, traffic optimization, predictive maintenance, renewable energy balancing, and anomaly detection.

Sustainability Performance Function

The overall sustainability impact is represented by

$$SD = f(E_c, E_n, S_o)$$

Where

SD = sustainable development performance or outcome

f(·) = function representing the relationship among sustainability dimensions

Ec = economic sustainability

En = environmental sustainability

So = social sustainability

The objective is

$$\max SD$$

Subject to

i. Minimum energy consumption;
ii. Maximum prediction accuracy;
iii. Acceptable deployment cost;
iv. Data privacy requirements;
v. Cyber security constraints.

Overall AIoT Optimization Model

The complete optimization objective becomes

$$\max (\alpha A + \beta Sc + \gamma EE + \delta Ex - \lambda C)$$

Where

A = predictive accuracy

Sc = scalability

EE = energy efficiency

Ex = explainability

C = computational/implementation cost

α,β,γ,δ,λ = weighting coefficients representing the relative importance of each objective.

The coefficients

$$\alpha A + \beta Sc + \gamma EE + \delta Ex - \lambda C$$

Represent weighting parameters satisfying

$$\alpha + \beta + \gamma + \delta + \lambda = 1$$

This multi-objective formulation reflects the practical reality that AIoT systems must balance predictive performance with computational efficiency, interpretability, scalability, and deployment cost rather than optimizing a single performance metric.

Discussion

The mathematical representation demonstrates that intelligent IoT systems operate as a sequence of interconnected processes beginning with data acquisition, followed by preprocessing, machine

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learning prediction, optimization, decision support, and sustainability evaluation. Unlike many existing review papers that describe these processes conceptually, the proposed formulation explicitly defines the mathematical relationships among system components and provides a generalized analytical model applicable across multiple IoT application domains.

Furthermore, the multi-objective optimization framework recognizes that practical AIoT deployment requires simultaneous consideration of predictive accuracy, scalability, energy efficiency, explainability, and implementation cost. This provides a theoretical foundation for evaluating future AI-powered IoT architectures designed to support the Sustainable Development Goals.

Conclusion

The integration of the Internet of Things (IoT) and Machine Learning (ML) has become a transformative approach for enabling intelligent digital transformation and sustainable development across sectors such as healthcare, agriculture, energy, transportation, manufacturing, and environmental monitoring. This review demonstrates that IoT-ML integration enhances real-time monitoring, predictive decision-making, resource optimization, and autonomous system control. However, the comparative analysis reveals that no single machine learning algorithm is universally optimal, emphasizing the need for hybrid and adaptive AIoT architectures that balance predictive accuracy, computational efficiency, scalability, interpretability, and sustainability.

The review also identifies persistent challenges, including interoperability, cyber security, privacy, computational complexity, infrastructure limitations, and policy constraints, particularly in developing countries. To address these issues, it proposes a Conceptual IoT–Machine Learning Framework for Sustainable Development, integrating IoT infrastructure, intelligent analytics, governance mechanisms, and sustainability outcomes. Furthermore, the review highlights emerging technologies such as Edge AI, TinyML, Explainable AI (XAI), Federated Learning, Digital Twins, and Green AI as key enablers of future AIoT ecosystems. Overall, the study provides both theoretical and practical guidance for researchers, policymakers, and industry practitioners while establishing a roadmap for developing secure, scalable, and sustainable AI-powered IoT systems that contribute to achieving the United Nations Sustainable Development Goals (SDGs).

Theoretical Implications

This review advances the understanding of Internet of Things (IoT) and Machine Learning (ML) integration by providing a comprehensive and critical synthesis of recent AIoT research for sustainable development. It goes beyond descriptive reviews by evaluating competing machine learning techniques, identifying key research gaps, and proposing a Conceptual IoT–Machine Learning Framework for Sustainable Development that integrates IoT sensing, intelligent analytics, distributed computing, governance, and sustainability outcomes within a unified architecture. The framework also incorporates emerging technologies such as Edge AI, TinyML, Explainable AI (XAI), Federated Learning, Digital Twins, and Green AI, providing a strong foundation for future interdisciplinary research.

In addition, the review demonstrates that the effectiveness of machine learning algorithms depends on application context, data characteristics, computational requirements, scalability, and interpretability, highlighting the need for context-aware and hybrid AI approaches rather than a single optimal algorithm. Finally, the proposed mathematical representation offers a generalized analytical foundation for understanding AIoT systems by describing the relationships among data acquisition, intelligent learning, optimization, decision support, and sustainability outcomes, thereby supporting future empirical validation and computational modelling.

Practical Implications

The findings of this review provides practical guidance for policymakers, industry practitioners, technology developers, and researchers involved in deploying intelligent IoT ecosystems for sustainable development. It emphasizes the need for investments in digital infrastructure, advanced communication networks, cybersecurity, and AI governance, while encouraging organizations to adopt scalable, secure, explainable, and cost-effective AIoT architectures. The proposed conceptual framework offers a roadmap for integrating emerging technologies such as Edge AI, TinyML, Federated Learning, Explainable AI (XAI), and Digital Twins to improve efficiency, privacy, energy management, and autonomous decision-making.

For researchers, the review identifies promising directions including lightweight machine learning models, energy-efficient AI, sustainable AI, intelligent digital twins, privacy-preserving federated learning, and AI-driven decision-support systems. From a societal perspective, widespread adoption of AIoT has the potential to improve healthcare, agriculture, renewable energy, environmental protection, transportation, and smart city development, thereby contributing significantly to the achievement of the United Nations Sustainable Development

Goals (SDGs) related to health, clean energy, sustainable cities, climate action, and responsible resource management.

Policy Implications for Developing Countries

Although developed countries continue to lead AIoT innovation, many developing countries face significant barriers related to inadequate digital infrastructure, limited financial resources, shortage of skilled professionals, unreliable electricity supply, and weak regulatory frameworks. Addressing these challenges requires coordinated national strategies involving governments, universities, research institutions, industry, and international development organizations.

Governments should prioritize investment in broadband connectivity, affordable cloud services, digital literacy programmes, and research funding while establishing national standards for interoperability, cyber security, and ethical AI. Public-private partnerships can accelerate technology transfer and facilitate the deployment of scalable AIoT solutions tailored to local socio-economic conditions. Such initiatives will help reduce the digital divide and enable developing countries to benefit from intelligent technologies that support inclusive and sustainable development.

Future Research Directions

The review identifies several key future research directions for advancing the integration of the Internet of Things (IoT) and Machine Learning (ML) to support sustainable development. Promising areas include Edge AI and TinyML for real-time, low-latency intelligence on resource-constrained devices; Explainable Artificial Intelligence (XAI) to improve transparency and trust in AI-driven decisions; Digital Twins for predictive simulation and infrastructure optimization; Federated Learning for privacy-preserving distributed intelligence; and Sustainable/Green AI to reduce the energy consumption and environmental impact of AI models. In addition, future AIoT systems should leverage emerging technologies such as 6G networks, satellite IoT, and block chain to enhance connectivity, scalability, security, and resilience across diverse application domains.

The review further emphasizes that successful AIoT deployment requires more than technological innovation. Future research should focus on developing integrated AI-powered architectures aligned with the United Nations Sustainable Development Goals (SDGs) while addressing interoperability, governance, ethical AI, cyber security, and international standardization. Achieving fully autonomous, adaptive, and sustainable cyber-physical ecosystems will require close collaboration among researchers, governments, industry, and policymakers. The proposed conceptual framework provides a comprehensive foundation for designing, implementing, and evaluating next-generation intelligent IoT ecosystems that promote environmental sustainability, economic resilience, and social well-being.

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